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Factors Influencing the Pedestrian Injury Severity of Micromobility Crashes

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Abstract: The growth of micromobility transport in cities has created a new mobility paradigm, but this has also resulted in increased traffic conflicts and collisions. This research focuses on understanding the impacts of micromobility vehicles on pedestrian injury severity in urban areas of Spain between 2016 and 2021. The Random Forest classification model was used to identify the most significant factors and their combinations affecting pedestrian injury severity. To address the issue of unbalanced data, the synthetic minority oversampling technique was employed. The findings indicate that pedestrians' age, specifically those 70 years or older, is the most important variable in determining injury severity. Additionally, collisions at junctions or on weekends are associated with worse outcomes for pedestrians. The results highlight the combined influence of multiple factors, including offenses and distractions by micromobility users and pedestrians. These factors are more prevalent among younger micromobility users and those riding for leisure or on weekends. To enhance micromobility road safety and reduce pedestrian injuries, separating micromobility traffic from pedestrian areas is recommended, restricting micromobility vehicle use on sidewalks, providing training and information to micromobility users, conducting road safety campaigns, increasing enforcement measures, and incorporating buffer zones in bike lanes near on-street parking.

Keywords: injury severity; micromobility crashes; random forest; pedestrian; Personal Mobility Devices (PMDs); road safety

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1. Introduction

In recent years, the growth of micromobility transport in cities has led to a paradigm shift in mobility, especially since the COVID-19 pandemic [1]. Micromobility vehicles include bicycles and other personal mobility devices (PMDs), such as hoverboards, segways, electric wheelchairs, and especially stand-up electric scooters (e-scooters) [2,3].

These vehicles have been recognized as effective alternative modes of transportation for short-distance travel [4]. They offer environmental benefits and can help reduce traffic congestion [3]. Furthermore, micromobility transport has emerged as a suitable mobility alternative during the COVID-19 pandemic [5]. However, micromobility transport and vehicles face several challenges: (i) Traffic regulations are not uniformly established and differ across countries [6–8]; (ii) these vehicles interact with various road users due to the lack of dedicated infrastructure in many cities [9,10]; and (iii) the increased use of micromobility vehicles has led to a rise in the number of crashes involving them [11,12].

To address these issues, several countries have implemented measures to regulate the use of micromobility vehicles and reduce collisions. For instance, France, Germany, the United Kingdom, and Spain have banned the use of e-scooters on sidewalks [13,14]. However, in many cities and urban environments, the circulation space for micromobility vehicles remains undefined, forcing them to share infrastructure with other road users, such as motor vehicles and pedestrians, which increases the occurrence of traffic conflicts [15,16]. Additionally, the shared road space has not been thoroughly analyzed [17].

From a road safety perspective, it is necessary to analyze the impacts of increased micromobility vehicles use on other road users. Most studies have focused on crashes between micromobility and motorized vehicles, as they are more frequent and often result in severe injuries [18,19]. However, pedestrians are the most vulnerable road users, and they have received less attention in research [15]. Pedestrians suffer more severe injuries than micromobility users [20], and collisions between pedestrians and micromobility vehicles are expected to increase in the coming years [21]. Consequently, there is growing concern about the risks that micromobility vehicles pose to pedestrians [7,22]. Moreover, some pedestrian injuries resulting from collisions with micromobility vehicles may go unreported, leading to an underestimation of these incidents [22]. Understanding the impacts of the rising use of micromobility vehicles on public health is crucial for enhancing road safety in cities [8]. This entails conducting in-depth analyses of crashes involving micromobility vehicles and pedestrians.

Several studies have been conducted to analyze pedestrian injuries resulting from collisions with micromobility vehicles. First, some of the studies use medical data from patients who sustain injuries because of impacts with micromobility vehicles. One study focused on the safety risks and incidence of pedestrian injuries associated with electric scooters, using a case involving a sixty-year-old female pedestrian [10]. They concluded that future studies should include all pedestrian injuries because these studies can inform future policy proposals to improve pedestrian safety. Another study aimed to characterize injuries associated with e-scooter use, finding that 8.4% of e-scooter injuries involved pedestrians who were hit by an e-scooter [8]. However, the use of hospital datasets has some limitations. On the one hand, sometimes there exists the inability to generalize results because only specific cases are analyzed [10]. On the other hand, these studies are limited to the analysis of the available clinical variables, and some patients may not be considered. For instance, in [8], some data were not considered because researchers did not know with certainty that the injuries had been produced by collisions with micromobility vehicles. In addition, hospital data may present special limitations in minor injuries, which are often not treated in hospital settings [21].

Secondly, other studies analyzed traffic conflicts between pedestrians and micromobility vehicles. The researchers in [7] studied illegal and risky behaviors and interactions between e-scooters and pedestrians in six sites in Brisbane (Australia). They pointed out that, despite conflict rates being low, further studies are recommended to better understand the factors influencing the perceptions and behaviors of e-scooters and pedestrians. Another study examined traffic conflicts between bicycles and pedestrians in shared spaces, observing that there is a positive correlation between the traffic volume and the number of conflicts [23]. The main limitations of the studies that analyzed traffic conflicts is that the data collection was very limited to specific locations, making it challenging to generalize the findings [7,23]. In addition, data collection is usually limited to specific times of the day and/or specific days (peak hour, weekday, ...), and the characteristics and behaviors of road users may be different in other circumstances [7].

Other studies utilized traffic simulations and controlled experiments to assess the impacts of micromobility vehicles on pedestrians. Ref [17] used a traffic simulation model to evaluate the safety of mixed traffic flow between pedestrians and standing-type PMDs. Their results showed that the objective risk was affected by sidewalk width, traffic demand, and PMD movement parameters, and they concluded that a further analysis of intersections is required. Additionally, Ref [15] conducted controlled experiments to assess conflicts between pedestrians and PMDs. These studies provide valuable insights, but are constrained by the ability to simulate real-world scenarios [17].

Furthermore, some studies rely on crash databases to analyze the impacts of micromobility vehicles on pedestrians. One of these studies was conducted to improve the safety of micromobility users and pedestrians by identifying factors that affect these crashes [24]. The researchers pointed out that individual-level factors such as age, gender, and injury severity should be explored in future studies to provide better insights. Another study analyzed pedestrian injuries resulting from collisions with cyclists in Melbourne (Australia) [21]. The researchers used police report crash data and medical records, and concluded that pedestrian injuries were less severe in collisions with bicycles than with motor vehicles, although significant injuries have also been identified in collisions with bicycles. The use of crash databases to analyze the impacts of micromobility vehicles also face limitations. On the one hand, the underreporting problem has been observed in collisions between pedestrians and micromobility vehicles that do not report any physical harm to both road users [21]. On the other hand, due to the lack of data on collisions with micromobility vehicles (other than bicycles), some studies identified these types of collisions from news reports that reported these incidents. This approach provides limited and sometimes biased information [25].

This research focused on analyzing collisions between micromobility vehicles and pedestrians on urban roads in Spain from 2016 to 2021. The crash dataset, provided by the Spanish General Directorate of Traffic, contains information on crashes involving micromobility vehicles that resulted in at least one slightly injured road user.

The aim of this study is to identify the key factors and their combinations that contribute to the severity of pedestrian injuries. The Random Forest methodology was employed to create a classification model for this analysis. To address the issue of imbalanced data in pedestrian injury severity, the synthetic minority oversampling technique (SMOTE) was applied. This technique helped to address the lower representation of fatal and seriously injured pedestrians compared to slightly injured ones in the dataset.

The study yields several decision rules that enable the assessment of the collective influence of various factors on pedestrian injury severity. These factors encompass aspects related to the collision itself, the micromobility vehicle and user, the pedestrian, and the infrastructure. The findings offer relevant insights for authorities in formulating road policies aimed at reducing the severity of these collisions from the perspective of pedestrians, who are the most vulnerable users of the road.

The remaining sections of this study are structured as follows: section 2 presents the crash database and the methodology used in this research. In section 3, the results are presented and discussed. Finally, section 4 concludes the study, outlines directions for future research, and discusses the practical applications of the findings.

2. Materials and Methods

2.1. Data Description

The Spanish crash databases, provided by the Spanish General Directorate of Traffic, include information about the collisions and vehicles involved, the drivers, and the pedestrians, from 2016 to 2021. To create a comprehensive dataset, the five initial crash databases were merged, resulting in a single database with 363,381 collisions that occurred in urban areas during the specified time frame.

From this merged database, only crashes involving at least one micromobility vehicle were selected, resulting in 38,092 crashes. Subsequently, collisions involving one micromobility vehicle and one pedestrian were identified, leading to a subset of 3212 crashes. To ensure data quality, a thorough debugging procedure was conducted to remove records with inconsistent or incomplete information. As a result, the final database consisted of 3205 crashes involving one micromobility vehicle and one pedestrian.

Between 2016 and 2021, a total of 82,529 pedestrians were involved in collisions with motor vehicles or micromobility vehicles in Spain. The number of pedestrian collisions in Spain remained relatively stable over the years, both in urban areas (around 13,200 collisions) and interurban areas (around 869 collisions), until 2020. However, in that year, there was a significant decrease in the number of pedestrian collisions (around 8300 in urban areas and 636 in interurban areas), which can be attributed to the COVID-19 lockdown.

More than 90% of the injured pedestrians were involved in collisions on urban roads; thus, the data analysis in this study focused exclusively on this area. Throughout the 2016–2021 period, most pedestrian collisions were due to motor vehicles (on average about 94.6%). However, there is an average of 532 collisions between micromobility vehicles and pedestrians on urban roads in Spain each year, which, on average, indicates that over 8% of micromobility collisions occur with pedestrians. Figure 1 displays the annual trend for all micromobility collisions, and the trend for collisions between one PMD and one pedestrian.

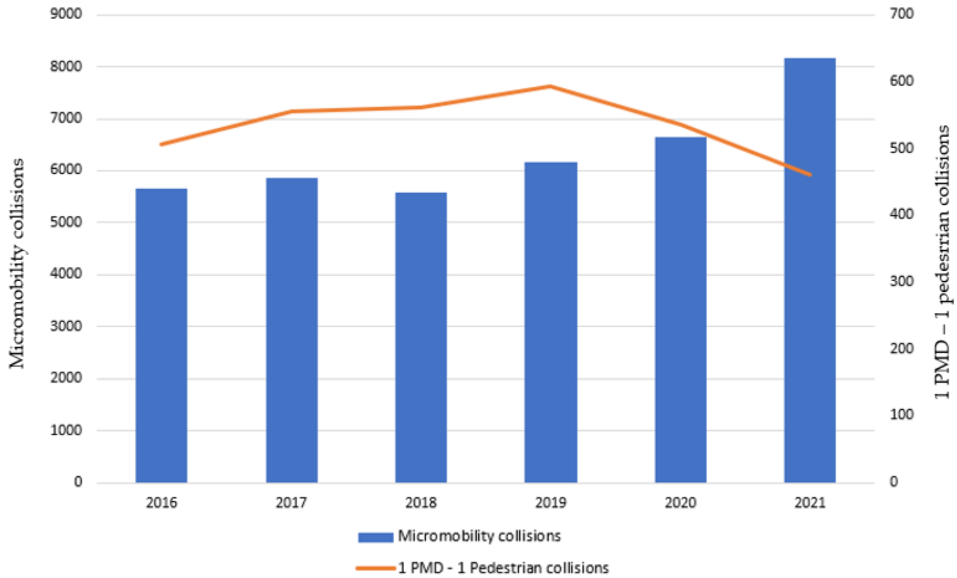

Figure 1. Trends in micromobility collisions vs. 1 PMD-1 pedestrian collisions in Spain (2016–2021).

Collisions involving motor vehicles are associated with the most severe consequences for pedestrians, with approximately 16% resulting in serious or fatal injuries, as depicted in Figure 2. However, more than 7% of collisions between micromobility vehicles and pedestrians also lead to serious or fatal injuries (Figure 2). This percentage should not be overlooked, as it affects a significant number of pedestrians. Moreover, it is expected that this percentage may further increase in the coming years, due to the expected rise in the use of micromobility vehicles. Therefore, it is essential to address this type of collision to mitigate its consequences, especially from the perspective of the most vulnerable road users.

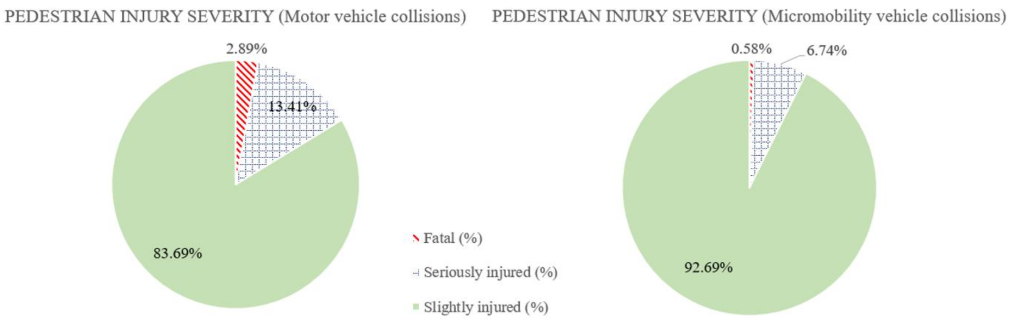

Figure 2. Pedestrian injury severity by collision type in Spain (2016–2021).

2.2. Variables

The model in this study considers the pedestrian injury severity as the dependent variable, categorized into "slightly injured" (value 0) and "fatal and seriously injured" (value 1). The category "slightly injured" encompasses pedestrians who have sustained minor injuries in micromobility vehicle collisions. Conversely, the "fatal and seriously injured" group pertains to pedestrians with severe injuries (hospitalization exceeding 24 h) and fatalities resulting from such collisions.

The independent variables are defined as binary variables, where a value of 0 indicates the absence of the condition represented by the variable, and a value of 1 indicates its presence. The exception to this rule is seen in the gender variables, where the value 0 represents women and the value 1 represents men. Additionally, the variable indicating the type of micromobility vehicle ("Bicycle") takes the value 0 to represent PMDs, mainly e-scooters, and the value 1 to represent bicycles.

Table 1 presents all of the variables used in this research, along with their respective categories. It also includes the number of crashes resulting in fatal/serious injuries, and slightly injured pedestrians for each value of the variable.

Table 1. Variables description.

	Variables	Coded Variable	Values	Fatal/Seriously Injured	Slightly Injured
	Weekend	WEEKEND	0—Weekday	153	2323
			1—Weekend	48	681
	Night	NIGHT	0—No	171	2614
			1—Yes	30	390
	Junction	JUNCTION	0—No	163	2338
			1—Yes	38	666
	Bicycle	BICYCLE	0—PMD	33	471
			1—Bicycle	168	2533
	Bad pavement	BAD_PAVEMENT	0—No	191	2860
			1—Yes	10	144
Crash location	Vehicle lane	VH_LANE	0—No	144	2403
			1—Yes	57	601
	Shoulder	SHOULDER	0—No	201	3000
			1—Yes	0	4
	Sidewalk	SIDEWALK	0—No	184	2771
			1—Yes	17	233
	Bike sidewalk	BIKE_SIDEWALK	0—No	195	2864
			1—Yes	6	140
	Bike lane	BIKE_LANE	0—No	179	2703
			1—Yes	22	301
	Bus lane	BUS_LANE	0—No	201	2996
			1—Yes	0	8
Rider Characteristics	Young (<18 years)	m_YOUNG18	0—No	166	2553
			1—Yes	35	451
	Older (≥65 years)	m_OLDER64	0—No	200	2934
			1—Yes	1	70
	Rider gender	m_GENDER	0—Female	27	631
			1—Male	174	2373
	Leisure	m_LEISURE	0—No	117	2278
			1—Yes	84	726
	Commute	m_COMMUTE	0—No	185	2828
			1—Yes	16	176
	Professional	m_PROFESSIONAL	0—No	199	2983
			1—Yes	2	21
	Alcohol	m_ALCOHOL	0—No	196	2991
			1—Yes	5	13
	Not respecting priority signs	m_NPRIORITY	0—No	149	2604
			1—Yes	52	400

	Unsafe ride	m_UNSAFERIDE	0—No	169	2601
			1—Yes	32	403
	Speed offense	m_SPEED	0—No	185	2884
			1—Yes	16	120
	Distraction	m_DISTRACTION	0—No	179	2889
			1—Yes	22	115
Pedestrian Characteristics	0–14 years	p_0_14	0—No	184	2657
			1—Yes	17	347
	15–44 years	p_15_44	0—No	187	2245
			1—Yes	14	759
	45–69 years	p_45_69	0—No	130	1894
			1—Yes	71	1110
	≥70 years	p_70_more	0—No	114	2366
			1—Yes	87	638
	Pedestrian gender	p_GENDER	0—Female	125	1799
			1—Male	76	1205
	Exit vehicle	p_EXITVH	0—No	190	2901
			1—Yes	11	103
	Cross vehicle lane	p_CROSSVHLANE	0—No	138	2417
			1—Yes	63	587
	In vehicle lane	p_VHLANE	0—No	185	2812
			1—Yes	16	192
	Burst into the vehicle lane	p_BURST	0—No	197	2918
			1—Yes	4	86
	In sidewalk	p_SIDEWALK	0—No	154	2382
			1—Yes	47	622
	Not respecting traffic lights	p_NOTRAFFICLIGHTS	0—No	190	2934
			1—Yes	11	70
	Not respecting pedestrian cross	p_NOPEDCROSS	0—No	175	2800
			1—Yes	26	204
	Distraction	p_DISTRACTION	0—No	171	2771
			1—Yes	30	233
	Other pedestrian offenses	p_OTHEROFFENCE	0—No	186	2806
			1—Yes	15	198

The information presented in Table 1 is derived from the original databases. However, certain variables had to be created based on the available information. For instance, the "WEEKEND" variable was established by considering the crash date, categorizing it as a weekend or weekday. Similarly, the "NIGHT" variable distinguishes between nighttime (from sunset to sunrise) and daytime.

Regarding the micromobility vehicle type, the databases only indicate whether the vehicle is a bicycle or not, lacking specific information on PMDs. To address this, the vehicle brand and model data were utilized to identify the other types of micromobility vehicles, predominantly electric scooters. Consequently, the "BICYCLE" variable in this study includes two categories: "bicycle" (value 1) and "PMDs" (value 0).

Concerning the behaviors and offenses of micromobility users, the "m_NPRIORITY" variable encompasses offenses related to not respecting priority rules or traffic signals. On the other hand, the "m_UNSAFERIDE" variable includes other offenses such as partial lane invasion, zigzag riding, unnecessary braking, failure to maintain a safe distance, and more.

Additionally, the "m_DISTRACTION" and "p_DISTRACTION" variables were created to indicate distractions specific to micromobility users and pedestrians, respectively. Some distractions are common to both, such as mobile phone use, headphone use, observing the surroundings (landscape, advertising, signs), and being lost in thought. Exclusive distractions for micromobility users include GPS use, smoking, and engaging in simultaneous activities while riding, such as eating or drinking.

Regarding the age ranges for pedestrians, an analysis of fatal and serious crashes by age group was conducted. The selected age distribution ensures a balanced representation of serious and minor crashes. It is worth noting that if all age variables are zero, it indicates that the pedestrian's age is unknown, which applies to 5% of the analyzed collisions. For micromobility users, when both "m_YOUNG18" and "m_OLDER64" variables are zero, it signifies a micromobility user is aged between 18 and 64 years.

Lastly, the p_OTHEROFFENCE variable encompasses other pedestrian offenses not mentioned previously, including walking illegally, disregarding traffic agent instructions, and other offenses not specified in the database.

2.3. Methodology

The Random Forest methodology was employed to develop a classification model and identify the most significant variables and their combinations affecting pedestrian injury severity. The model's decision rules provide valuable insights into this severity. To address the issue of unbalanced data, the synthetic minority oversampling technique was applied.

2.3.1. Synthetic Minority Oversampling Technique (SMOTE)

In this study, pedestrian injury severity was selected as the response variable, and was categorized into "slightly injured" (value 0) and "fatal and seriously injured" (value 1). However, a data imbalance issue arose, as the number of crashes with fatal and seriously injured pedestrians (201 crashes) is significantly lower than the number of crashes with slightly injured pedestrians (3004 crashes). This imbalance can lead to biased models [26,27], which often result in classification errors, and lack accuracy in predicting the minority class [26,28]. Simply relying on overall accuracy can be misleading in imbalanced data scenarios [28].

Furthermore, uncommon values of the target variable (the minority class) often represent significant events, such as rare diseases or more severe collisions [29]. Thus, accurately predicting the minority class, despite its scarcity, is of utmost importance [30].

To address the data imbalance problem, undersampling and oversampling techniques are commonly employed. Among them, the synthetic minority oversampling technique (SMOTE) is a widely applied and recognized oversampling technique [31,32].

The SMOTE technique was applied in this study to create new minority data from the original data. The new data, which are the random synthetic examples, were generated through an interpolation among nearest neighbors of each minority class instance, and from the original features [26,27,31,32].

2.3.2. Random Forest

Random Forest is a powerful and widely recognized supervised machine learning technique for classification problems [33]. It outperforms simpler methods like classification and regression trees (CART), due to its ability to build multiple individual decision trees and aggregate their predictions [34–37].

In Random Forest, each tree is trained on a bootstrap sample, a random subset of the original data, and only a subset of independent variables is considered at each split [37]. The inclusion of out-of-bag (OOB) samples, which are data points not used in the training of a specific tree, allows for performance evaluation and estimation of the model's accuracy [36,38].

In this study, the Random Forest model underwent a second validation step. The model was initially trained using the training set, which comprised 70% of the final database, and then validated using the remaining 30%, called the validation set. It has been demonstrated that the 70:30 training-to-test data ratio consistently yields the highest performance scores across all tree-based machine learning models, making it the most frequently recommended choice [39].

Additionally, there are two variable importance measures that can be used for ranking variables [40,41]. The first one is the Mean Decrease Gini (GINI), which quantifies the total decrease in node impurity attributed to a given variable when creating splits in the Random Forest. This value is normalized by the number of trees. The second measure is the Mean Decrease Accuracy (MDA), which assesses variable importance based on the change in prediction accuracy (measured by the OOB error) when the variable values are randomly permuted relative to the original data [41]. The GINI index typically provides more stable and reliable results compared to the MDA [41].

The Random Forest model was created using the variables described in section 2.1. The performance of the model was evaluated by analyzing the evolution of the out-of-bag (OOB) errors as the number of trees created (ntree) varied. Classification error 1 represents the OOB error related to the misclassification of crashes involving slightly injured pedestrians, while Classification error 2 represents the OOB error associated with the incorrect classification of crashes involving fatal and seriously injured pedestrians. The OOB error curve depicts the average evolution of this error for the model. Figure 3 provides a visual representation of these OOB errors and their variations.

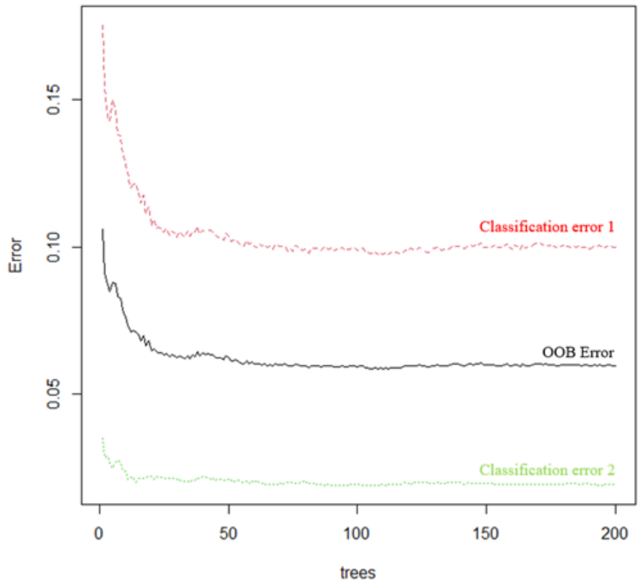

Figure 3. OOB Errors.

Figure 3 illustrates that the OOB errors reach a stable state at approximately 50 trees. For this study, a value of ntree = 200 was chosen as the selected hyperparameter, resulting in stable OOB errors. The model achieved an overall OOB error rate of 5.97%, indicating an accuracy of approximately 94% on the training set. Furthermore, the classification error for crashes involving slightly injured pedestrians (error 1) is 9.98%, while the classification error for crashes involving fatal and seriously injured pedestrians (error 2) is 1.92%. Although both errors are relatively small, the model demonstrates better performance in classifying crashes with fatal/seriously injured pedestrians, which is crucial for road safety as the cost of error 2 is higher than that of error 1.

The second validation procedure used the validation set to predict the response variable of the model, namely pedestrian injury severity. These predictions were utilized to assess the model's performance through the construction of a confusion matrix and ROC curve.

Figure 4 displays the confusion matrix, where the diagonal represents correctly classified data, and the values outside the diagonal indicate classification errors made by the Random Forest model trained solely on the training set.

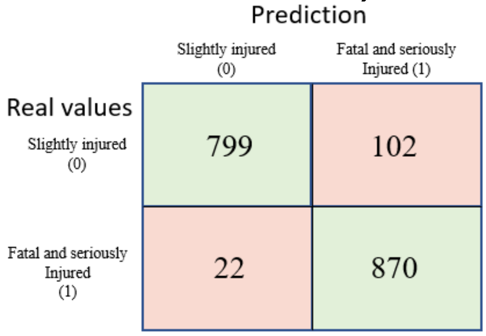

Figure 4. Confusion matrix for the Random Forest model.

The validation data accuracy of the model is 93.08%, indicating high predictive accuracy. The confusion matrix further demonstrates that the classification errors for crashes involving fatal and seriously injured pedestrians are lower compared to those for slightly injured pedestrians.

The performance of the model was also evaluated through the ROC curve, which depicts the sensitivity (true positive rate, TPR) and specificity (false positive rate, FPR) of the model. These measures are represented by Equations (1) and (2), and can be visualized in Figure 5. The area under the curve (AUC) serves as an estimate of the model's classifying ability [34].

$$\text{Sensitivity} = \text{TPR} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}, \tag{1}$$

$$\text{Specificity} = \text{FPR} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}}, \tag{2}$$

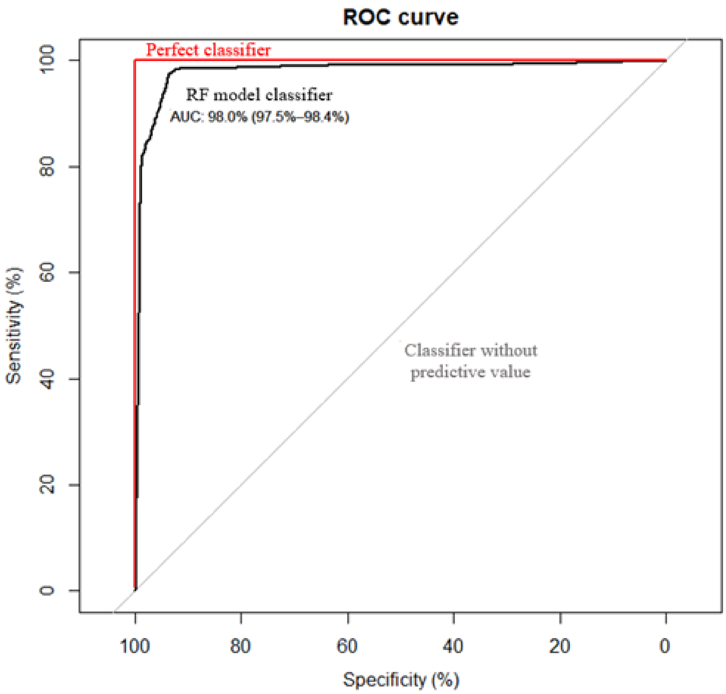

Figure 5. ROC curve.

A perfect classifier would have an AUC of 1, indicating flawless classification. As the AUC decreases, the classifier's performance deteriorates. In the case of the Random Forest model, it achieved an AUC of 0.98, which is very close to 1. This high AUC score indicates that the RF model performed exceptionally well in classifying crashes based on pedestrian injury severity.

Consequently, the Random Forest model was successfully validated for its accurate classification of crashes according to the severity of pedestrian injuries.

3. Results and Discussion

In this study, the Random Forest model developed in the previous section was utilized to analyze collisions between one micromobility vehicle and one pedestrian. The aim is to identify the key factors influencing pedestrian injury severity in these crashes, and to examine different combinations of these factors through the most important decision rules. This analysis will provide valuable insights into understanding these types of collisions, enabling authorities to implement effective measures to mitigate their impact on pedestrians.

3.1. Variable Importance Ranking

In this subsection, the importance rankings of variables as determined by Random Forest were analyzed. To ensure the robustness of the results due to the random initialization of the model, the Gini and MDA rankings were obtained multiple times (more than 10). The analysis reveals the following conclusions: (i) The Gini and MDA rankings produce similar results for the most and least relevant variables, indicating that they provide consistent information; (ii) the Gini index exhibits greater stability in its results compared to the MDA criteria, which is consistent with the findings of previous studies [41]. Therefore, the Gini index ranking of variable importance, as shown in Figure 6, was used in this study.

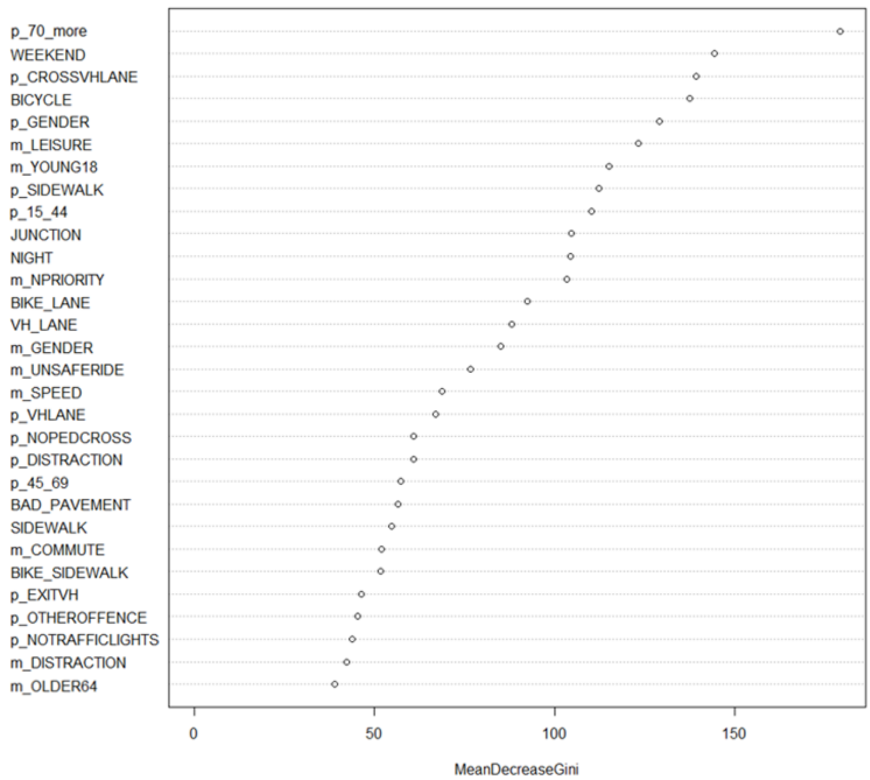

Figure 6. Variable importance ranking by GINI criteria.

Figure 6 shows the importance of various factors related to the pedestrian, micromobility user, collision, and micromobility vehicle in determining the severity of pedestrian injuries during collisions with micromobility users.

Regarding pedestrian factors, an age equal to or greater than 70 years (p_70_more) emerged as a highly significant variable impacting injury severity. Additionally, pedestrian gender (p_GENDER) and the action of crossing the road (p_CROSSVHLANE) were identified as influential factors.

Among the micromobility user factors, the variables m_LEISURE, m_YOUNG18, and m_NPRIORITY were the three most significant. The variable "m_LEISURE" denotes whether the micromobility user rides for leisure, probably implying that those riding for leisure may exhibit different riding patterns compared to other purposes.

Furthermore, collision-related factors also contributed to pedestrian injury severity. The variables WEEKEND (indicating whether the crash occurred on a weekend), JUNCTION (indicating collision at an intersection), and NIGHT (representing crashes occurring during nighttime) were identified as the three most relevant factors.

Finally, from the perspective of the micromobility vehicle, the type of vehicle, represented by the BICYCLE variable (distinguishing between bicycles and PMDs, especially e-scooters), also played a role in influencing the severity of pedestrian injuries.

Table 2 provides a summary of the three most relevant variables in relation to the response variable (pedestrian injury severity) for each factor.

Table 2. The most important variables obtained with Random Forest.

Most Important Variables			
Rider factors	m_LEISURE	Pedestrian factors	p_70_more
	m_YOUNG18		p_GENDER
	m_NPRIORITY		p_CROSSVHLANE
Crash factors	WEEKEND	Vehicle factors	BICYCLE
	JUNCTION		
	NIGHT		

Understanding the joint influence of multiple factors in pedestrian injury severity is crucial for effective resource management and decision-making by the authorities. While identifying the most and least important variables is valuable, it is the combined effect of these variables that provides highly relevant information. The decision rules generated by the Random Forest model aid in this task, enabling a comprehensive understanding of the simultaneous impact of various factors [35]. This knowledge can guide authorities in implementing targeted interventions and strategies to mitigate pedestrian injuries during collisions with micromobility users.

3.2. Decision Rules

In the Random Forest model, over 4000 decision rules (DRs) were generated. However, not all of these rules are unique, and their frequency of appearance and misclassification rates vary. Out of these, a set of 1795 unique decision rules was identified, and the model highlights the rules with the highest frequency (48 DRs). Table 3 presents the decision rules with higher frequencies and lower error rates. The Random Forest model's predictions, which are based on variable combinations (found in the 'Decision rule' column), are displayed in the 'THEN' column of Table 3. This table also provides the frequency (%) and estimated error (%) associated with each decision rule generated by the model.

Table 3. Decision rules with higher frequencies and lower errors.

Number	Decision Rule	THEN	Frequency (%)	Error (%)
1	IF (NIGHT = 0) AND (SIDEWALK = 0) AND (p_15_44 = 1) AND (p_CROSSVHLANE = 0) AND (p_VHLANE = 0) AND (p_NOPEDCROSS = 0)	Slightly injured	6.89	0
2	IF (BAD_PAVEMENT = 0) AND (m_NPRIORITY = 1) AND (m_DISTRACTION = 1) AND (p_15_44 = 0) AND (p_70_more = 1) AND (p_CROSSVHLANE = 0)	Fatal or seriously injured	1.27	0
3	IF (BICYCLE = 0) AND (BIKE_LANE = 0) AND (m_LEISURE = 1) AND (p_15_44 = 1) AND (p_CROSSVHLANE = 1)	Fatal or seriously injured	1.12	0
4	IF (BICYCLE = 1) AND (m_LEISURE = 0) AND (p_15_44 = 1) AND (p_CROSSVHLANE = 1)	Slightly injured	1.12	0
5	IF (JUCTION = 1) AND (m_LEISURE = 0) AND (m_COMMUTE = 1) AND (p_15_44 = 0) AND (p_70_more = 0) AND (p_SIDEWALK = 0)	Fatal or seriously injured	1.00	3.33
6	IF (VH_LANE = 0) AND (SIDEWALK = 0) AND (m_LEISURE = 0) AND (m_SPEED = 0) AND (p_15_44 = 1) AND (p_NOTRAFFICLIGHTS = 0)	Slightly injured	1.79	4.67
7	IF (WEEKEND = 1) AND (m_GENDER = 1) AND (m_LEISURE = 1) AND (m_SPEED = 1) AND (p_15_44 = 0) AND (p_70_more = 0)	Fatal or seriously injured	1.24	6.76
8	IF (BIKE_LANE = 0) AND (m_OLDER64 = 0) AND (m_LEISURE = 1) AND (m_DISTRACTION = 1) AND (p_15_44 = 0) AND (p_SIDEWALK = 1)	Fatal or seriously injured	2.22	8.27
9	IF (m_LEISURE = 1) AND (m_UNSAFERIDE = 0) AND (p_15_44 = 0) AND (p_70_more = 0) AND (p_GENDER = 0) AND (p_EXITVH = 1)	Fatal or seriously injured	1.67	9.00
10	IF (VH_LANE = 0) AND (m_LEISURE = 0) AND (m_NPRIORITY = 0) AND (p_15_44 = 0) AND (p_CROSSVHLANE = 1) AND (p_DISTRACTION = 1)	Fatal or seriously injured	1.56	11.83
11	IF (WEEKEND = 0) AND (m_LEISURE = 0) AND (m_COMMUTE = 0) AND (p_0_14 = 1) AND (p_70_more = 0)	Slightly injured	2.54	15.79
12	IF (WEEKEND = 1) AND (m_YOUNG18 = 1) AND (m_LEISURE = 1) AND (p_15_44 = 0) AND (p_70_more = 0) AND (p_SIDEWALK = 1)	Fatal or seriously injured	1.10	18.18
13	IF (NIGHT = 0) AND (m_SPEED = 0) AND (p_15_44 = 1) AND (p_CROSSVHLANE = 0) AND (p_NOTRAFFICLIGHTS = 0) AND (p_OTHEROFFENCE = 1)	Fatal or seriously injured	1.30	20.51
14	IF (SIDEWALK = 0) AND (m_OLDER64 = 0) AND (m_LEISURE = 1) AND (m_DISTRACTION = 0) AND (p_15_44 = 0) AND (p_EXITVH = 1)	Fatal or seriously injured	1.00	23.33
15	IF (m_OLDER64 = 0) AND (m_LEISURE = 1) AND (m_DISTRACTION = 0) AND (p_15_44 = 0) AND (p_NOPEDCROSS = 0) AND (p_OTHEROFFENCE = 1)	Fatal or seriously injured	2.63	26.75
16	IF (BAD_PAVEMENT = 0) AND (m_LEISURE = 0) AND (m_NPRIORITY = 0) AND (p_15_44 = 0) AND (p_45_69 = 1) AND (p_DISTRACTION = 0)	Slightly injured	9.38	41.00
17	IF (VH_LANE = 0) AND (BIKE_LANE = 0) AND (m_LEISURE = 0) AND (m_NPRIORITY = 0) AND (p_15_44 = 0) AND (p_70_more = 1)	Fatal or seriously injured	4.87	42.61

The analysis of decision rules provides valuable insights into the influence of various factors and their combinations on pedestrian injury severity in collisions with micromobility vehicles. These rules shed light on the joint effect of multiple factors, which is crucial for understanding the severity of these collisions and informing decision-making processes for authorities. Therefore, decision rules and the model's predictions offer valuable insights to aid traffic authorities, and can serve as practical guidelines for implementing effective road safety measures and policies.

The pedestrian's age emerged as a significant factor. For pedestrians aged 0–14, there is limited evidence to determine the influence on injury severity (DR 11). Pedestrians aged 15–44 are more likely to sustain minor injuries in crashes (DRs 1, 4, 6, and other DRs not included in Table 3). Specific conditions, such as crossing the road, involvement of a PMD rider traveling for leisure, and the presence of offenses or distractions, can elevate the likelihood of serious injuries (DRs 3, 13, and other DRs not included in Table 3). The conclusions regarding offences and distractions can be extended to other age groups as well (DRs 10, 15, and other DRs not included in Table 3). Studies have shown that distracted pedestrians are less attentive to their surroundings and take more risks [42].

For pedestrians aged 45–69, also only one decision rule was shown with an error of 41% that is not conclusive (DR 16). Therefore, there is insufficient evidence to draw conclusive results due to the absence of specific decision rules. However, some rules may indirectly refer to this age group, along with other age ranges, making it challenging to isolate their impact. Further analysis with more segregated age categories may be necessary, although the smaller sample size could limit the conclusiveness of the results.

Pedestrians aged 70 and above have a significantly higher likelihood of suffering severe injuries (DR 17 and other DRs not included in Table 3). More than 80% of the decision rules classify pedestrians of this age group as fatal or seriously injured in collisions with micromobility vehicles. These findings align with previous studies on pedestrian–cyclist collisions [43].

In addition, regarding elderly pedestrians, there are other factors that could further increase the probability that the collision would be considered serious, reducing the decision rule error. For example, it was observed that when the micromobility rider does not respect the priority rules (m_NPRIORITY = 1) or is distracted (m_DISTRACTION = 1), and has a collision with a pedestrian aged 70 or over (p_70_more = 1), the pedestrian is more likely to be seriously injured or die as a consequence of the crash (DRs 2 and other DRs not included in Table 3), with an error that oscillates between 0 and 0.33, depending on all variables present in the decision rule.

Factors related to the micromobility user, such as riding for leisure, show a correlation with increased distractions and speeding violations (DRs 7, 8, and other DRs not included in Table 3). Leisure trips are more prevalent among younger riders (under 18 years old) and on weekends (DRs 7, 12 and other DRs not included in Table 3). The severity of pedestrian injuries is observed to increase when the rider is traveling for leisure (DRs 3, 7, 8, 12, 15, and other DRs not included in Table 3). This may be attributed to differences in rider behavior, with more occurrences of speeding violations and distractions. Offenses and distractions heighten the risk of pedestrians suffering severe injuries. Previous research also highlights the increased risk of fatal crashes for pedestrians associated with these offenses [44].

Regarding collision-related variables, crashes occurring on weekends tend to have worse outcomes for pedestrians compared to those on weekdays (DRs 7 and 12). This can be attributed to a higher number of leisure trips and an increased occurrence of offenses. Collisions at intersections also tend to result in greater severity for pedestrians than those outside of intersections (DR 5 and other DRs not included in Table 3). In addition, it has also been observed that collisions occurring when the pedestrian is on the sidewalk increase the severity of their injuries (DRs 8, 12, and DRs not listed in Table 3).

Furthermore, collisions between micromobility users and pedestrians exiting vehicles tend to have more severe consequences, especially when the micromobility user is traveling for leisure (DRs 9 and 14). This finding is consistent with the result of another study that indicates a higher likelihood of sustaining severe injuries when cyclists use roads with on-street parking compared to roads without parking [45]. Therefore, it is important to incorporate a noticeable buffer zone when establishing a bike lane next to parked vehicles [46].

While some factors demonstrate a clear influence on pedestrian injury severity (e.g., p_70_more, m_DISTRACTION), there are others whose individual impacts remain unclear. Variables such as the type of micromobility vehicle (bicycle or PMD) and the NIGHT factor (indicating nighttime collisions) appear in several decision rules. However, their effects are inconclusive when combined with other more significant factors, particularly "p_70_more". Further analysis is necessary to explore the influence of these factors and their interactions with other variables.

It is important to note that the influence of certain factors may depend on their interaction with other variables involved in the collision. Isolating the impact of individual variables may not fully determine pedestrian injury severity, as the collective influence of all contributing factors is more significant. Decision rules, therefore, provide valuable insights by considering the joint effects of multiple factors, enhancing the value of this research.

4. Conclusions

The increasing use of micromobility vehicles in urban areas has led to a rise in collisions involving these vehicles. Pedestrians, being the most vulnerable road users, are particularly susceptible to serious injuries in such collisions. In this study, a Random Forest classification model was developed and validated to identify the key variables and their combinations that influence pedestrian injury severity in collisions with micromobility vehicles on urban roads in Spain between 2016 and 2021.

The model provided insights into the individual impacts of the analyzed factors on pedestrian injury severity, and examined their joint influence through decision rules. These decision rules are a valuable contribution to research, as they consider the simultaneous occurrence of multiple factors, which is often the case in traffic collisions, and determines the severity of the injuries sustained.

The results highlight several variables that significantly influence pedestrian injury severity in collisions with micromobility vehicles on urban roads. Age, particularly for pedestrians aged 70 and above, emerged as the most important variable. Collisions at junctions and on weekends also exhibited a higher severity prognosis for pedestrians. Additionally, pedestrian injuries are also more severe when offenses and distractions are present from both road users, when the collision between the micromobility user and pedestrian occurs on the sidewalk, and when the crash occurs while the pedestrian is exiting a parked vehicle.

Furthermore, the decision rules demonstrate the combined influence of various factors on the severity of pedestrian injuries. In cases where pedestrians aged 70 and above are involved, the severity is further intensified when offenses and distractions linked to micromobility users and pedestrians are involved, particularly among younger micromobility users and those engaged in leisure activities or weekend travel.

However, this study has certain limitations. The influence of some factors remains unclear due to their interactions with other variables in the collision. Further research is needed to gain a better understanding of these factors and their impacts.

The findings from this study provide valuable insights to authorities regarding the significance of specific factors and their combinations in pedestrian injuries resulting from collisions with micromobility vehicles. This information can guide the development of new measures, the modification of existing ones, and the implementation of road safety campaigns aimed at minimizing the negative consequences for vulnerable road users. By addressing the identified risk factors and promoting safer behaviors among micromobility users and pedestrians, authorities can work towards creating a safer urban environment for all road users.

Based on the findings, several recommendations can be made to mitigate the severity of injuries to pedestrians involved in collisions with micromobility vehicles. Firstly, in areas with a significant elderly pedestrian population, it is advisable to separate the flow of micromobility vehicles from pedestrian traffic as much as possible. This can help reduce the likelihood of severe injuries, particularly among pedestrians aged 70 and above.

Secondly, it is advisable to restrict the circulation of micromobility vehicles on sidewalks in order to reduce collisions with pedestrians on the sidewalk, as these collisions tend to result in severe injuries.

Furthermore, providing training and information to micromobility users, especially younger users, could be beneficial, since no special permits or traffic education are currently required for their operation. Road safety campaigns could also raise awareness about these collisions, and be accompanied by increased enforcement measures for micromobility users to prevent offenses, speeding, and distractions.

Lastly, to prevent crashes when a micromobility vehicle collides with a pedestrian exiting a parked vehicle, it is essential to incorporate buffer zones for vehicle door opening in bike lanes located near on-street parking.

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