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Parametric and Non-Parametric Analyses for Pedestrian Crash Severity Prediction in Great Britain

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Abstract: The study aims to investigate the factors that are associated with fatal and severe vehicle–pedestrian crashes in Great Britain by developing four parametric models and five non-parametric tools to predict the crash severity. Even though the models have already been applied to model the pedestrian injury severity, a comparative analysis to assess the predictive power of such modeling techniques is limited. Hence, this study contributes to the road safety literature by comparing the models by their capabilities of identifying the significant explanatory variables, and by their performances in terms of the F-measure, the G-mean, and the area under curve. The analyses were carried out using data that refer to the vehicle–pedestrian crashes that occurred in the period of 2016–2018. The parametric models confirm their advantages in offering easy-to-interpret outputs and understandable relations between the dependent and independent variables, whereas the non-parametric tools exhibited higher classification accuracies, identified more explanatory variables, and provided insights into the interdependencies among the factors. The study results suggest that the combined use of parametric and non-parametric methods may effectively overcome the limits of each group of methods, with satisfactory prediction accuracies and the interpretation of the factors contributing to fatal and serious crashes. In the conclusion, several engineering, social, and management pedestrian safety countermeasures are recommended.

Keywords: random parameter multinomial logit; ordered logit; association rules; classification trees; random forests; artificial neural networks; support vector machines; pedestrian crashes

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1. Introduction

The identifying factors that affect the crash injury severity, and understanding how these factors affect the injury severity, are critical in the planning and implementation of highway safety improvement programs. There is also great emphasis on serious injury crashes in the EU Road Safety Policy Framework 2021–2030 [1], which has the target of halving the serious injuries by 2030, and the goal of enhancing the accessibility and safety of vulnerable road users. Moreover, the number of pedestrians that were injured or that are dead as a consequence of vehicle–pedestrian crashes is increasing over time. As an example, in Great Britain, the proportion of fatal and severe injuries that involved pedestrians increased from 22.5% in 2011, to 28.9% in 2019 [2].

Since the risk factors that are associated with pedestrian-related crashes on transportation networks are usually different than those for motor vehicles, further actions are strongly needed to improve pedestrian safety. The main aim of our study is to investigate the factors that are associated with fatal and severe pedestrian crashes in Great Britain by developing four parametric models and five non-parametric tools in order to explore the co-existence of the pedestrian, driver, vehicle, roadway, and environmental factors. When the

interactions between these factors and the severity are co-considered and co-investigated, the severe injury causes and the related solutions can be better identified [3], which can assist in the selection of appropriate safety countermeasures in order to contribute to the EU goals. Furthermore, in order to provide support for the choice of the appropriate prediction method, the nine parametric and non-parametric methods are compared by their capabilities of identifying the significant explanatory variables that affect the crash severity, and by their performances. Finally, the study also addresses the issue of the imbalanced distributions of the crash severity levels. A small proportion of fatal crashes is a common feature of most crash datasets [4] and, hence, many researchers merge fatal crashes with severe crashes in order to gain better performances from the implemented models [5–7]. However, in our study, we decided not to join fatal and serious injury crashes together in order to identify both of the factors that contribute to fatal and serious injury crashes. The unbalanced data issue was treated by introducing weights, which forced the estimator to learn on the basis of the importance (which is based on the weight) that was given to a particular severity level.

2. Prior Research

The analysis of prior research highlights the presence of two main groups of methods that are usually implemented in crash severity analyses. The two groups consist of parametric models and non-parametric tools.

Among the parametric models, the most widely used is the multinomial logit (MNL) model (e.g., [8–10]). However, over the past decade, several studies have highlighted some multinomial logit methodological limitations that could affect the study results with erroneous inferences and biased crash predictions [11,12]. Indeed, the multinomial logit model does not account for the unobserved heterogeneity, which forces the effects of the observable variables to be the same across all observations. Consequently, the model may be misspecified, and the estimated parameters may be biased and inefficient.

Thus, methodological approaches have been performed in order to gain more precise estimations by explicitly accounting for the observation-specific variations in the effects of the explanatory variables [13,14]. Among them, the random parameter (or simply the "mixed" parameter) model allows the parameters to vary across individual crashes, which range from negative to positive, and which are of varying magnitudes [15].

On the other hand, by recognizing the ordinal nature of the crash severity data, other studies have been conducted by performing ordered response models [12,16]. Thus, among the most popular discrete choice approaches, discrete ordered probability methods (such as ordered logit models) have shown great appeal. Yamamoto et al. [17] further suggest that the traditional unordered models may provide unbiased estimates of the parameters, especially in cases of missing data and under-reporting. Despite the ordinal nature of the injury severity variable, many researchers [18–20] point out that the traditional ordered response structure may impose a certain kind of monotonic effect of the independent variables on the injury severity levels. A chance to overcome the ordered logit model limitation comes with the mixed ordered response logit model, which generalizes the standard ordered response model, allows the flexibility of the effects of the covariates on the threshold value for each ordinal category, and captures the heterogeneous effects [21].

Hence, both the ordered and unordered models have their benefits and limitations, and the choice of one method over the others is governed by the availability and characteristics of the data and involves considering the trade-offs [16]. However, all of the parametric models suffer fundamental limitations, such as the presumption of the crash data distribution, and their restrictions on the linear relationship between the severity outcomes and the explanatory variables. Furthermore, it is also well known that no-injury and minor injury crashes are very rarely reported to the police [14,16], and an outcome-based model may result in biased parameter estimates when traditional statistical estimation techniques are used, which limits the ability to manage road safety. Another downside of the traditional statistical models is related to their difficulties in handling and processing

very large amounts of data, so that, in the last few years, data-driven methods have been applied to crash analyses in an attempt to overcome the issue.

Free from a priori parametric assumptions [5], data-driven methods, which are also known as "non-parametric algorithms", include association rules (ARs), classification trees (CTs), random forests (RFs), artificial neural networks (ANNs), and support vector machines (SVMs). Association rules discovery (which is also known as the "supervised association mining technique") has been widely used to discover patterns from crash databases [22–24]. Classification trees have already been developed to uncover the patterns that influence the crash severity for different road users in several papers [25]. Recently, other researchers have implemented the random forest in lieu of the classification tree since it considers an ensemble of trees instead of one [26,27]. Another tree-structure algorithm is the ANN tool [28], which has been used to investigate vehicle–pedestrian crashes. Among the non-parametric methods, there is also an increasing interest in using the SVM tool to investigate the patterns that contribute to the pedestrian crash severity [29], which is due to the straightforward algorithm abilities that the tool has demonstrated in providing a better prediction performance than other traditional methods.

The parametric and non-parametric model limitations in predicting the fatal and serious injury crashes in the presence of imbalanced data have been demonstrated by several studies [30,31]. To date, two common approaches have been proposed over the years to address the problem [32,33]: (1) The application of learning approaches at the algorithm level, and then, the calculation of the performance measures on the original dataset; and (2) Sampling techniques that are used at the database level. The latter implies both oversampling and undersampling. Oversampling replicates the instances from the minor class, and it repeats them until all of the classes have an equal frequency. Undersampling discards the majority class instances until the majority class reaches the size of the minor classes. It only considers the closeness of the data, and the intrinsic characteristics are not taken into consideration [34]. The main drawback of the two sampling techniques is that they change the original dataset by creating a new distorted sample around the decision boundary of the majority and minority classes. Table 1 provides a summary of the key literature findings.

Table 1. Summary of the key literature findings.

Issue	References
The MNL is the most widely used model to investigate the crash contributory factors.	[8–10]
The MNL limits the effect of each attribute so that they are the same across all observations.	[11,12]
Random parameter models overcome the limits of the fixed formulation of the MNL.	[13–15]
Multinomial parametric models do not consider the ordered nature of the crash severity.	[16,17]
Standard ordered models impose a monotonic effect of the independent variables on all the injury severity levels.	[18,20]
Random parameter models overcome the limits of the fixed formulations of the standard unordered and ordered models.	[11–15,21]
All parametric models require a priori assumptions.	[14]
Non-parametric models do not require a priori assumptions and they handle large amounts of data.	[13]
Limited prediction abilities of both parametric and non-parametric models in the presence of imbalanced data.	[30,31]

3. Crash Data

The crash data that was used in this study refer to the crashes that occurred in Great Britain in the three-year period of 2016–2018. The detailed road safety data were collected in the STATS19 dataset that is provided by the Department of Transport. The crash information

was collected by the police at the scene of the crash, or it was reported by a member of the public at a police station. All of the reported crashes occurred on public highways (including footways), and they included crashes with at least one vehicle (or a vehicle in collision with a pedestrian) that was involved, and that resulted in personal injury. Originally, the crash data were provided in three subsets that reported the crash, the vehicle, and the casualty-related information. In order to obtain a unique set of information, the three subsets were merged by using the crash index as a key reference. Finally, only the pedestrian crashes (67,356 pedestrian crashes, or 17.3% of the total crashes) were considered. The final dataset was rearranged by using 34 explanatory variables, as is shown in the Appendix A section, Tables A1–A6. The variables were divided into: crash (Tables A1 and A2); vehicle (Tables A3 and A4); driver (Table A5); and pedestrian (Table A6) characteristics. Several of the categories were aggregated and recoded in order to avoid extremely small occurrences, to remove redundant information, and to make the models easier to interpret.

The Great Britain crash database provides three different crash severity levels: slight injury, serious injury, and fatal crashes. The crash severity is classified according to the injury severity of the most seriously injured person involved in the crash. A fatal crash is a crash where at least one person dies within 30 days of the crash. A serious injury crash is a crash where a person is detained in the hospital as an "in-patient", or where a person suffers from any of the following injuries: fractures, concussion, internal injuries, burns, severe cuts, severe general shock that requires medical treatment, and injuries that result in death within 30 days of the crash. Lastly, it is considered that a slight injury of a minor character, such as a sprain (which includes a neck whiplash injury), a bruise or a cut that is not judged to be severe, or a slight shock that requires roadside attention, are injuries for which medical treatment is not required. In our database, the crash severities were as follows: fatal (n = 1366; 2.0% of the total crashes); serious (n = 16,359; 24.3% of the total crashes); and slight (n = 49,631; 73.7% of the total crashes).

4. Method

In our study, the crash severity is assumed to be the dependent variable. The investigation of the contributory factors that affect the crash severity was carried out using parametric and non-parametric models. The methodological process is presented in Figure 1. Figure 1 also contains information on the kinds of outputs that were provided by each group of models. Furthermore, links to the paper sections are provided as well.

4.1. Parametric Models

4.1.1. General Issues

Econometric models, which are also referred to as "discrete choice models", are widely used in crash severity analyses. These models use the theoretical utility (U_{ij}), which, in the context of road safety applications, represents the propensity that a crash (i) will be recorded with a severity level (j), following the expression reported below [35]:

$$U_{ij} = V_{ij} + \varepsilon_{ij} \quad (1)$$

where V_{ij} is the systematic component; and ε_{ij} is the disturbance term.

The crash severity, as a three-level variable, is very adaptable to econometric models with both unordered and ordered formulations. Indeed, each level of crash severity is linked to: (1) The increasing severity of the most seriously injured person that is involved in the crash; and to (2) The increasing costs in terms of the human, medical, and damage factors, which involve losses in terms of the life years and the quality of life. Thus, the crash severity has an ordinal nature, which could be addressed by performing the analysis with the ordered formulation. In this study, we used both unordered and ordered logit models. Furthermore, both unordered and ordered models were used in the standard formulation with fixed parameters, as well as in the formulation with random parameters (Figure 2).

The random parameter models allow the effects of the independent variables to vary across different observations (i.e., the crashes in our study).

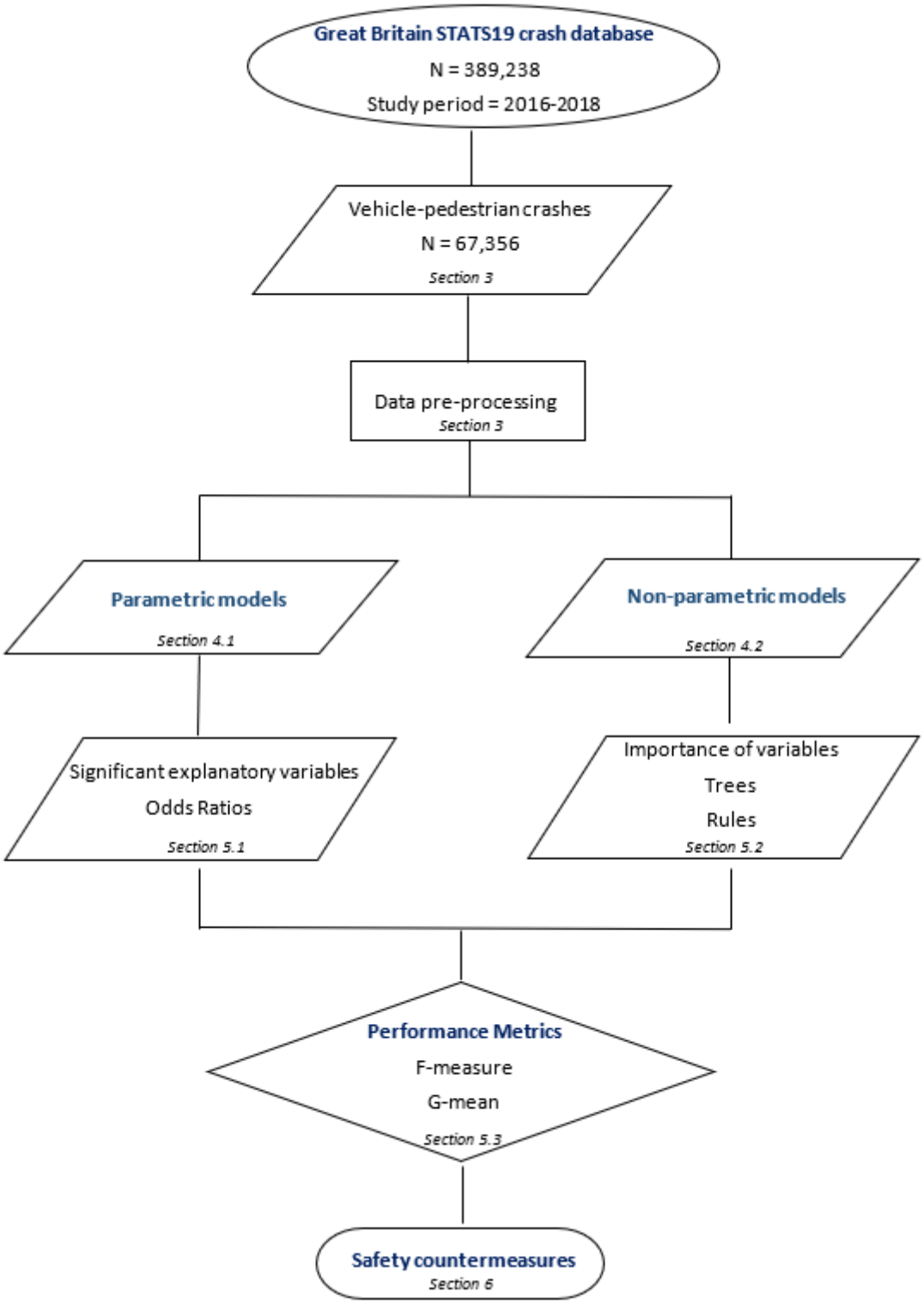


Figure 1. Methodological process.

All of the models were estimated by maximum likelihood stepwise methods. The forward stepwise approach to choosing a model begins with a null model, and it adds terms sequentially until further additions do not improve the fit. At each stage, it selects the term that produces the greatest improvement in the fit [36,37].

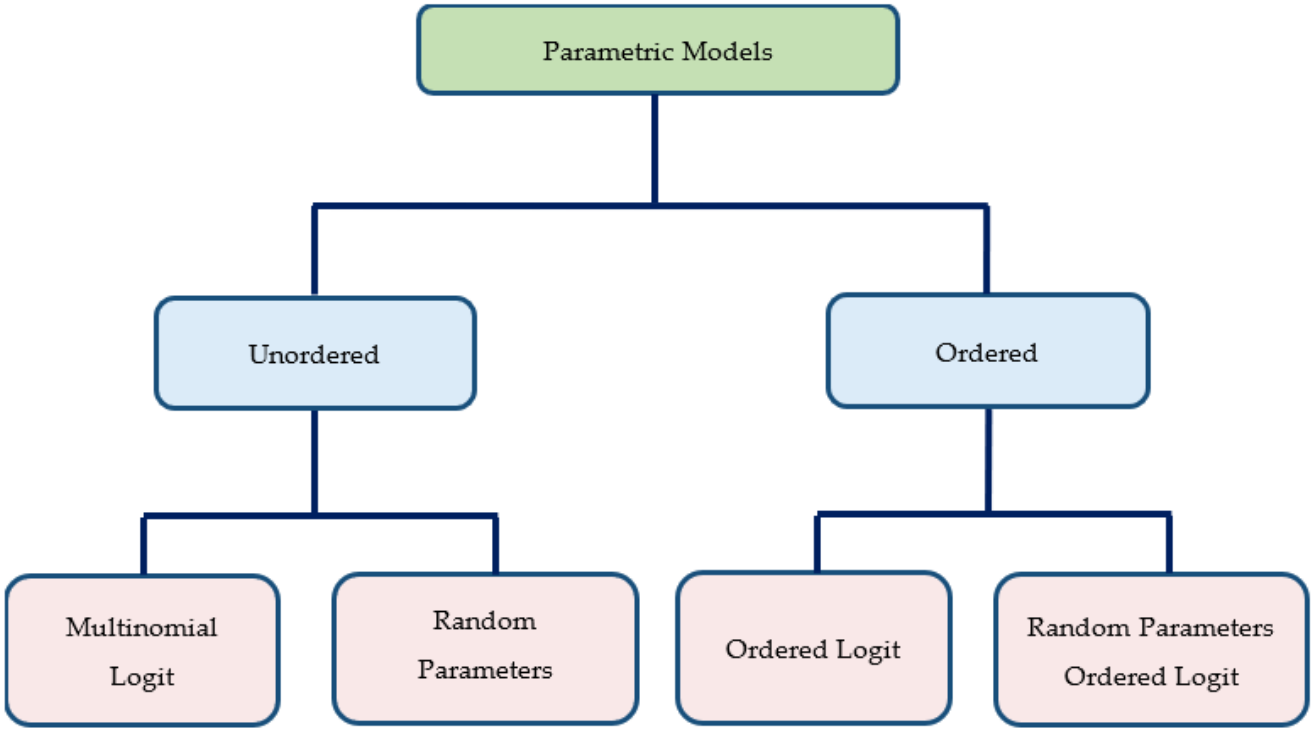


Figure 2. Parametric models that were used in the study.

For choosing the correct model, the likelihood ratio (LR) test is estimated as part of the random ordered/unordered model in order to determine the significance of the random formulation relative to the standard ordered/unordered logit model. The LR test compares the likelihood of the mixed model to the likelihood of the standard model:

$$\text{LR test} = -2\log\left(\frac{L_{MIXED}}{L_{ST}}\right) = -2(\log L_{MIXED} - \log L_{ST}) \quad (2)$$

where L_{MIXED} is the likelihood of the mixed model; and L_{ST} is the likelihood of the fixed parameter model.

The likelihood ratio test statistic has an approximate χ^2 distribution, with k (the number of predictors) degrees of freedom. If the LR test *p*-value is less than 0.05, the random parameter logit model is superior to the standard model, with over 95% confidence. This indicates that the random parameter multinomial logit model provides a statistically superior fit relative to the traditional fixed parameter model [38].

Cross-validation was used to determine the generalizability and the overall utility of the prediction models.

All of the explanatory variables were transformed into dummy variables through a complete disjunctive decoding process. The predictors with multiple categories (k) were converted to a series of indicator variables (dummy variables) with k−1 variables, and the k-th dummy variable was not inserted into the model in order to avoid incurring the problem of perfect multicollinearity. All of the indicator variables were used to estimate the four logistic regression models and were tested for inclusion. Each indicator variable was assessed for its importance to the injury severity by using the z-test, with a significance level of 10%. All four models were developed using the STATA software.

4.1.2. Multinomial Logit Model

The crash severity analysis can be carried out by considering the three classes (slight injury, serious injury, and fatal crashes) as the possible discrete outcomes. In the general case of a multinomial logit model for the crash injury severity outcomes, the propensity of

the crash (i) (i = 1, . . . , I) towards the severity category (j) (j = 1, . . . , J) is represented by the severity propensity function [14]:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \beta_j' x_{ij} + \varepsilon_{ij} \quad (3)$$

where V_{ij} is the systematic component;

ε_{ij} is the disturbance term, which is assumed to be independently and identically distributed following the Type I generalized extreme value distribution (i.e., the Gumbel distribution), with the mean equal to zero and the variance equal to one, and the scale parameter is η [14,39];

x_{ij} is a (K × 1) column vector of K exogenous attributes (geometric variables, environmental conditions, driver characteristics, etc.) that affects the pedestrian injury severity level (j); and

β_j is a (K × 1) column vector of the estimable parameters for the crash severity category (j).

For a standard multinomial logit, the utility is linear in β, and then $V_{ij} = \beta_j x_{ij}$. Each β_j represents the estimated impact of the variable, x_{ij}, on the response variable, y_i. The standard multinomial logit formulation takes the following form:

$$P(y_i = j) = P_i(j) = \frac{e^{(\beta_j' x_{ij} + \varepsilon_{ij})}}{\sum_{j=1}^{J} e^{(\beta_j' x_{ij} + \varepsilon_{ij})}} \quad (4)$$

In a standard multinomial logit formulation, the βs are assumed to be fixed across the observations, and the standard multinomial logit model is considered to be a fixed parameter model.

The factor exp(β) is the odds ratio (OR), and it indicates the relative amount by which the odds of the outcome increase (OR > 1) or decrease (OR < 1) when the value of the corresponding indicator variable is 1.

4.1.3. Random Parameter Multinomial Logit Model

The random parameter multinomial logit model, which is also known as the "mixed multinomial logit model", is the generalized form of the multinomial logistic regression model, in which the coefficients of any of the variables are not limited to a fixed value but are allowed to vary across observations, or the analyst-specified groups of observations. This specification is the same as for the standard logit, except that, instead of being fixed, the β varies among the observations. The β coefficients are random and can be decomposed into their means and standard deviations [11]:

$$U_{ij} = V_{ij} + \varepsilon_{ij} = \beta_j' x_{ij} + \varepsilon_{ij};\ \beta_j' = B + \widetilde{\beta}_j \quad (5)$$

where V_{ij} is the systematic component; ε_{ij} is the disturbance term, which is assumed to be independently and identically distributed across the crash severity levels and the crashes; x_{ij} is a (K × 1) column vector of K exogenous attributes (geometric variables, environmental conditions, driver characteristics, etc.) that are specific to the crash (i) and that affect the pedestrian injury severity level (j); β_j' is a crash-specific (K × 1) column vector of the corresponding parameters that varies across the crashes on the basis of the unobserved crash-specific attributes; b are the means of the β' random coefficients; and $\widetilde{\beta}_j$ are the standard deviations of the β' random coefficients.

Hence, the standard multinomial logit hypotheses are relaxed (i.e., the mixed logit does not exhibit independence from the irrelevant alternatives), and one or more parameters can be randomly distributed in the mixed model. Indeed, the presence of correlations between the unobserved characteristics of each observation violates the disturbance independence assumptions for the error terms, which leads to erroneous parameter estimates, whereas the random parameter model addresses the unobserved heterogeneity within the parameters that vary across the individual observations. If unobserved heterogeneity is allowed, then

β_j is a vector with a continuous density function, which means that the unconditional probability of an individual (i) experiencing the severity level (j) from the set of severity outcomes (J) is obtained by considering the integrals of the standard multinomial logit probabilities over the density of the parameters, and it can be expressed in the form [40]:

$$P_i(j) = \int \frac{e^{\beta_j' x_{ij}}}{\sum_J e^{\beta_j' x_{ij}}} f(\beta\,|\theta\,)d\beta \quad (6)$$

where x_{ij} is a (K × 1) column vector of K exogenous attributes (geometric variables, environmental conditions, driver characteristics, etc.) that are specific to the crash (i), and that affect the pedestrian injury severity level (j); β_j' is a crash-specific (K × 1) column vector of the corresponding parameters that varies across the crashes on the basis of the unobserved crash-specific attributes; $f\,(\beta\,|\theta\,)$ is the density function of the β coefficients; and θ is a vector of the parameters that describes the density function of the β coefficients in terms of the mean and the variance.

The random multinomial logit probability is expressed as the weighted average of the probability that is evaluated with the multinomial logit formula at different values of β, with the weights provided by the density function (f(β)). The standard multinomial logit is a special case of the mixed logit formulation because if β_j = b for each observation, there is no crash-specific unobserved heterogeneity among the data, and the random parameter model coincides with the standard multinomial logit with fixed parameters (b), and f(β) = 1 for β_j = b, while it is 0 for $\beta_j \neq b$.

4.1.4. Ordered Logit Model

The multinomial logit model disregards the ordered nature of the injury severity levels and treats them as independent alternatives; thus, the ordering information is lost [21]. The model is based on the cumulative probabilities of the response variables, and it is assumed that the logit of each cumulative probability is a linear function of the covariates, with regression coefficients that are constant across the response categories. In this case, the effects of the explanatory variables on the severity levels are assumed to be fixed across the observations. In other words, ordered logistic regression assumes that the coefficients that describe the relationship between the lowest versus all of the higher categories of the dependent variable (which is the crash severity in our study) are the same as those that describe the relationship between the next lowest category and all of the higher categories. This is also called the "proportional odds assumption", "the parallel regression assumption", or the "grouped continuous model" [41]. Assuming that the severity of a crash is an ordered discrete variable with j categories (slight, serious, and fatal), three levels are given meaningful numeric values, usually 0, 1, . . . , J (J is the upper limit). Slight, serious, and fatal might be labeled as "0", "1", and "2", respectively, and the numerical values represent a ranking so that, for the crash severity, the "1" label is more severe than the "0" label in a qualitative sense, and the difference between the "2" and the "1" is not the same as for that between the "1" and the "0". In this case, although the numerical outcomes are merely the labels of the non-quantitative outcomes, the analysis will nonetheless have a regression-style motivation [42]. The severity propensity function is assumed as it is reported in Equation (7), and the ordinal response (y_i) can be expressed as:

$$y_i = \begin{cases} 0 \text{ if } -\infty \leq U_i \leq \mu_1 \\ j \text{ if } \mu_{j-1} < U_i \leq \mu_j \\ J \text{ if } \mu_{J-1} < U_i \leq +\infty \end{cases} \quad (7)$$

where μ_j represents the upper threshold for the injury severity (J); μ_{j-1} represents the lower threshold for the injury severity (J); and μ_j and μ_{j-1} are the values of the cutoff, or the cut-points.

The cumulative probability can be written as [41]:

$$P_i(j) = \frac{e^{(\beta_j' x_{ij} + \varepsilon_{ij} - \mu_j)}}{1 + e^{(\beta_j' x_{ij} + \varepsilon_{ij} - \mu_j)}}, \; j = 1, 2, \ldots, J-1 \tag{8}$$

4.1.5. Random Parameter Ordered Logit Model

The random parameter ordered logit model allows the thresholds in the ordered logit model to vary on the basis of both the observed, as well as the unobserved, characteristics. It also accommodates the unobserved heterogeneity in the effects of the exogenous variables on the injury propensity and on the threshold values through a suitable specification of the thresholds that relaxes the restriction of identical thresholds [21]. As for the mixed multinomial logit model, Equation (10) determines the probability that the crash (i) will result in the injury-severity level (j). Hence, both the βs and the threshold (μ) can systematically vary across crashes because of the observed and unobserved factors: in an ordered random parameter logit model, the thresholds also consist of a systematic component and unobserved disturbance error terms, which thus allows for unobserved variability and randomness in the thresholds, as is expressed by the formula below:

$$\mu_{ij} = V_j + \tau_{ij} \tag{9}$$

where V_j is a systematic component; and τ_{ij} is the unobserved disturbance error term.

Finally, the likelihood function for the individual (i) represents the probability of the injury severity that will be experienced by that individual, and it can be evaluated as:

$$P_i(j) = \int \frac{e^{(\beta_j' x_{ij} + \varepsilon_{ij} - \mu_j)}}{1 + e^{(\beta_j' x_{ij} + \varepsilon_{ij} - \mu_j)}} f(\beta\,|\theta)\,d\beta \; j = 1, 2, \ldots, J-1 \tag{10}$$

Therefore, in order to account for these circumstances, a random parameter ordered logit model was developed to capture the unobserved heterogeneity, which is achieved by adding a randomly distributed error term.

4.2. Non-Parametric Models

Five popular non-parametric algorithms, namely, association rules, classification trees, random forests, artificial neural networks, and support vector machines, were used to predict the injury severities of the pedestrian crashes. As data-driven and non-parametric methods, the machine learning algorithms do not require any a priori assumptions about the relationships between the variables.

4.2.1. Association Rules

As a descriptive–analytic methodology, the association rules are used for extracting knowledge from large datasets by generating rules that have the form: A→B. Each rule contains at least one pattern, which is called the "antecedent" (A), as well as a "consequent" (B). In our study, the latter consists of the fatal or serious injury severities. The a priori algorithm (which was introduced by Agrawal et al. [43]) generates rules by using simple and repetitive steps, and by examining all of the candidate item-sets in order to find the frequent item-sets, until no new ones can be produced. All of the valid rules satisfy the support, confidence, and lift thresholds, where the support is the percentage of the entire dataset that is covered by the rule (Equation (11)), the confidence measures the reliability of the inference of the rule (Equation (12)), and the lift is a measure of the statistical interdependence of the rule (Equation (13)):

$$S(A \to B) = \frac{\#(A \cap B)}{N}; \; S(A) = \frac{\#(A)}{N}; \; S(B) = \frac{\#(B)}{N}; \tag{11}$$

$$\text{Confidence} = \frac{S(A \rightarrow B)}{S(A)} \quad (12)$$

$$\text{Lift} = \frac{S(A \rightarrow B)}{(S(A) \times S(B))} \quad (13)$$

where S(A→B) is the support of the association rule; S(A) is the support of the antecedent; S(B) is the support of the consequent; #(A→B) is the number of crashes, where both Conditions A and B occur; #(A) is the number of crashes with A as the antecedent; #(B) is the number of crashes with B as the consequent; and N is the total number of crashes in the dataset.

A rule with a single antecedent and a single consequent is defined as a "two-item rule"; similarly, a rule with two antecedents and a single consequent is defined as a "three-item rule". Each rule with $n + 1$ items is validated by verifying that each variable produces a lift increase (LIC). The LIC ensures that each additional item in the rules leads to an increase in terms of the lift.

The rules with only one item in the antecedent are used as a starting point, and the rules with more items are selected over simpler ones by verifying that each variable produces a lift increase (LIC) that is not smaller than 1.05 [44]. The LIC ensures that each additional item in the rules leads to an increase in terms of the lift. The LIC is calculated as follows:

$$\text{LIC} = \frac{\text{Lift}_{A_n}}{\text{Lift}_{A_{n-1}}} \quad (14)$$

where A_{n-1} is the antecedent of the rule with n−1 items; and A_n is the antecedent of the rule with n items.

The threshold values of the support (S), the confidence (C), and the lift (L) were set as follows: S ≥ 0.1%; C ≥ 4.0%; L ≥ 1.2; and LIC ≥ 1.05. The association rules were performed in the R-CRAN software environment using the package, "arules".

4.2.2. Classification Trees

A classification tree is a nonlinear tool and an oriented graph, where the root node is divided into leaf nodes by an explanatory variable that is also called the "splitter". All of the independent variables are candidates for the splits at each internal node of the tree. However, only the predictor that provides the best partition is chosen. In our study, we developed the CART algorithm, which was introduced by Breiman et al. [45], and the impurity at each node was assessed by the Gini reduction criterion (the higher the value of the Gini index, the higher the homogeneity of the node that is due to the split), which can be calculated as follows:

$$i_Y(t) = 1 - \sum_j p(j|t)^2 \quad (15)$$

where P(j | t) is the proportion of the observations in the node (t) that belong to the class (j).

If a node is "pure", all of the observations in the node belong to one class, and the impurity of that node is zero.

The total impurity of any tree (T) is defined as follows:

$$i_Y(T) = \sum_{t \in \widetilde{T}} i_Y(t) p(t) \quad (16)$$

where $i_Y(t)$ is the impurity of the node (t); p(t) = N(t)/N is the weight of the node (t); N(t) is the number of observations that fall in the node (t); N is the total number of observations; and $\widetilde{T}$ is the set of terminal nodes of the tree (T).

By definition, the terminal nodes present low degrees of impurity compared with the root node.

The total impurity of the tree is reduced by finding, at each node of the tree, the best partition of the observations into disjoint classes, which are externally heterogeneous and internally homogeneous.

The choice of the best classification rule was made through the V-fold cross-validation estimate. The initial set (S) is randomly divided into a V > 2-fold (S_v for v = 1, 2 . . . , V). The corresponding estimate of the error rate is given by:

$$ER_v{}^{CART} = \frac{\sum_{i=1}^{N_v}\left(\hat{Y}^{CART}(X_i) \neq Y_i\right)}{N_v} \quad (17)$$

where $\hat{Y}^{CART}(X_i)$ is the predicted class for the i^{th} observation; X_i is the vector of the descriptors of the i^{th} observation; Y_i is the class label of the i^{th} observation; and N_v is the numerosity of the set (S_v).

The estimate of the error rate, which is based on cross-validation (ER), is obtained by combining the individual estimates for all the possible subsets (S_v).

$$ER = \frac{\sum_{v=1}^{V} ER_v{}^{CART}}{V} \quad (18)$$

The tree growing was stopped on the basis of two criteria: (1) If the reduction in the Gini measures was less than a prespecified minimum fixed value that was equal to 0.0001 (default value); and (2) If the maximum number of levels of the tree were equal to 4. These parameters were chosen to minimize the error rate.

The class assigned to each node was selected according to the greatest value of the posterior classification ratio (PCR) that was evaluated for that node. The PCR compares the classification of the terminal nodes of the tree with the classification of the root node, and it is calculated as follows [24]:

$$PCR(j|t) = \frac{p(j|t)}{p(j|t_{root})} \quad (19)$$

where $p(j \mid t)$ is the proportion of the observations in the node (t) that belong to the class (j); and t_{root} is the root node of the tree.

One of the outputs that is provided by the CART technique is the variable importance, which defines the variable's ability to influence the model. The relative importance of the variable (VI) (X_j) is calculated as follows:

$$VI = \sum_{t=1}^{T} \frac{N(t)}{N} \Delta i_Y(t, s) \quad (20)$$

where VI represents the relative importance of the variable (X_j); $\Delta i_Y(t,s)$ is the reduction in the Gini index that is obtained by splitting the variable (X_j) at the node (t); N is the total number of observations; and T is the number of nodes in the tree.

The classification trees were carried out with SPSS software.

4.2.3. Random Forests

Classification trees, despite their advantages, have sometimes been found to generate unstable predictions given certain perturbations; thus, in order to improve the stability, Breiman [46] proposed the RF method. RFs are an ensemble of B trees $\{T_1(X), \ldots, T_B(X)\}$, where $X_i = \{x_{i1}, \ldots, x_{ip}\}$ is a p-dimensional vector of the descriptors or properties that are associated with the i^{th} crash. The ensemble produces B outputs $\{\hat{Y}_1 = T_1(X), \ldots, \hat{Y}_B = T_B(X)\}$, where $\hat{Y}_b$, b = 1, . . . , B, is the prediction for a crash by the b^{th} tree. The outputs of all of the trees are aggregated to produce one final prediction: $\hat{Y}$. For classification problems, $\hat{Y}$ is the class that is predicted by the majority of the trees.

Given the data on a set of *n* crashes, $D = \{(X_1, Y_1), \ldots, (X_n, Y_n)\}$, where X_i is a vector of the descriptors, and Y_i is the corresponding class label for the i^{th} crash, with i = 1, . . . , n. The algorithm proceeds as follows:

1. A bootstrap sample, which creates a random sample with a replacement from the original sample, with the sample size (N_t) replicated B times.

2. For each bootstrap sample, the growing of a tree uses the CART algorithm, and chooses, at each node, the best split among a randomly selected subset of descriptors;
3. Repeat the above steps until B trees are generated.

However, it has been shown that there is a potential overestimate of the true prediction error, depending on the choices of the random forest hyperparameters, such as the number of trees (B), and the number of descriptors. To reduce the true prediction error, the out-of-bag estimate of the error rate (ER^{OOB}) was estimated by varying the B and the number of descriptors:

$$ER^{OOB} = \frac{\sum_{i=1}^{N}\left(\hat{Y}^{OOB}(X_i) \neq Y_i\right)}{N} \quad (21)$$

where $\hat{Y}^{OOB}(X_i)$ is the predicted class for the i^{th} crash; X_i is the vector of the descriptors of the i^{th} crash; Y_i is the class label of the i^{th} crash; and N is the total number of crashes.

The values of the number of trees and the number of descriptors were chosen so that the ER^{OOB} tends to stabilize around the minimum value.

The variable importance measure for the variable, x_j, $(VI(x_j))$, is computed as the sum of the importances over all of the trees in the forest:

$$VI(x_j) = \frac{\sum_{t=1}^{ntrees} VI^t(x_j)}{ntrees} \quad (22)$$

where $Vi^t(x_j)$ is the variable importance of the t^{th} tree that is calculated using Equation (20); and ntrees is the number of trees.

The RF was performed in the R-CRAN software environment using the packages, "randomForest", and "randomForestSRC".

4.2.4. Artificial Neural Networks

As is the classification tree and the RF, the ANN is also an oriented graph that is inspired by a biological neural network. Similar to the structure of the human brain, the ANN models consist of neurons in complex and nonlinear forms. The ANN models work by creating a nonlinear relationship between the dependent and independent variables, depending on a set of experimental data. The neurons are connected to each other by weighted links. ANNs consist of a layer of input nodes and a layer of output nodes that are connected by one or more layers of hidden nodes. The input-layer nodes pass information to the hidden-layer nodes by firing the activation functions, and the hidden-layer nodes fire, or remain dormant, depending on the evidence that is presented. The hidden layers apply weighting functions to the evidence, and, when the value of a particular node or set of nodes in the hidden layer reaches a certain threshold, the value is passed to one or more nodes in the output layer.

The technique creates a feed-forward multilayer perceptron ANN, which consists of multiple nodes (or neurons) that are organized into three or more layers, with a backpropagation learning process to minimize the classification errors. In our study, a three-layer network was implemented, as previous studies suggest that ANNs with singular hidden layers are less likely to be trapped at a local minimum [47,48]. Thus, the information flows from the input layer, passes through the hidden layer, and then flows to the output layer to produce a classification. The hidden layer has $1 + \sum_{p=1}^{P} k_p$ neurons (consider a dataset that contains P independent variables that are classified on the k_p potential risk factors that have effects on the crash severity), and each risk factor is represented by a node, while another constant node is included, which represents the bias. The output layer has three neurons, which accord with the three severity levels in the study.

The neurons of the input layer transfer information to the hidden layer through the hyperbolic tangent activation function, and from the hidden layer to the output layer through the softmax function.

$$z = \text{softmax}\left[\sum_{j=1}^{J} w_j^{(2)} \tanh\left(\sum_{p=1}^{P} w_{j,p}^{(1)} k_p\right)\right] \quad (23)$$

where J is the number of neurons in the hidden layer; $w_{j,p}^{(1)}$ is the connection weight between the hidden node (j, j = 1, ... J) and the input node (p, p = 1, ... , P); k_p are the factors; and $w_j^{(2)}$ is the weight of the connection between the output node (z) and the hidden node (j).

In the output layer, Z = 3 nodes expresses the severity outcomes that are predicted by the ANN, and y_i is the i^{th} observed response in the dataset. If, for the i^{th} crash, y_i = z, then z = 1, while z = 0 if otherwise.

The connection weights were estimated by using a backpropagation learning process to minimize the classification errors. Standard backpropagation is a gradient descent algorithm in which the network weights are moved along the negative of the gradient of the performance function. The combination of weights that minimize the error function is considered to be a solution to the learning problem. The backpropagation algorithm proceeds as follows:

1. The backpropagation algorithm starts with random weights, and the goal is to adjust them to reduce this error until the ANN learns the training data;
2. If the expected output is not obtained, backward propagation begins. The difference between the actual and the expected outputs is calculated recursively and step by step, and the error is returned through the original link access;
3. The weight and the value of each neuron are then modified and are transmitted successively to the input layer, and the forward multilayer perceptron restarts.

These two processes (forward multilayer perceptron and backpropagation error) are repeated so that the error gradually decreases. The goal is to minimize the error by adjusting the weights so that the optimum weights are obtained after the error backpropagation.

The gradient (G) of a weighting to the error, the total error (E), and the total mean square errors (e_p) are defined as:

$$G = \frac{\partial E}{\partial w} \quad (24)$$

$$E = \sum e_p \quad (25)$$

$$e_p = \frac{1}{2}\sum_{k-1}^{m}\left(y_k^p - \overline{y}_k^p\right)^2 \quad (26)$$

where w is one of the network weightings (w_{pl}, w_{jp}, w_{kj}); y_k^p is the actual output; and $\overline{y}_k^p$ is the expected output.

The adjustment of the weight is calculated as:

$$\Delta w^{new} = -\eta G + \alpha \Delta w^{old} \quad (27)$$

where Δw^{new} is the present adjustment for the weighting or for the threshold; Δw^{old} is the immediate past value of its counterpart; α is a dynamic coefficient, and it takes a value in the range of between 0 and 1; and G is the gradient of a weighting to the error.

This procedure was applied to the categorical data after transforming the categorical variables into dummy variables through a complete disjunctive decoding process. The predictors with multiple categories (k) were converted into a series of indicator variables (dummy variables) with k variables.

Moreover, the k-fold cross-validation procedure was used in each modeling phase of the ANN.

The importance of a specific explanatory variable is determined by identifying all of the weighted connections between the nodes of interest. All of the weights that connect the specific input node, which passes through the hidden layer to the specific response variable, are identified. This is repeated for all of the other explanatory variables, until all of the weights that are specific to each input variable are determined.

The ANN was performed with the SPSS software.

4.2.5. Support Vector Machines

A SVM, which was developed by Cortes and Vapnik [49], is used to develop an optimal separating hyperplane to categorize the observations into several groups, while maximizing the margin between the decision boundaries and minimizing the empirical error. The predictors are defined as the vectors ($X_i = \{x_{i1}, \ldots, x_{ip}\}$), where p represents the full set of crash-related variables, and the outcome is defined as y_k, which represents the injury severity levels of the crashes. Hence, the plane constitutes the decision boundaries, and the hyperplane is a $p-1$ dimensional plane. The decision boundaries may or may not be linear, depending on the pre-set kernel function. The radial basis function (RBF) is the most commonly used for crash severity analyses since it is capable of capturing the nonlinearity relationships between the crash severity and the explanatory variables [50]:

$$K(X_i, X_j) = \exp(-\gamma \mid X_i - X_j \mid^2), \gamma > 0 \quad (28)$$

c where X_i and X_j are the vectors of the explanatory variables for the i^{th} and the j^{th} crashes; $\mid X_i - X_j \mid^2$ is the Euclidean distance between the two crashes, X_i and X_j; and $\gamma = 1/\sigma^2$, where σ^2 is the variance of the samples selected by the model as support vectors.

The development of the SVM model also depends on the penalty parameter (C) of the error term. It controls the trade-off between smooth decision boundaries, and the correct classification of the points, and it is calculated as follows:

$$ER^{SVW} = \frac{\sum_{i=1}^{N}\left(\hat{Y}^{SVM}(X_i) \neq Y_i\right)}{N} \quad (29)$$

where $\hat{Y}^{SVM}(X_i)$ is the predicted class for the i^{th} crash; X_i is the vector of the descriptors of the i^{th} crash; Y_i is the lass label of the i^{th} crash; and N is the total number of crashes.

To determine the separability of the optimal hyperplane, a grid search was used for the joint optimization of the C and γ parameters and for the feature selection. This approach methodically builds and evaluates a model for each combination of algorithm parameters (γ and C) that are specified in a grid. For each model, the classification error was used as a performance measure. The combination of the hyperparameters with the lower classification error was chosen in order to develop the optimal hyperplane.

To effectively combine these parameters, and to avoid overfitting, the cross-validation method was used for each developed model, which provided information about how well the SVM generalizes, specifically in terms of the range of expected errors.

The variables that contribute to the separability of the optimal hyperplane provide an indication of the relative importances of the variables to the separation.

The SVM was performed in the R-CRAN software environment using the packages, "caret" and "e1071".

4.3. Dealing with Imbalanced Data

The study data are characterized by imbalanced classes, with order ratios of 2:100 for the fatal crashes, and of 25:100 for the serious injury crashes. The issues that are relative to the classification performance with imbalanced data have been highlighted in previous studies (e.g., [30,31,33,51]).

To take into account the skewed distribution of the classes, different weights were given to both the majority and minority classes. The difference in the weights influenced

the classification of the classes during the learning phase. The whole purpose is to penalize the misclassification that is made by the minority class by setting a higher class weight and, at the same time, reducing the weight for the majority class. The weight was assigned so that the response variable was equally distributed among the categories. The class weights are inversely proportional to their respective frequencies [52–54]. Each weight can be assessed as follows:

$$W_k = \frac{N_{crashes}}{n_c \times N_k} \tag{30}$$

where k is the number of the crash severity level, with 1 = slight injury; 2 = serious injury; and 3 = fatal; w_k is the weight that is assigned to the respective level of severity (k); $N_{crashes}$ is the total number of crashes in the dataset; n_c = 3, which is equal to the number of crash severity levels that are considered in the study; and N_k is the number of crashes with a severity level (k).

4.4. Comparison among the Models

A classifier aims to minimize the false positive rates (which represent Type I errors) and the false negative rates (which represent Type II errors), which maximizes the true negative and positive rates. Among the common performance metrics that are used to evaluate the classification performance, the accuracy and the error rate are the most widely used. However, when the distribution of the response variable is extremely imbalanced, the accuracy has certain limitations. The error rate suffers from similar drawbacks. First, it is easy to obtain high accuracies (or low error rates) under highly imbalanced problems. Secondly, these classifiers assume that the errors are of equal value, which is not true for the imbalanced data, where misclassifying the instances of the minority classes (fatal and serious injury crashes) is generally much costlier than misclassifying the instances of the majority class (slight injury crashes) [55,56]. Moreover, the correct classification of the factors that contribute to fatal and serious injury crashes is a far cry from the correct identification of the factors that contribute to slight injury crashes.

Hence, we chose to assess the multiparameter indicators, namely, the F-measure, the G-mean, and the area under the curve (AUC), in order to evaluate the performances of the implemented models in a single measure.

The performance measures are expressed as follows [33]:

$$Acc^- = \frac{TN}{TN + FP} = \text{specificity} \tag{31}$$

where Acc^- is the true negative rate, which is also known as the "specificity"; TN is the number of true negatives; and FP is the number of false positives.

$$Acc^+ = \frac{TP}{TP + FN} = \text{Recall} = \text{sensitivity} \tag{32}$$

where Acc^+ is the true positive rate, which is also known as the "recall", or the "sensitivity"; TP is the number of true positives; and FN is the number of false negatives.

$$G - \text{mean} = \left(Acc^- \times Acc^+\right)^{\frac{1}{2}} \tag{33}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{34}$$

$$F - \text{measure} = \frac{\left(1 + \beta^2\right) \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{35}$$

where β is a coefficient for adjusting the relative importance of the precision and recall, which is set at a value that is equal to 1.

The G-mean combines the performances of the positive and negative classes, whereas the F-measure combines the cases that are correctly classified with the Type I and Type II errors. Indeed, when the errors increase, the F-measure decreases. The F-measure is also the weighted harmonic mean of the precision and recall (which are both referred to as the "minority class"), and a high F-measure usually indicates the model's good overall performance. The AUC is the area under the receiving operating curve (ROC), and it is a widely used graphical plot that illustrates the ability of a classifier that is assessed by plotting the true positive rate (TPR) (which is also known as the "sensitivity") on the vertical axis against the false positive rate (FPR) (which is also known as the "specificity") on the horizontal axis at various threshold settings. When the ROC curve is created, the AUC can be assessed. The AUC represents the probability that the classifier correctly identifies an observation that is randomly selected among the positive cases. An AUC value varies between 0 and 1. An AUC greater than 0.60 is considered satisfactory [57].

Once the performance metrics for each class are evaluated, the final values are the weighted mean, in which the relative frequencies of the classes on the data are their weights [58].

5. Results

5.1. Parametric Models

All the explanatory variables that are reported in the appendix section (Tables A1–A6) were tested for inclusion in the econometric models. The estimation results are reported in Tables 2–5. The variable indicators that are not statistically significant at the 0.10 level of significance, either for the fatal crashes or for the serious injury crashes, were removed from the tables.

Table 2. Multinomial logit model: parameter estimates and goodness-of-fit measures.

Variable	Fatal				Serious			
	Estimate	**OR**	**Std. Err.**	**P > |z|**	**Estimate**	**OR**	**Std. Err.**	**P > |z|**
Intercept	−5.215	0.005	0.129	<0.001	−1.529	0.217	0.031	<0.001
Number of vehicles ("1 vehicle" as baseline)								
2	0.682	1.978	0.106	<0.001	0.183	1.201	0.042	<0.001
≥3	1.170	3.222	0.187	<0.001	0.498	1.645	0.091	<0.001
First Road class ("C" as baseline)								
B					0.091	1.095	0.031	0.004
A	0.558	1.747	0.067	<0.001	0.095	1.100	0.022	<0.001
Motorway	0.979	2.662	0.263	<0.001	0.484	1.623	0.230	0.035
Speed limit ("20 mph" as baseline)								
30 mph	0.382	1.465	0.125	0.002	0.073	1.076	0.037	0.044
40 mph	1.384	3.991	0.163	<0.001	0.565	1.759	0.057	<0.001
≥50 mph	2.227	9.272	0.164	<0.001	0.638	1.893	0.064	<0.001
Area ("Urban" as baseline)								
Rural	0.347	1.415	0.086	<0.001				
Junction detail ("T or staggered junction" as baseline)								
Not at junction					−0.034	0.967	0.015	0.021
Roundabout	−0.353	0.703	0.187	0.059	−0.082	0.921	0.048	0.091
Pedestrian-crossing human control ("None within 50 m" as baseline)								
School-crossing patrol					−0.204	0.815	0.120	0.089
Pedestrian-crossing physical facilities ("None within 50 m" as baseline)								
Zebra	−0.743	0.476	0.169	<0.001	−0.212	0.809	0.037	<0.001
Pelican	0.254	1.289	0.094	0.007	0.114	1.121	0.033	0.001

Table 2. *Cont.*

Variable	Fatal				Serious			
	Estimate	**OR**	**Std. Err.**	**P > |z|**	**Estimate**	**OR**	**Std. Err.**	**P > |z|**
Lighting ("Daylight" as baseline)								
Darkness	1.090	2.974	0.066	<0.001	0.290	1.336	0.022	<0.001
Pavement ("Dry" as baseline)								
Wet or damp	0.142	1.153	0.078	0.069	0.049	1.050	0.027	0.075
Snow	−0.877	0.416	0.306	0.004				
Day of week ("Weekday" as baseline)								
Weekend	0.356	1.428	0.066	<0.001	0.126	1.134	0.023	<0.001
Vehicle maneuver ("Moving off" as baseline)								
Going ahead	1.126	3.083	0.073	<0.001	0.505	1.657	0.026	<0.001
Turning maneuver					0.140	1.150	0.035	<0.001
Reversing maneuver					−0.152	0.859	0.044	0.001
Vehicle skidding and overturning ("No" as baseline)								
Yes	1.165	3.206	0.117	<0.001	0.480	1.616	0.056	<0.001
Vehicle type ("Car" as baseline)								
Bicycle	−1.290	0.275	0.366	<0.001	0.141	1.151	0.064	0.028
Bus	0.710	2.034	0.164	<0.001				
PTW < 500	−1.122	0.326	0.224	<0.001	−0.103	0.902	0.051	0.044
Truck	1.515	4.549	0.124	<0.001				
Vehicle towing and articulation ("No towing/articulation" as baseline)								
Articulated vehicle	1.228	3.414	0.221	<0.001	0.855	2.351	0.141	<0.001
Vehicle propulsion code ("Petrol" as baseline)								
Heavy oil vehicles	0.284	1.328	0.072	<0.001	0.170	1.185	0.033	<0.001
Hybrid vehicles	−0.466	0.628	0.283	0.100	−0.289	0.749	0.062	<0.001
Vehicle age ("≤15 years" as baseline)								
>15 years	0.327	1.387	0.128	0.011	0.213	1.237	0.043	<0.001
Driver gender ("Male" as baseline)								
Female	−0.293	0.746	0.078	<0.001				
Driver age ("35–44 years" as baseline)								
≤24 years	0.596	1.815	0.091	<0.001	0.272	1.313	0.030	<0.001
25–34 years	0.293	1.340	0.076	<0.001	0.145	1.156	0.024	<0.001
Pedestrian gender ("Male" as baseline)								
Female	−0.155	0.856	0.064	0.015	−0.072	0.931	0.019	<0.001
Pedestrian age ("35–44 years" as baseline)								
0–14 years	−0.837	0.433	0.137	<0.001				
15–24 years	−0.534	0.586	0.105	<0.001				
25–34 years	−0.303	0.739	0.103	0.003				
45–54 years					0.154	1.166	0.031	<0.001
55–64 years	0.633	1.883	0.110	<0.001	0.417	1.517	0.033	<0.001
65–74 years	1.295	3.651	0.111	<0.001	0.770	2.160	0.035	<0.001
≥75 years	2.578	13.171	0.092	<0.001	1.111	3.037	0.034	<0.001

Table 2. *Cont.*

Variable	Fatal				Serious			
	Estimate	**OR**	**Std. Err.**	**P > |z|**	**Estimate**	**OR**	**Std. Err.**	**P > |z|**
Log likelihood null model					−48,217.27			
Log likelihood full model					−40,469.52			
R^2McFadden					0.161			
AIC					81,079.04			
BIC					81,717.28			

Note: "Slight injury" was the severity outcome baseline, and its severity function was constrained to zero.

Table 3. Random parameter multinomial logit model: parameter estimates and goodness-of-fit measures.

Variable	Fatal				Serious			
	Estimate	**OR**	**Std. Err.**	**P > |z|**	**Estimate**	**OR**	**Std. Err.**	**P > |z|**
Intercept	−5.364	0.005	0.196	<0.001	−1.041	0.353	0.043	<0.001
Number of vehicles ("1 vehicle" as baseline)								
2	0.735	2.085	0.117	<0.001	0.175	1.191	0.042	<0.001
≥3	1.218	3.380	0.199	<0.001	0.493	1.637	0.090	<0.001
First Road class ("C" as baseline)								
B					0.108	1.114	0.032	0.001
A	0.577	1.781	0.072	<0.001	0.104	1.110	0.022	<0.001
Motorway	1.043	2.838	0.284	<0.001	0.448	1.565	0.215	0.037
Speed limit ("20 mph" as baseline)								
30 mph	0.423	1.527	0.137	0.002	0.051	1.052	0.030	0.088
40 mph	1.478	4.384	0.178	<0.001	0.524	1.689	0.055	<0.001
≥50 mph	2.431	11.370	0.186	<0.001	0.582	1.790	0.061	<0.001
Area ("Urban" as baseline)								
Rural	0.377	1.458	0.096	<0.001				
Junction detail ("T or staggered junction" as baseline)								
Not at junction					−0.044	0.957	0.021	0.035
Roundabout	−2.477	0.084	0.966	0.010	−0.107	0.899	0.059	0.069
Pedestrian-crossing human control ("None within 50 m" as baseline)								
School-crossing patrol					−0.207	0.813	0.123	0.093
Pedestrian-crossing physical facilities ("None within 50 m" as baseline)								
Zebra	−0.781	0.458	0.188	<0.001	−0.231	0.794	0.039	<0.001
Pelican	0.280	1.323	0.098	0.004	0.103	1.108	0.030	0.001
Lighting ("Daylight" as baseline)								
Darkness	1.164	3.203	0.076	<0.001	0.289	1.335	0.022	<0.001
Pavement ("Dry" as baseline)								
Wet or damp	0.153	1.165	0.075	0.041	0.040	1.041	0.023	0.078
Snow	−1.045	0.352	0.359	0.004				
Day of week ("Weekday" as baseline)								
Weekend	0.373	1.452	0.074	<0.001	0.123	1.131	0.023	<0.001

Table 3. *Cont.*

Variable	Fatal				Serious			
	Estimate	**OR**	**Std. Err.**	**P > |z|**	**Estimate**	**OR**	**Std. Err.**	**P > |z|**
Vehicle maneuver ("Moving off" as baseline)								
Going ahead	0.831	2.296	0.154	<0.001	0.513	1.670	0.027	<0.001
Turning maneuver					0.143	1.154	0.037	<0.001
Reversing maneuver					−0.255	0.775	0.051	<0.001
Vehicle skidding and overturning ("No" as baseline)								
Yes	1.266	3.457	0.133	<0.001	0.450	1.568	0.054	<0.001
Vehicle type ("Car" as baseline)								
Bicycle	−1.427	0.240	0.403	<0.001	0.223	1.250	0.067	0.001
Bus	0.634	1.885	0.147	<0.001				
PTW < 500	−1.288	0.276	0.254	<0.001	−0.112	0.894	0.053	0.033
Truck	1.674	5.333	0.151	<0.001				
Vehicle towing and articulation ("No towing/articulation" as baseline)								
Articulated vehicle	1.272	3.568	0.234	<0.001	0.833	2.300	0.141	<0.001
Vehicle propulsion code ("Petrol" as baseline)								
Heavy oil vehicles	0.284	1.328	0.072	<0.001	0.170	1.185	0.033	<0.001
Hybrid vehicles	−0.466	0.628	0.283	0.100	−0.289	0.749	0.062	<0.001
Vehicle age ("≤15 years" as baseline)								
>15 years	0.317	1.373	0.086	<0.001	0.153	1.165	0.023	<0.001
Driver gender ("Male" as baseline)								
Female	−0.343	0.710	0.092	<0.001				
Driver age ("35–44 years" as baseline)								
≤24 years	0.635	1.887	0.101	<0.001	0.294	1.342	0.031	<0.001
25–34 years	0.336	1.399	0.084	<0.001	0.152	1.164	0.025	<0.001
Pedestrian gender ("Male" as baseline)								
Female	−0.156	0.856	0.070	0.027	−0.097	0.908	0.020	<0.001
Pedestrian age ("35–44 years" as baseline)								
0–14 years	−0.884	0.413	0.148	<0.001				
15–24 years	−0.592	0.553	0.116	<0.001				
25–34 years	−0.342	0.710	0.114	0.003				
45–54 years					0.157	1.170	0.031	<0.001
55–64 years	0.668	1.950	0.118	<0.001	0.426	1.531	0.033	<0.001
65–74 years	1.367	3.924	0.120	<0.001	0.785	2.192	0.035	<0.001
≥75 years	2.279	9.767	0.223	<0.001	0.297	1.346	0.179	0.097
Standard deviation of random parameter								
Going-ahead vehicle maneuver	0.997	2.710	0.195	<0.001				
Roundabout	2.583	13.237	0.643	<0.001				
Pedestrian age ≥ 75 years					3.853	47.134	1.036	<0.001
Log likelihood null model					−48,217.21			
Log likelihood full model					−39,565.46			
R^2McFadden					0.179			
AIC					79,274.93			
BIC					79,931.41			

Table 4. Ordered logit model: parameter estimates and goodness-of-fit measures.

Variable	Estimate	OR	Std. Err.	P > |z|
Number of vehicles ("1 vehicle" as baseline)				
2	0.262	1.300	0.039	<0.001
≥3	0.613	1.846	0.083	<0.001
First road class ("C" as baseline)				
B	0.108	1.114	0.030	<0.001
A	0.172	1.188	0.021	<0.001
Motorway	1.003	2.726	0.184	<0.001
Speed limit ("20 mph" as baseline)				
30 mph	0.076	1.079	0.029	0.008
40 mph	0.615	1.850	0.051	<0.001
≥50 mph	1.079	2.942	0.056	<0.001
Junction detail ("T or staggered junction" as baseline)				
Not at junction	−0.046	0.955	0.020	0.021
Roundabout	−0.099	0.906	0.055	0.071
Pedestrian-crossing human control ("None within 50 m" as baseline)				
School-crossing patrol	−0.244	0.783	0.120	0.042
Pedestrian-crossing physical facilities ("None within 50 m" as baseline)				
Zebra	−0.226	0.798	0.037	<0.001
Pelican	0.103	1.108	0.028	<0.001
Lighting ("Daylight" as baseline)				
Darkness	0.409	1.505	0.021	<0.001
Pavement ("Dry" as baseline)				
Wet or damp	0.047	1.048	0.022	0.035
Snow	−0.236	0.790	0.091	0.010
Day of week ("Weekday" as baseline)				
Weekend	0.150	1.162	0.022	<0.001
Vehicle maneuver ("Moving off" as baseline)				
Going ahead	0.587	1.799	0.023	<0.001
Turning maneuver	0.187	1.206	0.032	<0.001
Vehicle skidding and overturning ("No" as baseline)				
Yes	0.607	1.835	0.051	<0.001
Vehicle type ("Car" as baseline)				
Bus	0.184	1.202	0.046	<0.001
PTW < 500	−0.158	0.854	0.051	0.002
Truck	0.462	1.587	0.066	<0.001
Vehicle towing and articulation ("No towing/articulation" as baseline)				
Yes	1.260	3.525	0.129	<0.001
Vehicle propulsion code ("Petrol" as baseline)				
Heavy oil vehicles	0.119	1.126	0.022	<0.001
Hybrid vehicles	−0.340	0.712	0.071	<0.001
Vehicle age ("≤15 years" as baseline)				
>15 years	0.232	1.261	0.042	<0.001
Driver age ("35–44 years" as baseline)				
≤24 years	0.304	1.355	0.029	<0.001
25–34 years	0.155	1.168	0.024	<0.001
Pedestrian gender ("Male" as baseline)				
Female	−0.080	0.923	0.019	<0.001

Table 4. *Cont.*

Variable	Estimate	OR	Std. Err.	P > |z|
Pedestrian age ("35–44 years" as baseline)				
0–14 years	−0.171	0.843	0.025	<0.001
45–54 years	0.233	1.262	0.031	<0.001
55–64 years	0.516	1.675	0.033	<0.001
65–74 years	0.895	2.447	0.035	<0.001
≥75 years	1.393	4.027	0.033	<0.001
Cut points				
Cut1	2.381		0.039	
Cut2	5.385		0.049	
Log likelihood null model			−48,217.27	
Log likelihood full model			−41,017.92	
R^2McFadden			0.149	
AIC			82,101.85	
BIC			82,402.74	

Table 5. Random parameter ordered logit model: parameter estimates and goodness-of-fit measures.

Variable	Estimate	OR	Std. Err.	P > |z|
Number of vehicles ("1 vehicle" as baseline)				
2	0.195	1.215	0.039	<0.001
≥3	0.571	1.770	0.083	<0.001
First road class ("C" as baseline)				
B	0.110	1.116	0.030	0.001
A	0.150	1.162	0.021	<0.001
Motorway	0.925	2.522	0.184	<0.001
Speed limit ("20 mph" as baseline)				
30 mph	0.090	1.094	0.029	0.002
40 mph	0.627	1.872	0.052	<0.001
≥50 mph	1.029	2.798	0.061	<0.001
Junction detail ("T or staggered junction" as baseline)				
Not at junction	−0.057	0.945	0.020	0.004
Roundabout	−0.133	0.875	0.056	0.017
Pedestrian-crossing human control ("None within 50 m" as baseline)				
School-crossing patrol	−0.274	0.760	0.121	0.024
Pedestrian-crossing physical facilities ("None within 50 m" as baseline)				
Zebra	−0.228	0.796	0.037	<0.001
Pelican	0.122	1.130	0.028	<0.001
Lighting ("Daylight" as baseline)				
Darkness	0.336	1.399	0.021	<0.001
Pavement ("Dry" as baseline)				
Wet or damp	0.071	1.074	0.022	0.001
Snow	−0.240	0.787	0.091	0.009
Day of week ("Weekday" as baseline)				
Weekend	0.133	1.142	0.022	<0.001
Vehicle maneuver ("Moving off" as baseline)				
Going ahead	0.536		0.025	<0.001
Turning maneuver	0.203		0.035	<0.001
Vehicle skidding and overturning ("No" as baseline)				
Yes	0.593	1.809	0.051	<0.001

Table 5. *Cont.*

Variable	Estimate	OR	Std. Err.	P > |z|
Vehicle type ("Car" as baseline)				
Bus	0.142	1.153	0.046	0.002
PTW < 500	−0.149	0.862	0.051	0.004
Truck	0.424	1.528	0.066	<0.001
Vehicle towing and articulation ("No towing/articulation" as baseline)				
Yes	1.299	3.666	0.129	<0.001
Vehicle propulsion code ("Petrol" as baseline)				
Heavy oil vehicles	0.209	1.232	0.020	<0.001
Hybrid vehicles	−0.252	0.777	0.070	<0.001
Vehicle age ("≤15 years" as baseline)				
>15 years	0.237	1.267	0.042	<0.001
Driver age ("35–44 years" as baseline)				
≤24 years	0.332	1.394	0.029	<0.001
25–34 years	0.171	1.186	0.023	<0.001
Pedestrian gender ("Male" as baseline)				
Female	−0.074	0.929	0.021	<0.001
Pedestrian age ("35–44 years" as baseline)				
0–14 years	−0.391	0.676	0.032	<0.001
45–54 years	0.334	1.397	0.037	<0.001
55–64 years	0.602	1.826	0.039	<0.001
65–74 years	0.305	1.357	0.040	<0.001
≥75 years	1.000	2.718	0.036	<0.001
Standard deviation of random parameter				
Pedestrian age ≥ 75 years	0.580	1.786	0.036	<0.001
Cut points				
Cut1	0.827		0.014	
Cut2	3.828		0.035	
Log likelihood null model			−48,217.27	
Log likelihood full model			−40,068.60	
R^2McFadden			0.169	
AIC			80,209.10	
BIC			80,537.34	

5.1.1. Multinomial Logit Model

There were 20 statistically significant explanatory variables, and 41 significant indicator variables that were associated with these categorical variables (Table 2). The model's McFadden Pseudo R^2 is equal to 0.16. The most influential variable is the pedestrian age. Compared to young pedestrians (35–44 years), the elderly pedestrians (aged 75 years or more) had increased probabilities of fatal crashes, with an OR of 13.17. Another significant indicator is speed limits ≥ 50 mph., for which the indicator exhibited an OR equal to 9.27.

5.1.2. Random Parameter Multinomial Logit Model

The results for both the fixed and random variables are reported in Table 3. The log-likelihood at zero (−48,217) and at convergence (−39,565) give a McFadden R^2 of 0.18, which is a good result. It is also the highest value that is exhibited among the parametric models that were performed in this study. The goodness-of-fit results and the LR test results show that the random model provides a significant improvement compared to the fixed parameter model. The χ^2 of the LR test is 1808.11, with 3 degrees of freedom, and a p-value < 0.001, which shows that the random parameter multinomial logit model is superior to the standard multinomial logit model, with over 99.9% confidence. Three of the indicator variables show normally distributed random parameters, with statistically

significant standard deviations, which indicates a significant unobserved heterogeneity in the data (Table 3). These variables are: (1) Going-ahead vehicle maneuvers (fatal); (2) Roundabouts (fatal); and (3) A pedestrian age greater or equal to 75 (serious injury). In the prediction of fatal severity, the indicator variable, "roundabout", shows a normal distribution, with a mean of −2.477, and a standard deviation of 2.583. This means that, for 83.1% of the crashes at roundabouts, the probability of the fatal outcome decreased, while, for 16.9% of the observations, the probability of a fatal outcome increased. Similarly, the indicator variable, "going-ahead maneuver", shows a normal distribution, with a mean of 0.831, and a standard deviation of 0.997. This means that, for 79.8% of the observations with vehicles that maneuvered going ahead, the probability of a fatal outcome increased, while, for 20.2% of the observations, the probability of a fatal outcome decreased. In the prediction of severe injury, the indicator variable, "pedestrian age $\geq$ 75", shows a normal distribution, with a mean of 0.297, and a standard deviation of 3.852. This means that, for 53.1% of the observations with pedestrian ages $\geq$ 75, the probability of severe injury increased, while, for 46.9% of the observations, the probability of severe injury decreased. The fixed coefficients of the random parameter multinomial logit were similar in sign and magnitude to the standard multinomial model.

5.1.3. Ordered Logit Model

The ordered logit model was carried out to capture the ordinal nature of the response variable. A positive (or negative) parameter implied the likelihood (or unlikelihood) of a severe injury, with an increasing value of the explanatory variable, and a reduction in the likelihood of a slight injury. There were 18 statistically significant explanatory variables, and 35 significant indicator variables that were associated with these categorical variables (Table 4). The model's McFadden Pseudo R^2 is equal to 0.15, which is the lowest value of fit that is exhibited by the parametric models in the study. Consistent with the unordered models, the most influential variable was the "pedestrian age", which is also the case in the ordered logit model.

5.1.4. Random Parameter Ordered Logit Model

The results for both the fixed and the random variables are reported in Table 5. The goodness-of-fit results and the LR test results show that the random model provides a significant improvement compared to the fixed parameter model. The χ^2 of the LR test is 1832.61, with 1 degree of freedom, and a p-value < 0.001, which shows that the random parameter ordered logit model is superior to the standard ordered logit model, with over 99.9% confidence.

One indicator variable showed normally distributed random parameters, with statistically significant standard deviation, which indicates significant unobserved heterogeneity in the data (Table 5). This variable is the "pedestrian age $\geq$ 75". In the prediction of both the fatal and severe injury severities, the indicator variable, "pedestrian age $\geq$ 75", showed a normal distribution, with a mean of 0.258, and a standard deviation of 0.580. This means that, for 67.8% of the observations with pedestrian ages $\geq$ 75, the probability of the most severe injury increased, while, for 32.8% of the observations, the probability decreased. Similar to the unordered models, the fixed coefficients of the random parameter ordered logit model were similar in sign and magnitude to the standard ordinal model.

5.2. Non-Parametric Models

5.2.1. Association Rules

The a priori algorithm generated 254 rules with the fatal crash as the consequent, and 475 rules with the serious injury crash as the consequent. Furthermore, the extracted rules exhibited, at most, three items as antecedents. Among the rules with the fatal crash as the consequent, 97 rules include the "pedestrian age $\geq$ 75" as the first antecedent, 53 rules include "vehicle engine capacities (CCs) not smaller than 3000+", 33 rules include "rural area", 26 rules include "vehicle skidding and overturning", and 15 include "lighting equal

to darkness—no lighting". Table 6 contains a selection of the high-lift rules with the fatal crash as the consequent. The pedestrian age also generated a considerable number of significant rules for the serious injury crash as the consequent. Out of the 475 rules with the serious injury crash as the consequent, 237 rules exhibited the "pedestrian age" as the first item, which were followed by 74 rules with the "number of pedestrians involved in a crash", and "driver age < 25", with 33 rules.

Table 6. Association rules with the fatal crash as the consequent.

ID Rule	Antecedents			S%	C%	L	LIC
	Item 1	Item 2	Item 3				
1	Vehicle towing and articulation = Yes			0.14	28.87	14.24	n.a.
2	Lighting = Darkness—no lighting			0.33	17.80	8.78	n.a.
3	Lighting = Darkness—no lighting	Speed limit ≥ 50 mph		0.29	30.06	14.82	1.69
4	Speed limit ≥ 50 mph			0.51	16.74	8.25	n.a.
5	Speed limit ≥ 50 mph	Day of week = Weekend		0.16	18.41	9.08	1.10
6	Vehicle type = Truck			0.30	13.64	6.73	n.a.
7	Vehicle skidding and overturning = Yes			0.21	7.63	3.76	n.a.
8	Pedestrian age ≥ 75 years			0.56	7.46	3.68	n.a.
9	Pedestrian age ≥ 75 years	Lighting = Darkness—lights lit		0.15	13.96	6.88	1.87
10	Pedestrian age ≥ 75 years	Lighting = Darkness—lights lit	Vehicle 1st point of impact = Front	0.12	16.94	8.35	1.21
11	Pedestrian age ≥ 75 years	Lighting = Darkness—lights lit	Driver home area = Urban	0.11	14.72	7.26	1.05
12	Pedestrian age ≥ 75 years	Lighting = Darkness—lights lit	Vehicle age ≥ 15 years	0.11	14.68	7.24	1.05
13	Pedestrian age ≥ 75 years	Vehicle Maneuver = Going ahead		0.37	12.30	6.07	1.65
14	Pedestrian age ≥ 75 years	Vehicle Maneuver = Going ahead	Pavement = Wet or damp	0.11	14.14	6.97	1.15
15	Pedestrian age ≥ 75 years	Vehicle Maneuver = Going ahead	Vehicle propulsion = Petrol	0.18	13.87	6.84	1.13
16	Pedestrian age ≥ 75 years	Vehicle Maneuver = Going ahead	Junction detail = T or staggered	0.12	13.42	6.62	1.09
17	Pedestrian age ≥ 75 years	Vehicle 1st point of impact = Front		0.40	10.41	5.13	1.40
18	Pedestrian age ≥ 75 years	Vehicle 1st point of impact = Front	Junction control = Not at junction or within 20 m	0.18	13.16	6.49	1.26
19	Pedestrian age ≥ 75 years	Vehicle 1st point of impact = Front	Vehicle propulsion = Heavy oil	0.17	12.71	6.27	1.22
20	Pedestrian age ≥ 75 years	Vehicle 1st point of impact = Front	Vehicle age ≥ 15 years	0.30	11.18	5.51	1.07
21	Pedestrian age ≥ 75 years	Day of week = Weekend		0.14	9.76	4.81	1.31
22	Pedestrian age ≥ 75 years	Day of week = Weekend	Driver gender = M	0.10	11.09	5.47	1.14
23	Pedestrian age ≥ 75 years	Driver journey purpose = Journey as part of work		0.16	9.70	4.79	1.30
24	Pedestrian age ≥ 75 years	Pavement = Wet or damp		0.15	8.88	4.38	1.19
25	Pedestrian age ≥ 75 years	Vehicle Propulsion = Heavy oil		0.25	8.82	4.35	1.18
26	Pedestrian age ≥ 75 years	Driver gender = M		0.43	8.74	4.31	1.17
27	Pedestrian age ≥ 75 years	Pedestrian gender = M		0.31	8.47	4.17	1.13
28	Pedestrian age ≥ 75 years	Driver age = 25–34 years		0.11	8.10	3.99	1.09
29	Vehicle engine capacity (CC) = 3000+			0.35	6.89	3.40	n.a.

Table 6. *Cont.*

ID Rule	Antecedents			S%	C%	L	LIC
	Item 1	Item 2	Item 3				
30	Vehicle engine capacity (CC) = 3000+	Speed limit ≥ 50 mph		0.10	39.53	19.49	5.74
31	Vehicle engine capacity (CC) = 3000+	Driver journey purpose = Journey as part of work		0.31	8.17	4.03	1.19
32	Vehicle engine capacity (CC) = 3000+	Driver gender = M		0.33	7.33	3.61	1.06
33	Area = Rural			0.68	5.71	2.82	n.a.
34	Area = Rural	Number of vehicles = 2		0.10	10.15	5.00	1.78
35	Area = Rural	Day of week = Weekend		0.22	8.04	3.96	1.41

Table 7 contains the strongest rules that predict serious crashes.

Table 7. Association rules with serious crashes as the consequent.

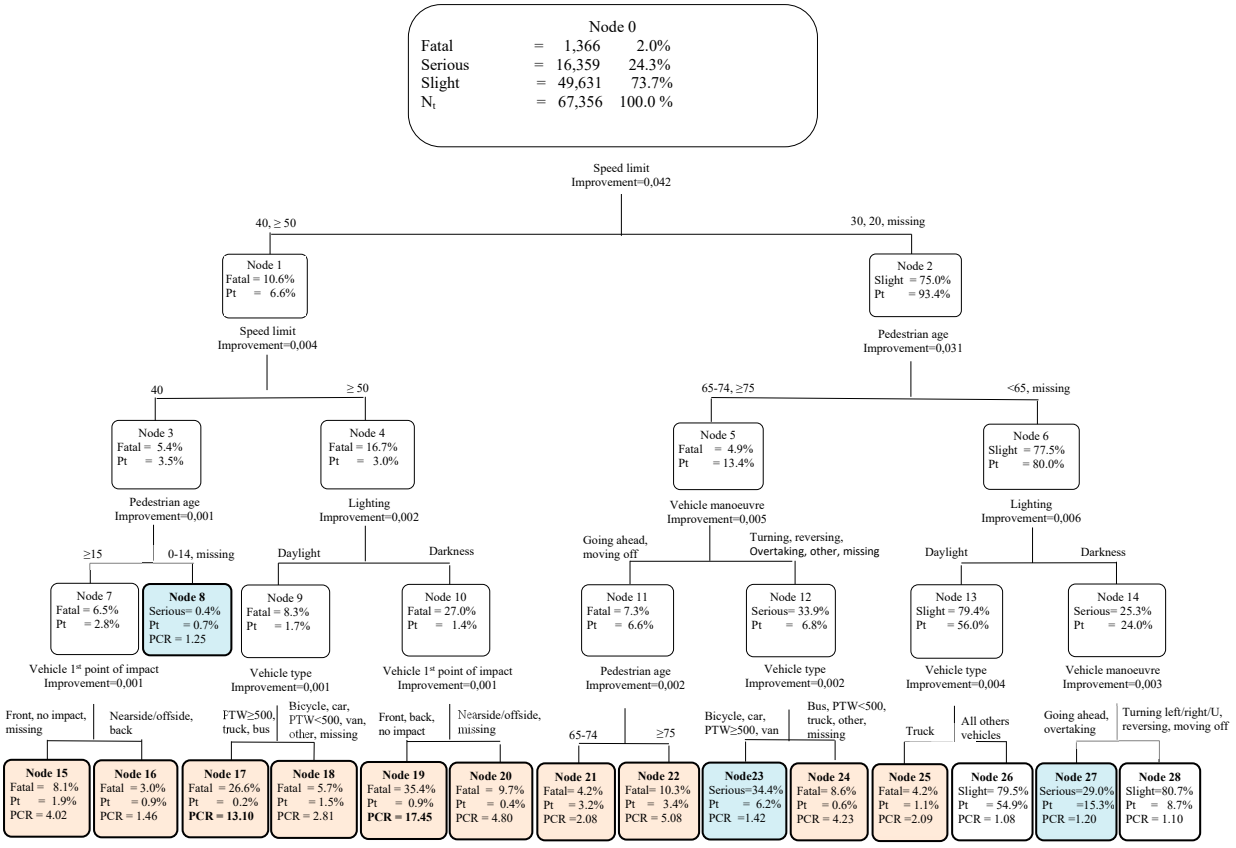
ID Rule	Antecedents			S%	C%	L	LIC
	Item 1	Item 2	Item 3				
36	Number of pedestrians involved ≥ 2			0.14	42.48	1.75	n.a.
37	Pedestrian age ≥ 75 years			2.82	37.35	1.54	n.a.
38	Pedestrian age ≥ 75 years	Vehicle age ≥ 15 years		0.18	46.88	1.93	1.26
39	Pedestrian age ≥ 75 years	Driver journey purpose = Commuting to/from work		0.26	44.53	1.83	1.19
40	Pedestrian age ≥ 75 years	Pavement = Wet or damp		0.74	42.93	1.77	1.15
41	Pedestrian age ≥ 75 years	Driver age ≥ 75 years		0.29	42.49	1.75	1.14
42	Pedestrian age ≥ 75 years	Driver home area = Small town		0.22	42.30	1.74	1.13
43	Pedestrian age ≥ 75 years	Pedestrian-crossing physical facilities = Zebra		0.20	41.77	1.72	1.12
44	Pedestrian age ≥ 75 years	Pedestrian-crossing physical facilities = Zebra	Driver gender = M	0.15	46.70	1.92	1.12
45	Pedestrian age ≥ 75 years	Vehicle type = Van		0.27	40.77	1.68	1.09
46	Pedestrian age ≥ 75 years	Vehicle type = Van	Junction control = T or staggered	0.11	48.10	1.98	1.18
47	Pedestrian age ≥ 75 years	Vehicle type = Van	Junction control = Give way/uncontrolled	0.15	45.02	1.85	1.10
48	Pedestrian age ≥ 75 years	Vehicle propulsion code = Petrol		1.23	40.68	1.67	1.09
49	Pedestrian age ≥ 75 years	Pedestrian gender = F		1.58	40.54	1.67	1.09
50	Vehicle Skidding and Overturning = Yes			0.97	35.37	1.46	n.a.
51	Speed limit = 40 mph			1.23	34.73	1.43	n.a.
52	Speed limit = 40 mph	Day of week = Weekend		0.32	39.63	1.63	1.14
53	Pedestrian age = 65–74 years			2.22	33.41	1.38	n.a.
54	Pedestrian age = 65–74 years	Driver journey purpose = Commuting to/from work		0.21	42.22	1.74	1.26
55	Pedestrian age = 65–74 years	Driver age = 0–24 years		0.27	39.57	1.63	1.18
56	Pedestrian age = 65–74 years	Driver age = 0–24 years	Vehicle age ≥ 15 years	0.22	42.44	1.75	1.07
57	Pedestrian age = 65–74 years	Pavement = Wet or damp		0.63	37.63	1.55	1.13

Table 7. *Cont.*

ID Rule	Antecedents			S%	C%	L	LIC
	Item 1	Item 2	Item 3				
58	Lighting = Darkness—no lighting			0.61	33.20	1.37	n.a.
59	Lighting = Darkness—no lighting	Speed limit ≥ 50 mph		0.34	35.51	1.46	1.07
60	Weather = Raining + high winds			0.31	31.09	1.28	n.a.
61	Driver age = 0–24 years			3.06	29.32	1.21	n.a.
62	Driver age = 0–24 years	Speed limit ≥ 50 mph		0.14	38.56	1.59	1.31
63	Driver age = 0–24 years	Speed limit ≥ 50 mph	Vehicle 1st point of impact = Front	0.10	41.72	1.72	1.08
64	Driver age = 0–24 years	Day of week = Weekend		0.81	31.21	1.29	1.06
65	Lighting = Darkness—lights unlit			0.22	29.32	1.21	n.a.

5.2.2. Classification Tree

The classification tree is reported in Figure 3. The tool generated 15 terminal nodes, 10 of which predicted fatal crashes, 3 of which predicted serious crashes, and 2 of which predicted slight injury crashes. The posterior classification ratio (PCR) was assessed for all the nodes, but it was reported only for the terminal nodes in order to understand how representative each terminal node is in relation to the predicted class. Node 17 and Node 19 exhibited very high PCRs (13.10 and 17.45, respectively), which implies the robustness of both terminal nodes for the "fatal" classification.



Darkness includes: darkness—lights lit, darkness—lighting unknown, darkness—lights unlit, and darkness—no lighting; All other vehicles includes vehicle type equal to: bus, bicycle, car, PTW<500, PTW≥500, van, other, and missing.

Figure 3. Classification tree.

The analysis of the variable importance (Figure 4) identified four variables as having the most influence on the classification accuracy of the pedestrian crash severity: (1) The speed limit; (2) The pedestrian age; (3) The lighting; and (4) The area.

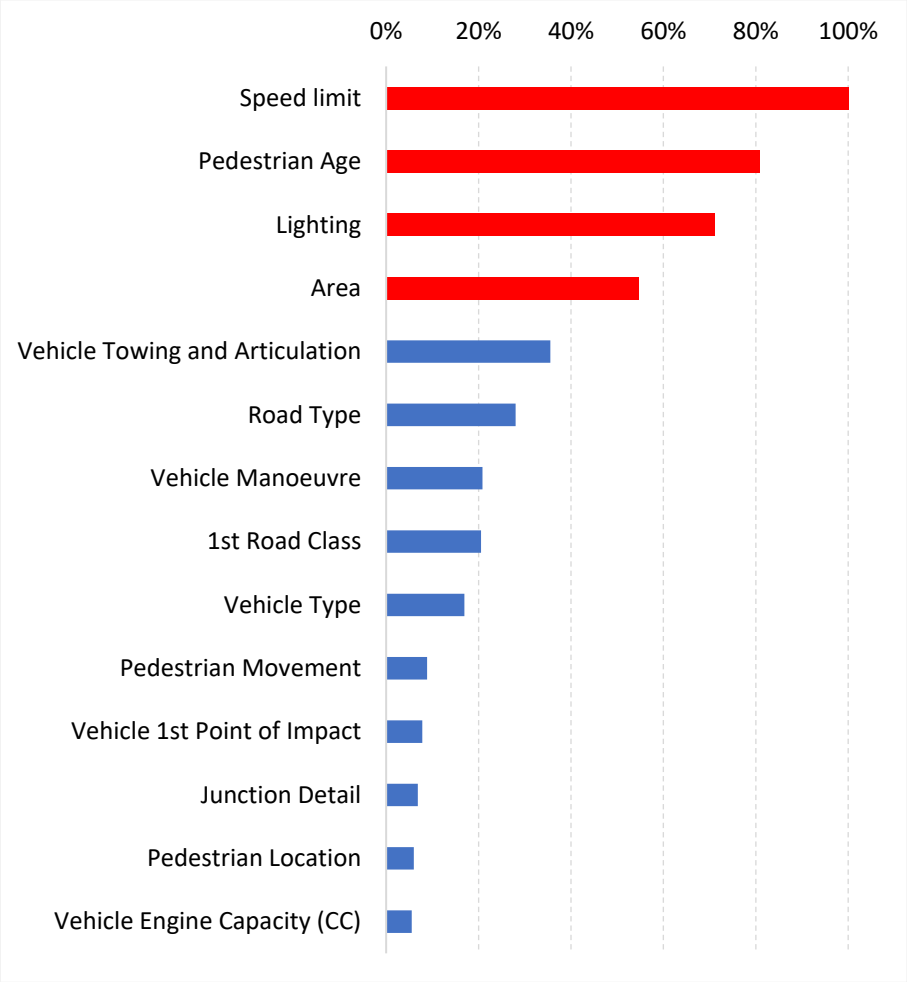


Figure 4. Classification tree variable importances.

5.2.3. Random Forests

Initially, a RF was implemented, which generated 500 trees. However, the hyperparameter-tuning process provided the RF optimal number of trees as 42. Then, the RF was performed again, and the most important predictors that were associated with the fatal and severe pedestrian crashes were determined. The importance of each explanatory variable is assessed by observing how the prediction error increases when the data that are not in the bootstrap sample (what Breiman calls, "OOB data") are permuted for that variable, while all of the others are left unchanged. The score rankings of the explanatory variable importances are provided in Figure 5 below. According to the Gini impurity, four variables were identified as having the most influence on the classification process of fatal pedestrian crashes: the vehicle maneuver, the pedestrian age, the vehicle's first point of impact, and the driver gender, whereas, as far as serious crashes are concerned, the RF highlights the severe impact on the pedestrian crash severity of factors such as the vehicle maneuver and the driver gender, and it also identifies as critical the presence of "vehicle towing and articulation", and of the vehicle type.

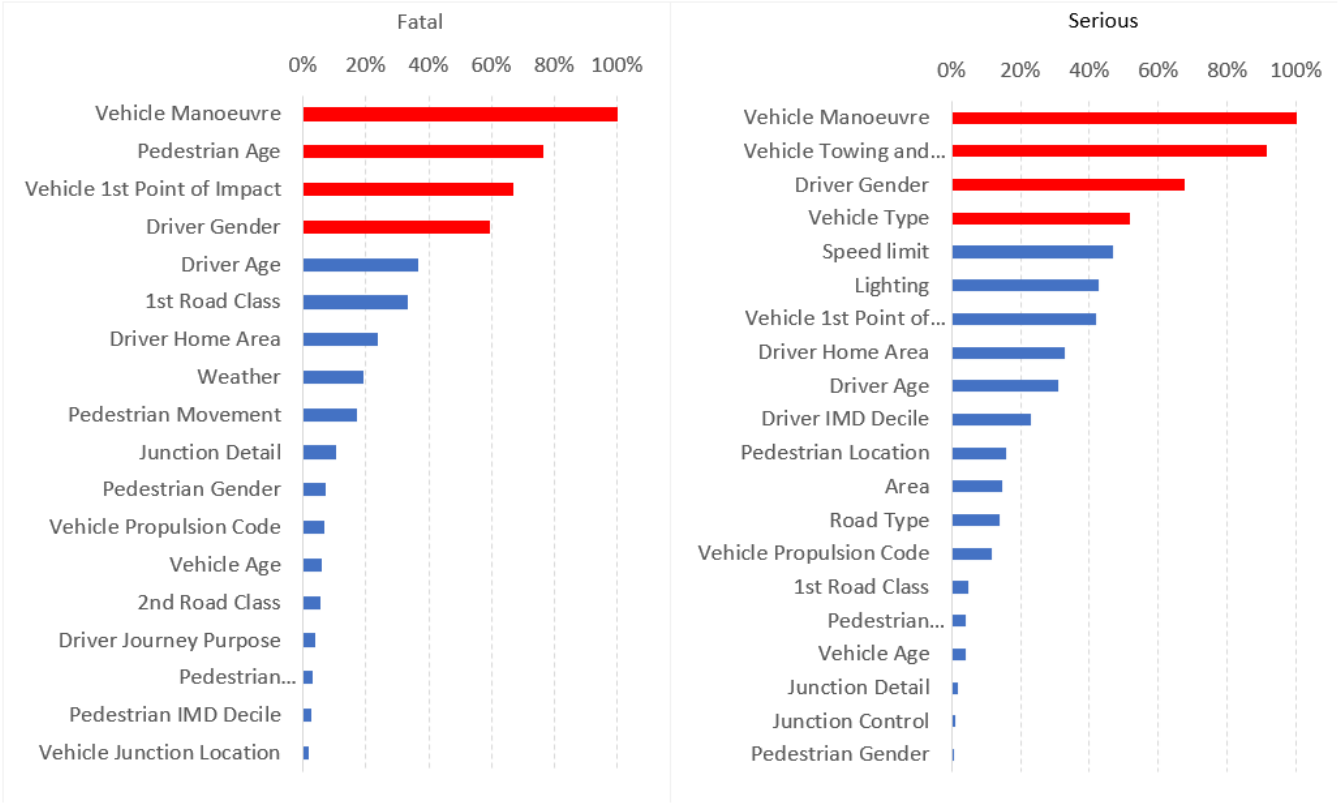


Figure 5. RF variable importance for fatal and serious crashes.

5.2.4. Artificial Neural Networks

The ANN tool generated a graph that contains 26 factors and 132 neurons in the input layer (excluding the bias unit), and 13 hidden nodes in the hidden layer, whereas the output layer had three neurons that represented the three injury levels.

The input and hidden layers were linked through the hyperbolic tangent transfer functions, whereas the transfer function between the hidden layer and the output layer was the softmax function. A total of 13 factors exhibited high impacts on the pedestrian crash severity (Figure 6), with normalized importances greater than 50%: the driver and pedestrian ages; the vehicle engine; the lighting; the vehicles' first point of impact; the speed limit; the vehicle maneuver; the vehicle type; the area; the first road class; the weather; the junction detail; and the pedestrian-crossing physical facilities.

5.2.5. Support Vector Machine Model

The SVM model was performed with the RBF kernel function. The model returned 19,909 support vectors, which defined the complex hyperplane. The SVM model provides the visualization of the most relevant features through nonlinear kernels that are necessary to carrying out the classification process. The importance of the predictors that were exhibited by the tool (Figure 7) was used to compare the SVM output with the outputs of the other non-parametric algorithms that were implemented in the study. The SVM model identified four predictors, which mostly contributed to the correct classification of the pedestrian crash severity: the first road class; the pedestrian age; the pedestrian-crossing physical facilities; and the junction detail.

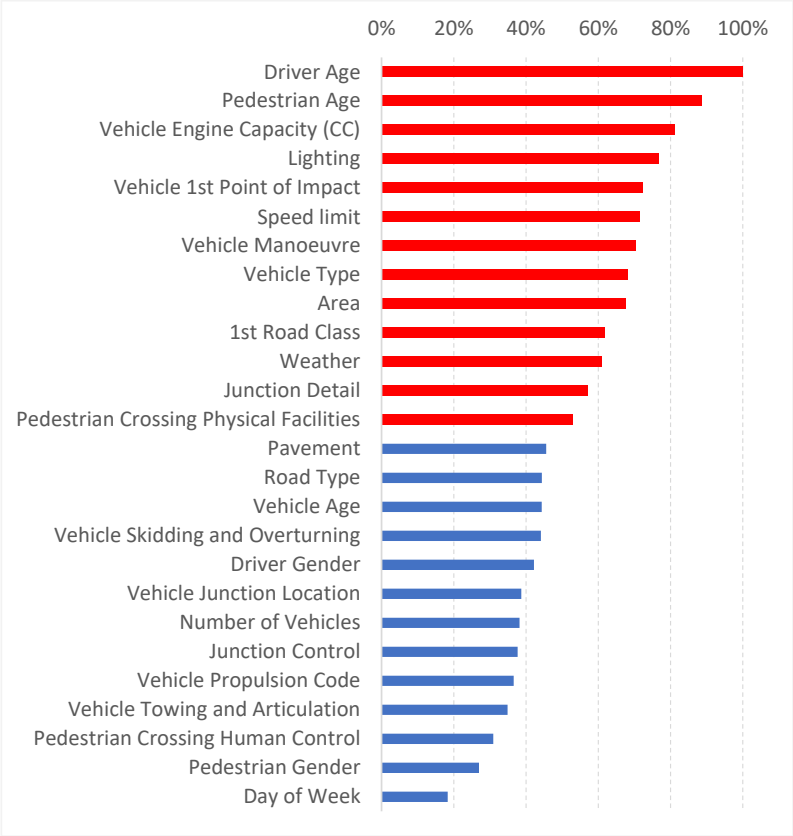


Figure 6. ANN variable importance.

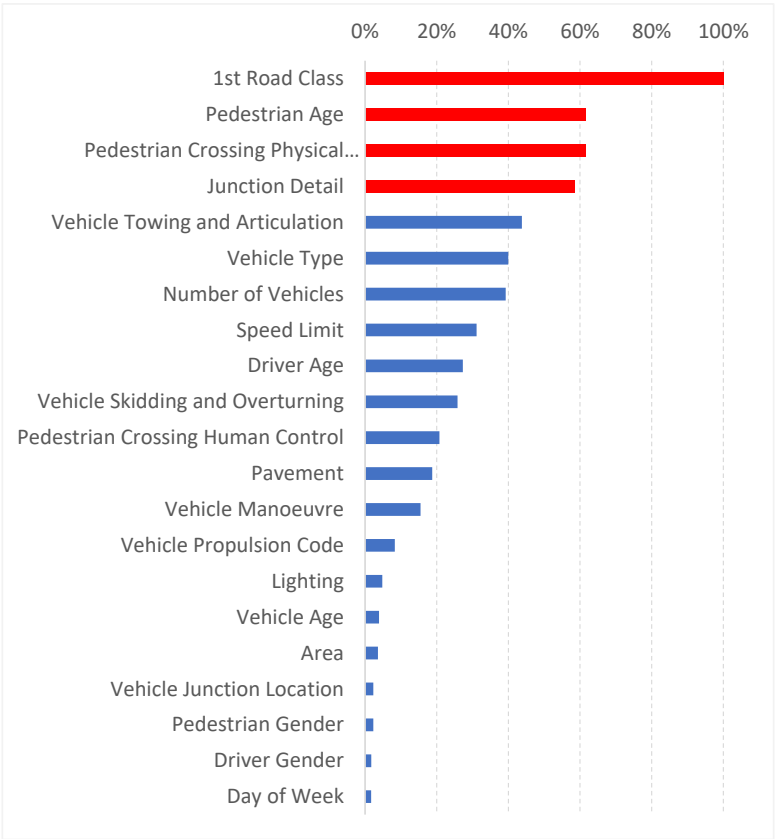


Figure 7. SVM variable importance.

5.3. Model Comparisons

In this section, the comparisons among the nine implemented methods are provided, with an analysis of both the significant explanatory variables that affect the crash severity (qualitative evaluation), as well as of the model performances (quantitative evaluation).

5.3.1. Significant Explanatory Variables and Effects on Crash Severity

The results of the parametric and non-parametric models highlight that the non-parametric models tend to uncover more hidden correlations among the data than the parametric models.

A total of 19 variables are significant in both the parametric and the non-parametric models, and 1 variable is identified only by the first group of models, whereas 7 variables turn out to be important in the non-parametric classification process.

The same variables are significant with reference to both fatal as well as serious injuries, except for the vehicle propulsion code (which is significant only for the fatal severity) and the number of pedestrians involved (which is significant only for serious injuries). The "pedestrian-crossing human control" is the variable that is significant only in the econometric model, while the variables that are significant only in the machine learning algorithms are the "driver home area"; the driver journey purpose; the number of pedestrians involved; the vehicle's first point of impact; the vehicle engine capacity; the weather; and the junction control. In the appendix, we summarize the significant explanatory variables that are associated with an increase in the crash severity. Table A7 contains the variables that associated with an increase in the fatal crash probability, while Table A8 contains the variables that are associated with an increase in the serious crash probability.

Pedestrian Characteristics

All of the methods found a correlation between the pedestrian age and gender, with both fatal and serious crashes. The results indicate that elderly pedestrians (at least 65 years old) are very exposed to the most serious crashes, even though the parametric models and the association rules highlight "pedestrians $\geq$ 75" as the most vulnerable once in a crash. The pedestrian age was also among the strongest predictors in the classification tree, the RF, the ANN, and the SVM variable importance lists, with over a 50% influence on the classification. As far as the pedestrian gender is concerned, only the parametric methods and the association rules found greater propensities of male pedestrians towards the most serious crashes.

Driver Characteristics

The driver gender was among one of the most important predictors that were identified by the RF for fatal crashes. The result was consistent with the association rule results and all of the parametric models, which identified males as the drivers that are most likely to be involved in fatal and serious crashes. Very young drivers (age $\leq$ 24 years) also showed great propensities towards the most severe crashes. The relation was identified by all the parametric models (both in fatal and serious crashes) and the association rules (in serious crashes). Furthermore, the driver age was the most important predictor among the variable importances that was exhibited by the ANN. Furthermore, only the association rules identified aspects related to the driver's purpose of the journey and the driver's home area. "Journey as part of work" and "commuting to/from work" were considered critical, both for fatal and serious pedestrian crashes.

Vehicle Characteristics

All of the parametric models and the association rules identified a significant effect of old vehicles (vehicle age $\geq$ 15 years) on the most serious crashes. The parametric models provide positive coefficients for both fatal and serious crashes, and the results are consistent with the association rules. The vehicle type involved in a pedestrian crash affects the pedestrian outcome. Specifically, a pedestrian struck by a truck has a higher injury risk.

The results were highlighted by all of the methods. A further risk for pedestrian safety was the presence of articulated vehicles, and the factor was identified by the association rules as the strongest two-item rule for fatal crashes. The relation was confirmed by the parametric models and the RF. By the parametric models, heavy oil vehicles were also identified as affecting the crash severity, with positive coefficients, whereas hybrid vehicles exhibited reductions in the crash severity. However, the association rules also found an association of fatal crashes to vehicles with petrol propulsion. Furthermore, the ANN tool identified the vehicle engine capacity as affecting the pedestrian crash severity.

Roadway Characteristics

The parametric models identified the increase in the speed limit as a contributory factor towards increasing the crash severity. The speed limit was also the first split for the classification tree growth, with higher speed limits associated with fatal crashes. The association rules identified high-lift rules with the fatal severity as the consequent, and a speed limit $\geq$ 50 mph as the antecedent. The speed limit was also identified as one of the most important predictors by the ANN, with 70% importance. All of the models also pointed to the "first road class equal to A" and "rural areas" as patterns that influence the crash severity, and this may be due to their correlations with higher speed limits.

Junction Characteristics

Pelican, puffin, toucan, or similar nonjunction pedestrian light crossings were found to increase the pedestrian crash severity. As far the junction detail is concerned, the econometric models did not provide the factors that influence the severity levels. By contrast, the association rules found that T or staggered junctions, or give-way/uncontrolled intersections, affected fatal and serious crashes in the presence of elderly pedestrians and van vehicles.

Environmental Characteristics

The day of the week, the lighting, the pavement, and the weather at the time of the crash were significant variables. The results indicate that the weekend is a predictor of fatal and serious crashes in both the parametric and the non-parametric models. In particular, this result of the parametric models was confirmed by the association rules. Darkness that is due to the absence of lights, or to inadequate lighting, increases the likelihood of the most severe crashes. The pavement condition affects the crash severity, particularly when it is wet or damp. The parametric models and the association rules found consistent results. The weather conditions were only highlighted by the ANN, which associates 60% of the importance in the classification to the weather variable. However, neither the other non-parametric models nor the parametric models confirm this result.

Crash Characteristics

The number of vehicles involved in the crash played a pivotal role. All of the parametric models show an increase in the probability of both fatal and serious injuries with multivehicle crashes. The relation was also captured by the association rules (Rule 34, L = 5.00). A frontal vehicle impact was identified as critical by the association rules, and this was confirmed by the RF and ANN tools. The association rules further identified the association of the number of pedestrians involved in the crash with serious crashes, and the association was identified only by the association rules. The generated two-item rule is the strongest one for serious crashes.

5.3.2. Measures of Performance

The performances of the models were evaluated by the F-measure, the G-mean, and the AUC. The results are shown in Tables 8 and 9. Table 8 reports the performance measures that were exhibited by the parametric models, both in their standard formulations, without applying any treatment to the imbalanced data, as well as in their weighted formulations,

after the implementation of the weighted approach that is presented in Section 4.3. Table 9 reports the performance measures of the non-parametric algorithms in the standard and weighted formulations. After the implementation of the weighted approach, all of the methods exhibited a relevant improvement in the classification performances, except for the association rules, where the weighted formulation did not significantly affect the model's performances. The comparison among the different models shows several interesting results.

Table 8. Measures of the performances of the standard and weighted parametric models.

	Standard Parametric Models				**Weighted Parametric Models**			
	MNL	**RPMNL**	**OL**	**RPOL**	**MNL**	**RPMNL**	**OL**	**RPOL**
				Fatal				
F-measure	0.16	0.23	0.00	0.02	0.28	0.53	0.00	0.16
G-mean	0.32	0.38	0.04	0.10	0.50	0.65	0.04	0.33
AUC	0.86	0.87	0.85	0.86	0.87	0.94	0.85	0.85
				Serious				
F-measure	0.06	0.32	0.05	0.14	0.21	0.41	0.41	0.40
G-mean	0.17	0.46	0.17	0.28	0.36	0.58	0.43	0.58
AUC	0.62	0.63	0.61	0.63	0.62	0.68	0.61	0.62
				Averaged performances				
F-measure	0.06	0.31	0.05	0.13	0.22	0.42	0.38	0.38
G-mean	0.18	0.45	0.16	0.27	0.37	0.59	0.40	0.56
AUC	0.64	0.65	0.63	0.64	0.64	0.70	0.63	0.63

Table 9. Measures of performances of standard and weighted non-parametric algorithms.

	Standard Non-Parametric Algorithms					**Weighted Non-Parametric Algorithms**				
	AR	**CT**	**RF**	**ANN**	**SVM**	**AR**	**CT**	**RF**	**ANN**	**SVM**
					Fatal					
F-measure	0.05	0.00	0.02	0.04	0.01	0.05	0.16	0.57	0.18	0.95
G-mean	0.36	0.00	0.09	0.15	0.07	0.36	0.72	0.77	0.66	0.96
AUC	0.79	0.80	0.23	0.83	0.76	0.79	0.82	0.88	0.78	0.88
					Serious					
F-measure	0.39	0.11	0.00	0.13	0.03	0.39	0.29	0.90	0.26	0.95
G-mean	0.54	0.24	0.04	0.27	0.12	0.54	0.46	0.92	0.43	0.96
AUC	0.58	0.61	0.56	0.61	0.55	0.58	0.47	0.71	0.76	0.76
					Averaged performances					
F-measure	0.36	0.10	0.00	0.12	0.02	0.36	0.28	0.87	0.25	0.95
G-mean	0.53	0.22	0.05	0.26	0.11	0.53	0.48	0.91	0.45	0.96
AUC	0.59	0.63	0.53	0.63	0.56	0.59	0.49	0.72	0.76	0.77

As far as the parametric models are concerned, the multinomial logit (fixed parameters) and random parameter multinomial logit (mixed parameters) models exhibited better classification performances, compared with their ordered versions (ordered logit and random parameter ordered logit models). Furthermore, the ordered logit model showed a poor ability in correctly classifying fatal crashes, even after the weighting procedure. Our results are consistent with previous studies [12,18]. The random parameter models (both the random parameter multinomial logit model and the random parameter ordered logit model) relax the restrictive assumption of the fixed model structure, which allows the exogenous variables to vary over the threshold parameters and to outperform their standard fixed parameter variants (multinomial logit and ordered logit models). Finally,

our results found out that, among all the parametric models that were implemented in the study, the random parameter multinomial logit model has the best predictive performances (on average, an F-measure equal to 0.42, a G-mean equal to 0.59, and an AUC equal to 0.70), and it provides additional insights into the distribution of the parameters (by capturing attributes with mixed effects).

As far as the non-parametric tools are concerned, the SVM outperformed the other methods, and it is the best-fit model, according to the F-measure, the G-mean, and the AUC, both for fatal and serious injury crashes. The model reached an accuracy in both the correct positive and negative case classifications that is equal to 95%. The RF exhibited performances that were only slightly worse to the SVM, with accuracies in both the positive and negative cases of 77% in the fatal classification, and of 92% in the serious injury crashes. The association rules and the classification tree exhibited similar performances, with a better performance of the classification tree in predicting fatal crashes (a G-mean equal to 0.72, and an AUC equal to 0.82), and better performance of the association rules in predicting severe injury crashes (a G-mean equal to 0.59, and an AUC equal to 0.58).

Overall, the non-parametric algorithms outperformed the parametric models, and the best performances were reached by the SVM and the RF.

6. Discussion and Conclusions

This study presents the results of a comprehensive analysis of four parametric models and five non-parametric tools to investigate the factors that contribute to fatal and serious injury crashes in Great Britain. Even though the models have already been applied to model the pedestrian injury severity, a comparative analysis of the predictive power of such modeling techniques is limited.

With regard to the parametric models, the multinomial logit model outperformed the ordered logit model. The main explanation for this difference is that ordered probability models place a strict restriction on how the exogenous variables affect the outcome probabilities. Previous studies [59] have already found the inconsistent estimates that were produced by the ordered logit model produced inconsistent estimates, as well as the elasticity effects that were constrained to be monotonic, from the lowest category of severity to the highest. This implies that the ordered logit model does not allow the probabilities of both the highest and lowest severity levels to increase or decrease. Thus, in order to increase the probability of the highest severity class (which is the "fatal" class in this study), a decrease in the probability of the lowest severity levels (which is "slight" in this study) is observed, and vice versa. Our study confirms that implementing the ordered crash severity nature on logistic regression models does not necessarily improve their predictive performances across all the severity levels, as the relationships between the predictors and the crash severity outcomes might not be monotonic.

As was expected, the random parameter models (the random parameter multinomial logit and random parameter ordered logit models) were statistically superior to their standard formulations, as they could accommodate the unobserved heterogeneity among the observations. Furthermore, their use provides evidence of the existence of heterogeneity among the data.

The likelihood ratio test shows that the random parameter multinomial logit model is superior to the standard multinomial logit model, with over 99.9% confidence. Similar results are also observed between the random parameter ordered logit model and the standard ordered logit model.

The significant variables that impacted the pedestrian crash severity in the standard logit models were tested for heterogeneity in the random parameter models: the random parameter multinomial logit identified two random variables (the "going-ahead vehicle maneuver" and the "roundabout") in predicting fatal crashes, and one random variable (the "pedestrian age greater $\geq$ 75") that affect the serious crashes. The random parameter ordered logit, instead, found one random variable (the "pedestrian age $\geq$ 75") that impacted both of the severity levels. The presence of such variability in the effect of the variables

across the sample population highlights the need to account for the potential unobserved heterogeneity, as this will improve our understanding, reduce erroneous inferences and predictions, and provide more accurate and informative results. Finally, in terms of the statistical fit, the value of the McFadden R^2 was the highest for the random parameter multinomial logit model, which indicates that the model statistically outperformed the other parametric models.

As far as the non-parametric methods are concerned, these models produced better prediction performances than the parametric models. The SVM outperformed the other methods, and it was the best fit model according to the F-measure, the G-mean, and the AUC, both for fatal and serious injury crashes. The RF also exhibited high predictive performances. However, the interpretability of the results of some of the non-parametric models is lower compared to the parametric models. For instance, a common output of the non-parametric models is the importance that the independent variables exhibit during the classification process. Even though the results of the most important variables that were identified by the non-parametric tools provide interesting information as well as a ranking of the most explanatory variables, the variable importance does not provide information about the directions and magnitudes of their impacts. Nevertheless, some algorithms also offer other interesting outputs. This is the case of the classification tree and the RF, which can both be graphically displayed as trees. Their structure enhances comprehension, with intuitive results. The association rules identify the specific patterns that are associated with pedestrian crashes and assign strength to the co-occurrence of several factors that affect the crash severity. For instance, the contributory factors that are associated with pedestrian crashes are the patterns with higher lift values, which can be considered as the parameters for determining the significance of the patterns from the base condition [23]. Furthermore, the rule structure allows for a clear framework of the attribute combinations.

Several factors were found to significantly increase the probability of fatal and serious injuries in pedestrian–vehicle crashes. Nineteen variables were significant, both in the parametric models as well as in the non-parametric algorithms, with one variable that was significant only in the parametric models, and seven variables that were significant only in the non-parametric algorithms. This means that the non-parametric algorithms uncover more hidden correlations among the data than the parametric models.

The type of vehicle that is involved in a pedestrian crash influences the crash severity. As is found in previous studies [8,60], the presence of a truck increases the crash severity because of the larger mass and the greater stiffness, the larger area of impact for pedestrians, the higher bumper height, the blunter geometry, and the longer stopping distances compared to other vehicles. Furthermore, the presence of articulated vehicles has been identified as a contributor to the most severe pedestrian crashes. The direct link of fatal/serious crashes with trucks, as well as with articulated vehicles, suggests the importance of planning specific routes for trucks. In order to avoid the transit of heavy vehicles in places that are highly frequented by pedestrians, it is crucial to establish a road hierarchy that gives the highest priority to pedestrians, and then to the other road users. Another relevant aspect is the point of the first impact in a crash. The frontal impacts resulted in more severe crashes, compared to all other kinds of impacts. This finding is also consistent with previous studies [20]. Rural areas and higher speed limits characterize the roads where the most severe crashes occurred. This may be a consequence of the typical rural road configuration, which has higher vehicle speeds combined with fewer separated facilities for pedestrians, such as sidewalk paths and trails, compared to urban areas.

As is found in previous studies [8,61], young drivers increase the probability of fatal and serious crashes. A possible explanation is that older drivers tend to drive more carefully and at lower speeds. Hence, as motorists become older, pedestrians are more likely to suffer no injuries once in a crash. Male drivers were also more likely to be involved in the most serious crashes, and our results confirm previous findings [22,62]. These factors may reflect the typically more aggressive way of driving of young male drivers. To reduce pedestrian crashes, programs are essential to the enforcement of the existing traffic laws

and ordinances for drivers. Furthermore, safety education should be integrated with school programs, and targeted safety campaigns should be a priority government task.

As was expected, the pedestrian crashes occurred during the night or under low-light conditions, which increased the likelihood of fatal consequences [63]. The driver may fail to see a pedestrian at night, and this was also associated with frontal vehicle impacts. This pattern highlights the importance of improving the pedestrian conspicuity. Babić et al. [64] found that drivers showed more active eye movements after noticing pedestrians in reflective vests than they did after noticing pedestrians in non–reflective clothing. Other than reflective clothes and markings, some studies [65,66] have examined elements of clothing (electroluminescent panels) that may be useful supplements since they are visible even when a pedestrian is not illuminated by approaching headlamps. Nevertheless, roads should be effectively illuminated as well, especially in areas where there is a high probability of observing pedestrians, such as in the proximity of pedestrian crossings. Furthermore, although pedestrian crashes are more likely to occur during the week, it is during the weekend that crashes are more likely to be severe. This may be due to more relaxed or distracted driver/pedestrian behaviors. The elderly pedestrians were more prone to severe outcomes relative to the younger individuals, once in a crash. This is due to the decrease in their perception and reaction times, and to the increase in their physical vulnerability and fragility and the suffering of various medical conditions, all of which contribute to their higher injury risk propensity [63]. Low-speed areas may be employed during the weekend to avoid the conflict between motor vehicles and pedestrians. The solution may be especially applied in areas with relevant pedestrian activities, especially for elderly pedestrians.

With consideration to the different contributory factors that are identified and their magnitudes, a combination of engineering, social, and management strategies, as well as appropriate safety countermeasures, should be implemented in order to effectively moderate pedestrian crash severities, and to increase the perceived safety of walking.

In conclusion, the joint use of parametric methods and non-parametric algorithms may provide powerful insights into the factors that contribute to fatal and serious crashes. The performance metrics demonstrate that each group of methods has its pros and cons. The parametric models confirm their advantages in offering easy-to-interpret outputs and understandable relations between the dependent and independent variables, whereas the non-parametric tools exhibit higher classification accuracies, and the ability to highlight hidden relations among the data. The study results show that the combined use of econometric methods and machine learning algorithms may effectively represent a satisfactory trade-off between the predictive ability of the classifier and its ability to clearly explain the phenomenon that is being investigated.

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Appendix A

Table A1. Descriptive statistics related to crash data (Part A).

Variable	Fatal		Serious		Slight		Total	
	N	%	N	%	N	%	N	%
First Road Class								
Motorway	47	32.2	49	33.6	50	34.2	146	0.2
A	747	3.3	5941	26.2	16,013	70.5	22,701	33.7
B	128	1.8	1819	25.7	5129	72.5	7076	10.5
C	78	1.6	1067	22.0	3712	76.4	4857	7.2
Missing	366	1.1	7483	23.0	24,727	75.9	32,576	48.4
Road Type								
Dual carriageway	296	5.2	1653	28.9	3763	65.9	5712	8.5
Single carriageway	990	1.8	13,285	24.4	40,200	73.8	54,475	80.9
One-way street	43	1.1	833	21.3	3026	77.5	3902	5.8
Roundabout	15	1.4	236	21.5	846	77.1	1097	1.6
Slip road	12	2.4	97	19.6	387	78.0	496	0.7
Missing	10	0.6	255	15.2	1409	84.2	1674	2.5
Second Road Class								
Motorway	5	17.9	9	32.1	14	50.0	28	0.0
A	97	1.8	1284	23.6	4051	74.6	5432	8.1
B	46	2.3	492	24.5	1471	73.2	2009	3.0
C	34	1.6	486	22.6	1631	75.8	2151	3.2
Missing	439	1.7	6553	24.7	19,574	73.7	26,566	39.4
n.a.	745	2.4	7536	24.2	22,891	73.4	31,172	46.3
Speed Limit								
20 mph	74	0.9	1840	21.9	6476	77.2	8390	12.5
30 mph	821	1.5	13,007	23.9	40,697	74.6	54,525	81.0
40 mph	129	5.4	829	34.7	1429	59.9	2387	3.5
≥50 mph	342	16.7	681	33.3	1020	49.9	2043	3.0
Missing	0	0.0	2	18.2	9	81.8	11	0.0
Junction Detail								
T or staggered junction	366	1.7	5472	24.8	16,240	73.6	22,078	32.8
Crossroads	108	1.9	1411	24.6	4208	73.5	5727	8.5
More than 4 arms (not roundabout)	14	1.6	199	23.4	638	75.0	851	1.3
Mini-roundabout	6	1.0	128	21.5	462	77.5	596	0.9
Roundabout	34	1.8	467	24.1	1438	74.2	1939	2.9
Slip road	27	7.2	103	27.5	244	65.2	374	0.6
Private drive or entrance	25	1.7	325	21.9	1135	76.4	1485	2.2
Not at junction	745	2.4	7536	24.2	22,891	73.4	31,172	46.3
Other junction	41	1.5	697	25.0	2051	73.5	2789	4.1
Missing	0	0.0	21	6.1	324	93.9	345	0.5
Junction Control								
Authorized person	2	0.6	60	17.9	273	81.5	335	0.5
Auto traffic signal	163	2.1	1939	25.5	5514	72.4	7616	11.3
Give way/uncontrolled	451	1.7	6669	24.8	19,792	73.5	26,912	40.0
Stop sign	3	0.9	64	19.9	254	79.1	321	0.5
Not at junction or within 20 m	747	2.3	7627	23.7	23,798	74.0	32,172	47.8

Table A2. Descriptive statistics related to crash data (Part B).

Variable	Fatal		Serious		Slight		Total	
	N	%	N	%	N	%	N	%
Area								
Rural	457	5.7	2149	26.9	5392	67.4	7998	11.9
Urban	909	1.5	14,208	23.9	44,232	74.5	59,349	88.1
Missing	0	0.0	2	22.2	7	77.8	9	0.0
Pedestrian-Crossing Human Control								
School-crossing patrol	2	0.4	88	17.8	403	81.7	493	0.7
None within 50 m	1345	2.1	15,918	24.6	47,494	73.3	64,757	96.1
Other	14	1.3	232	21.7	824	77.0	1070	1.6
Missing	5	0.5	121	11.7	910	87.8	1036	1.5
Pedestrian-Crossing Physical Facilities								
No physical crossing facilities within 50 m	931	2.1	10,567	24.1	32,387	73.8	43,885	65.2
Central refuge	67	2.7	702	28.1	1725	69.2	2494	3.7
Footbridge/subway	8	6.2	48	36.9	74	56.9	130	0.2
Pedestrian phase at traffic signal junction	125	1.8	1785	25.4	5108	72.8	7018	10.4
Pelican, puffin, toucan, or similar nonjunction pedestrian light crossing	192	2.5	2102	27.4	5368	70.1	7662	11.4
Zebra	39	0.8	1038	20.4	4005	78.8	5082	7.5
Missing	4	0.4	117	10.8	964	88.8	1085	1.6
Lighting								
Daylight	632	1.3	10,840	22.8	36,040	75.9	47,512	70.5
Darkness—lighting unknown	31	2.2	300	21.6	1056	76.1	1387	2.1
Darkness—lights lit	456	2.7	4654	27.9	11,585	69.4	16,695	24.8
Darkness—lights unlit	25	4.9	151	29.3	339	65.8	515	0.8
Darkness—no lighting	222	17.8	414	33.2	611	49.0	1247	1.9
Weather								
Fine no high winds	1127	2.1	13,423	24.4	40,369	73.5	54,919	81.5
Fine + high winds	17	2.7	180	29.0	423	68.2	620	0.9
Fog or mist	8	5.0	45	28.3	106	66.7	159	0.2
Raining + high winds	21	3.1	208	31.1	440	65.8	669	1.0
Raining, no high winds	137	2.0	1693	25.3	4857	72.6	6687	9.9
Snowing	13	3.4	101	26.2	272	70.5	386	0.6
Other	17	1.4	253	21.3	916	77.2	1186	1.8
Missing	26	1.0	456	16.7	2248	82.3	2730	4.1
Pavement								
Dry	921	1.8	12,158	23.8	37,997	74.4	51,076	75.8
Wet or damp	432	2.9	3914	26.6	10,393	70.5	14,739	21.9
Snowy/Frozen	12	1.7	173	24.7	515	73.6	700	1.0
Missing	1	0.1	114	13.6	726	86.3	841	1.2
Day of Week								
Weekday	955	1.8	12,413	23.7	39,094	74.5	52,462	77.9
Weekend	411	2.8	3946	26.5	10,537	70.7	14,894	22.1
Crash Severity	1366	2.0	16,359	24.3	49,631	73.7	67,356	100.0

Table A3. Descriptive statistics related to vehicle data (Part A).

Variable	Fatal		Serious		Slight		Total	
	N	%	N	%	N	%	N	%
Number of Vehicles								
1	1170	1.9	15,171	24.1	46,635	74.1	62,976	93.50
2	143	3.9	958	25.9	2603	70.3	3704	5.50
>2	53	7.8	230	34.0	393	58.1	676	1.00
Vehicle Type								
Bicycle	8	0.6	399	28.2	1006	71.2	1413	2.10
PTW < 500	23	0.9	614	24.9	1833	74.2	2470	3.67
PTW $\geq$ 500	32	4.7	206	30.2	445	65.2	683	1.01
Car	906	1.7	12,789	23.9	39,724	74.4	53,419	79.31
Van	92	2.3	1033	25.3	2960	72.5	4085	6.06
Bus	72	2.6	704	25.6	1976	71.8	2752	4.09
Truck	199	13.6	375	25.7	885	60.7	1459	2.17
Other	27	3.4	187	23.3	587	73.3	801	1.19
Missing	7	2.6	52	19.0	215	78.5	274	0.41
Vehicle Towing and Articulation								
Articulated vehicle	97	28.9	110	32.7	129	38.4	336	0.50
No tow/articulation	1252	1.9	15,989	24.4	48,280	73.7	65,521	97.28
Other	13	4.7	83	29.7	183	65.6	279	0.41
Missing	4	0.3	177	14.5	1039	85.2	1220	1.81
Vehicle Maneuver								
Going ahead	1060	2.7	10,717	26.9	28,032	70.4	39,809	59.10
Turning left/right/U	101	1.1	2127	23.6	6770	75.2	8998	13.36
Moving off	67	1.3	961	19.3	3943	79.3	4971	7.38
Overtaking	30	1.3	573	24.3	1755	74.4	2358	3.50
Reversing	61	1.2	964	19.1	4033	79.7	5058	7.51
Other	42	0.9	851	18.4	3738	80.7	4631	6.88
Missing	5	0.3	166	10.8	1360	88.8	1531	2.27
Vehicle Location								
At junction	620	1.8	8711	24.9	25,691	73.4	35,022	52.00
Not at junction	744	2.4	7533	24.2	22,895	73.4	31,172	46.28
Missing	2	0.2	115	9.9	1045	89.9	1162	1.73

Table A4. Descriptive statistics related to vehicle data (Part B).

Variable	Fatal		Serious		Slight		Tot	
	N	%	N	%	N	%	N	%
Vehicle Skidding and Overturning								
No	1222	1.9	15,508	24.3	47,089	73.8	63,819	94.75
Yes	141	7.6	654	35.4	1054	57.0	1849	2.75
Missing	3	0.2	197	11.7	1488	88.2	1688	2.51
Vehicle's First Point of Impact								
Back	63	1.2	1031	19.4	4230	79.5	5324	7.90
Front	1041	2.7	9932	26.1	27,023	71.1	37,996	56.41
Nearside/Offside	219	1.1	4577	23.4	14,755	75.5	19,551	29.03
No impact	35	1.1	631	20.4	2431	78.5	3097	4.60
Missing	8	0.6	188	13.5	1192	85.9	1388	2.06

Table A4. *Cont.*

Variable	Fatal		Serious		Slight		Tot	
	N	%	N	%	N	%	N	%
Vehicle Engine (CC)								
<1000	100	2.1	1271	27.0	3336	70.9	4707	6.99
1000–1500	236	1.8	3426	25.7	9692	72.6	13,354	19.83
1500–2000	417	1.9	5456	25.3	15,675	72.7	21,548	31.99
2000–3000	155	2.5	1594	25.8	4435	71.7	6184	9.18
>3000	233	6.9	932	27.7	2204	65.4	3369	5.00
Missing	225	1.2	3680	20.2	14,289	78.5	18,194	27.01
Vehicle Propulsion Code								
Heavy oil	650	2.9	5869	26.2	15,886	70.9	22,405	33.26
Hybrid electric	14	1.0	258	17.7	1184	81.3	1456	2.16
Petrol	479	1.9	6537	25.9	18,244	72.2	25,260	37.50
Other	2	1.0	60	29.0	145	70.0	207	0.31
Missing	221	1.2	3635	20.2	14,172	78.6	18,028	26.77
Vehicle Age								
≤15 years	1002	2.3	11,292	25.6	31,869	72.2	44,163	65.57
>15 years	79	2.6	853	28.3	2079	69.0	3011	4.47
Missing	285	1.4	4214	20.9	15,683	77.7	20,182	29.96

Table A5. Descriptive statistics related to driver data.

Variable	Fatal		Serious		Slight		Tot	
	N	%	N	%	N	%	N	%
Driver Journey Purpose								
Commuting to/from work	147	2.5	1759	30.1	3944	67.4	5850	8.69
Journey as part of work	399	3.4	3107	26.3	8299	70.3	11,805	17.53
To/from school	7	0.4	317	19.8	1277	79.8	1601	2.38
Other	108	2.6	1387	33.4	2653	64.0	4148	6.16
Missing	705	1.6	9789	22.3	33,458	76.1	43,952	65.25
Driver Gender								
F	217	1.3	3917	24.2	12,050	74.5	16,184	24.03
M	1079	2.7	10,503	26.2	28,529	71.1	40,111	59.55
Missing	70	0.6	1939	17.5	9052	81.8	11,061	16.42
Driver Age								
≤24 years	194	2.8	2062	29.3	4776	67.9	7032	10.44
25–34 years	284	2.3	3215	26.3	8718	71.4	12,217	18.14
35–44 years	230	2.2	2627	25.2	7550	72.5	10,407	15.45
45–54 years	242	2.4	2548	25.5	7191	72.0	9981	14.82
55–64 years	187	2.7	1800	26.2	4887	71.1	6874	10.21
65–74 years	95	2.5	987	26.0	2713	71.5	3795	5.63
≥75 years	60	2.3	740	28.6	1785	69.1	2585	3.84
Missing	74	0.5	2380	16.5	12,011	83.0	14,465	21.48
Driver IMD Decile								
Less deprived	441	2.7	4432	27.0	11,570	70.4	16,443	24.41
More deprived	542	2.2	6652	26.4	17,959	71.4	25,153	37.34
Missing	383	1.5	5275	20.5	20,102	78.0	25,760	38.24

Table A5. *Cont.*

Variable	Fatal		Serious		Slight		Tot	
	N	%	N	%	N	%	N	%
Driver Home Area								
Rural	126	3.6	995	28.6	2357	67.8	3478	5.16
Small town	108	3.4	922	29.4	2109	67.2	3139	4.66
Urban	899	2.3	10,462	26.3	28,415	71.4	39,776	59.05
Missing	233	1.1	3980	19.0	16,750	79.9	20,963	31.12

Table A6. Descriptive statistics related to pedestrian data.

Variable	Fatal		Serious		Slight		Tot	
	N	%	N	%	N	%	N	%
Number of pedestrians involved								
1	1,28	2.0	15,691	24.0	48,301	74.0	65,272	96.91
2	66	3.6	572	30.8	1220	65.7	1858	2.76
>2	20	8.8	96	42.5	110	48.7	226	0.34
Pedestrian gender								
F	458	1.6	6864	23.2	22,216	75.2	29,538	43.85
M	908	2.4	9494	25.1	27,406	72.5	37,808	56.13
Missing	0	0.0	1	10.0	9	90.0	10	0.01
Pedestrian age								
0–14 years	67	0.4	3442	22.9	11,516	76.6	15,025	22.31
15–24 years	148	1.3	2505	21.5	9002	77.2	11,655	17.30
25–34 years	160	1.6	2049	20.9	7593	77.5	9802	14.55
35–44 years	155	2.1	1578	21.1	5732	76.8	7465	11.08
45–54 years	153	2.1	1694	23.7	5306	74.2	7153	10.62
55–64 years	151	2.7	1551	27.6	3919	69.7	5621	8.35
65–74 years	152	3.4	1494	33.4	2826	63.2	4472	6.64
≥75 years	379	7.5	1897	37.3	2803	55.2	5079	7.54
Missing	1	0.1	149	13.7	934	86.2	1084	1.61
Pedestrian location								
Crossing elsewhere within 50 m of pedestrian crossing	118	2.1	1511	27.5	3866	70.4	5495	8.16
Crossing on pedestrian crossing facility	182	1.7	2518	24.1	7727	74.1	10,427	15.48
In carriageway, crossing elsewhere	516	1.8	7500	25.9	20,968	72.3	28,984	43.03
In carriageway, not crossing	220	3.2	1449	20.9	5272	76.0	6941	10.30
In center of carriageway	90	3.1	769	26.6	2034	70.3	2893	4.30
On footway or verge	125	1.8	1398	20.7	5238	77.5	6761	10.04
Missing	115	2.0	1214	20.7	4526	77.3	5855	8.69
Pedestrian movement								
Crossing from driver's nearside	440	2.0	5742	25.5	16,367	72.6	22,549	33.48
Crossing from driver's offside	315	2.3	3717	26.8	9863	71.0	13,895	20.63

Table A6. *Cont.*

Variable	Fatal		Serious		Slight		Tot	
	N	%	N	%	N	%	N	%
Crossing from nearside, masked by parked or stationary vehicle	19	0.4	1199	26.3	3344	73.3	4562	6.77
Crossing from offside, masked by parked or stationary vehicle	30	1.0	839	27.1	2222	71.9	3091	4.59
In carriageway, stationary—not crossing (standing or playing)	69	2.1	598	18.5	2565	79.4	3232	4.80
In carriageway, stationary—not crossing—masked by parked or stationary vehicle	8	1.5	112	21.6	399	76.9	519	0.77
Walking along in carriageway, back to traffic	64	4.3	329	21.9	1109	73.8	1502	2.23
Walking along in carriageway, facing traffic	40	4.2	200	21.0	711	74.8	951	1.41
Missing	381	2.2	3623	21.2	13,051	76.5	17,055	25.32
Pedestrian IMD decile								
Less deprived	412	2.4	4207	24.8	12,311	72.7	16,930	25.14
More deprived	541	1.6	7999	24.1	24,713	74.3	33,253	49.37
Missing	413	2.4	4153	24.2	12,607	73.4	17,173	25.50

Table A7. Variables related to an increase in probability of fatal crash.

Parametric/Non-Parametric Models.	Only Parametric Models	Only Non-Parametric Models
First road class	Pedestrian-crossing human control	Driver home area
Area		Driver journey purpose
Day of week		Vehicle's first point of impact
Driver age		Vehicle engine capacity (CC)
Driver gender		Weather
Lighting		Junction control
Number of vehicles		
Pavement		
Pedestrian age		
Pedestrian-crossing physical facilities		
Pedestrian gender		
Speed limit		
Vehicle age		
Vehicle maneuver		
Vehicle propulsion code		
Vehicle skidding and overturning		
Vehicle towing and articulation		
Vehicle type		
Junction detail		

Table A8. Variables related to an increase in the probability of a serious crash.

Parametric/Non-Parametric Models	Only Parametric Models	Only Non-Parametric Models
First road class	Pedestrian-crossing human control	Driver home area
Area		Driver journey purpose
Day of week		Number of pedestrians involved
Driver age		Vehicle's first point of impact
Driver gender		Vehicle engine capacity (CC)
Lighting		Weather
Number of vehicles		Junction control
Pavement		
Pedestrian age		
Pedestrian-crossing physical facilities		
Pedestrian gender		
Speed limit		
Vehicle age		
Vehicle maneuver		
Vehicle skidding and overturning		
Vehicle towing and articulation		
Vehicle type		
Junction detail		

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