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Identifying clusters and patterns of road crash involving pedestrians and cyclists. A case study on the Province of Brescia (IT)

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Abstract

Although road safety has improved in Italy over the last decade, the EU objective of halving the number of road deaths by 2020 has not been achieved yet. For pedestrians and cyclists, i.e., the most Vulnerable Road Users (VRUs), such trend is even worse: pedestrians' road crashes have plateaued around 0%, and the one of cyclists has increased by 10%, compared to 2010. Therefore, VRUs road safety requires further commitment. Clustering techniques have been used in road safety analysis to investigate crash patterns. Latent Class Clustering (LCC) and K-Means clustering were mostly applied and specifically as a pre-processing stage for further statistical analysis. This study proposes a framework to detect crash clusters and related patterns and associate with them specific solutions from a predefined set of solutions, mainly based on infrastructural and environmental attributes. Specifically, starting from raw official statistical crash data, the framework adopts hierarchical clustering to structure pedestrians' and cyclists' road crashes in urban areas. The framework is applied to the Province of Brescia (Northern Italy) using crash data collected for the five-year period 2014-2018. Three clusters for pedestrians' and five clusters for cyclists' road crashes are identified and specific solutions to mitigate crash occurrences are suggested, accordingly. The provided insights and solutions may be useful as a decision-support tool for public administrators in improving road safety.

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Keywords:. Vulnerable Road Users; Crash patterns; Solutions definition; Cluster analysis; Decision-support tool.

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1. Background

Road safety has slightly improved in Italy over the last decade. However, still too many people lost their lives or got injured in a road crash (ISTAT, (2020)). Focusing on the most Vulnerable Road Users -VRUs- (i.e., pedestrians and cyclists), statistics clearly show that the trend is even worse: compared to 2010, the involvement of pedestrians in road crashes has plateaued around 0%, that of cyclists has increased by approximately 10%, and 20,000+ pedestrians and 16,000+ cyclists were involved in a road crash in 2019 (Regione Lombardia, (2020a); (2020b)). In addition, pedestrians and cyclists represent roughly 25% of all road deaths. Indeed, being the most vulnerable among road users (due to lighter or null protection), they are exposed to more severe consequences when involved in a road crash (Bassani et al., (2020)). The Italian Road Safety National Plan (PNSS) 2010-2020 appointed VRUs as one of the strategic targets of road safety, and specific road safety actions are expected to decrease the number of pedestrians' and cyclists' deaths by 60%. However, such targets have not been achieved yet, and it is now necessary to put further commitment to improve road safety for VRUs.

Urban roads are the most critical sites for VRUs, due to the complexity of the urban environments both in terms of several coexisting traffic components and urban environment characteristics (Bonera and Maternini, (2020); Barabino et al., (2020)). Hence, the identification of road infrastructure and environmental related issues is not straightforward. Local Administrations (LAs) play a key role in such tasks, as they directly deal with urban road management. However, LAs, especially the smallest ones, might not have sufficient resources and expertise to identify crash patterns and promote related solutions. In addition, they might lack the availability of sufficient amount of data on road crash to draw some reliable conclusions. Therefore, LAs would benefit from the use of effective analytic tools, which help them in identifying specific risk factors and in defining the most appropriate road safety measures.

The literature provided several approaches to identify crash patterns. Tira et al. (1999), Fleury and Brenac (2001), and Tira et al. (2008) implemented the concept of "*accident prototypical scenario*" over VRUs and powered two-wheelers crashes, to produce a collection of solutions associated with each scenario. However, this approach is not suitable for LAs since it is manual and too expensive in terms of resources and time, requiring detailed data, especially that related to the pre-crash conditions (e.g. crash dynamics).

Recently, clustering techniques have been applied. Indeed, they enable detecting previously unknown relationships among data and homogeneous groups of data that are characterised by a high level of in-group similarity and inter-group dissimilarity. Different clustering techniques have been used in road crash analysis to investigate crash patterns at different levels and in different contexts. K-modes and Latent Class Clustering (LCC) are the most widespread clustering techniques (e.g., Kumar and Toshniwal (2015), Atalar and Thomas (2019), Janstrup et al. (2019), Mauro et al. (2013), Sun et al. (2019), Sivasankaran and Balasubramanian (2020)). These techniques can be used individually or combined with other specific techniques such as descriptive analysis (e.g., Atalar and Thomas (2019)), binary or multiple regressions (e.g., Sun et al. (2019), Sivasankaran and Balasubramanian (2020)). Other techniques were also applied for crash clusters detection, such as Kernel Density estimation (e.g., Bassani et al. (2020)) or hierarchical ascending clustering (e.g., Lenard et al. (2014)). As for the level and context analysis, the techniques were applied to investigate all types of road crashes (e.g., Mauro et al. (2013), Kumar and Toshniwal (2015), Janstrup et al. (2019)) or specific categories of users such as VRUs (e.g., Sun et al. (2019), Sivasankaran and Balasubramanian (2020), Bassani et al. (2020)).

All this literature provided valuable insights. Nevertheless, most of it employed clustering techniques as a pre-processing stage for the application of further statistical models aimed at investigating the influence of different factors over crash occurrence or severity. In addition, we observed that the LCC clustering and K-Means are the most employed techniques, while hierarchical clustering is less used. Some studies applied the analysis to different contexts or targets, so that differences may persist in the patterns of VRUs crash clusters. Moreover, almost none of such studies was conceived to provide specific infrastructural solutions to the VRUs clusters obtained.

This paper covers the former gaps, by extending the previous explorative analysis conducted as part of a project funded by Fondazione Cariplo (Maternini et al., (2020)). The paper proposes a framework to detect crash clusters and the related patterns and to subsequently associate with them specific solutions aimed at improving road safety for VRUs. More precisely, by focusing on pedestrians' and cyclists' road crashes occurred in urban areas of the Province of Brescia (Italy) from 2014 to 2018 and starting from raw official data a hierarchical clustering technique is applied to detect VRUs' clusters. Next, mainly based on infrastructural and environmental attributes, the related risk factors (or attributes, or variables) are identified and specific solutions are proposed.

This paper aims at contributing to both theory and practice. From a theoretical perspective, this paper contributes to improve the VRUs crash patterns knowledge. On the practical side, this study aims at making the process easier to be replicated and updated over time, since a set of publicly available data is adopted. In addition, this framework may support LAs, involved in the definition and implementation of safety measures (infrastructural and management interventions), to reduce the number of road crashes where VRUs were involved.

2. Methodological framework

In this section, the framework proposed is step-by-step described in detail. The structure of the framework is sketched in Figure 1, where the blue blocks represent the main tasks in each step of the framework.

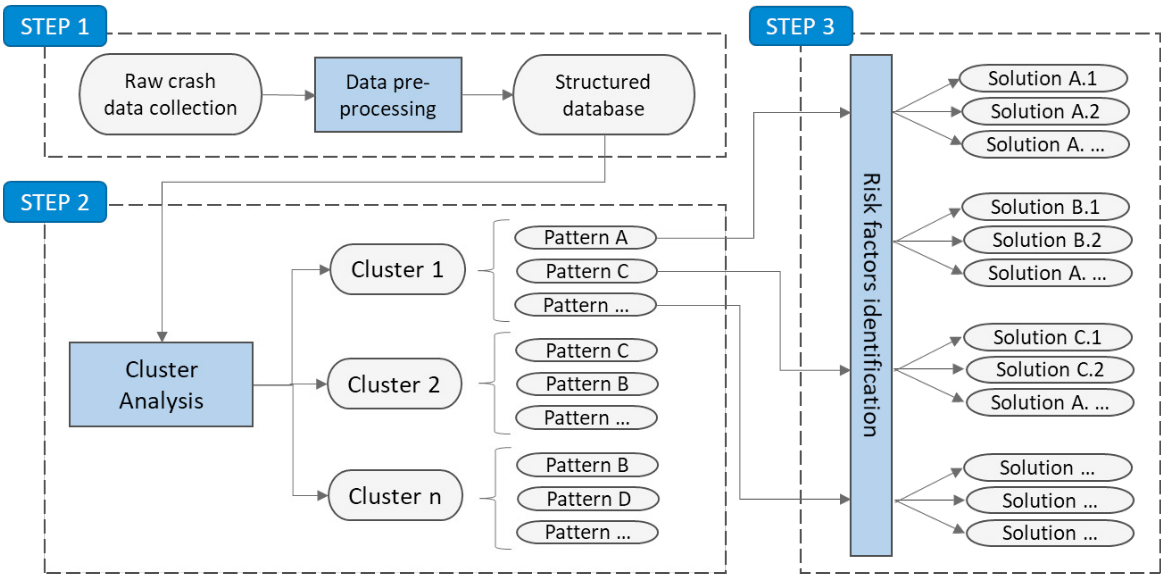

Figure 1 - VRUs road crash clusters and patterns framework

2.1. Step 1 - Data collection and pre-processing

First, road crashes data should be collected from an official statistical source for a large enough time (e.g., 5 years). This data should be publicly available and standardised at national level. Next, some pre-processing should be applied to this data to polish it and prepare it to become input to the following step. Data pre-processing comprises: (i) filtering data according to the scope of the analysis (e.g. users' type); (ii) handling missing values; (iii) replacing all non-numerical records with numerical values; and (vi) scaling values. Hence, a structured database is returned, comprising the data that is relevant to the scope of the analysis, including infrastructural and environmental attributes, besides those related to the crash general characteristics (e.g. location, date, number of people involved and consequences, etc.).

2.2. Step 2 – Cluster analysis

Cluster analysis aims at grouping a set of observations into subsets (clusters) so that, given a similarity measure, the observations within the same cluster are as similar as possible, and are as dissimilar as possible from those in the other clusters. Several cluster methods are available. Hierarchical clustering (h-clustering) method was chosen. The basic idea of h-clustering is that observations are more related to 'nearby' observations rather than to 'distant' observations.

Hence, the nature of the h-clustering method employed is aggregative. At the beginning, each observation represents a different cluster. Subsequently, at each iteration, the two closest clusters (based on the distance measure introduced above) are aggregated into a new cluster. Such procedure is iterated until all observations have been aggregated into one single cluster. On the one hand, h-clustering does not require the upfront specification of the number K of clusters to be generated, compared to K-Means and K-Modes methods. On the other hand, this method requires the definition of a distance measure. Let: D be a given database; X, Y be two generic observations belonging to D; n be the number of attributes, which characterize each observation; and x_i, y_i be the values taken by the i-attribute, with $i=1, \ldots, n$, in observations X, Y.

The distance between X and Y is computed according to the Euclidean distance as follows:

$$d(X,Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \quad (1)$$

The optimal number of clusters can be identified by computing the *silhouette* value, that is a measure of how similar an observation is to its own cluster (cohesion) compared to other clusters (separation). The silhouette value ranges from −1 to +1, where a high value indicates that the observation is well matched to its own cluster and poorly matched to neighbouring clusters (e.g., Kaufman and Rousseeuw, (2005)). The optimal number of clusters is the one that maximizes the average silhouette value.

H-clustering methods return a tree-based representation of the observations, called dendrogram, that visually helps in identifying clusters. At the bottom of the dendrogram, each observation is reported individually. As we move up along the tree, observations that are close to each other are aggregated into branches. The height of the aggregation (nodes) indicates the similarity between two observations so that the higher the height of the aggregation the less similar the observations. The height of the cut of the dendrogram controls the number of clusters produced (see the blue lines in Figure 2). At the end of step 2, a set of clusters is drawn with the related typifying patterns.

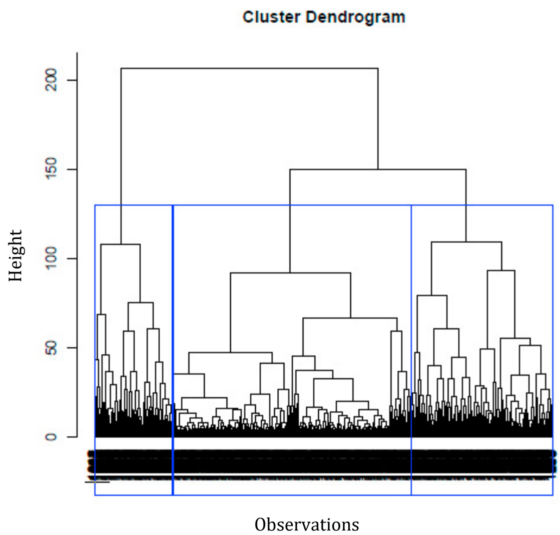

Figure 2 - Hierarchical clustering dendrogram of the pedestrian database.

2.3. Step 3 - Risk factors identification and solution association

For each pattern that typifies the clusters drawn from step 2, the related risk factors are identified, which may contribute to crash occurrence and its severity. Attention is mainly paid to road design and road environment. However, other variables such as weather conditions or time of the day are considered too, since they can help in pinpointing further safety shortcomings (e.g., lighting or surface conditions). Once the risk factors are detected for each pattern, an as complete as possible set of solutions is proposed to be implemented to mitigate the effects of those risk factors.

Therefore, each cluster is finally associated with the most appropriate solutions, either oriented towards a design and infrastructural intervention or a road-management measure.

3. Experimentation in a real case study

The proposed framework has been applied to the Province of Brescia (Italy), to investigate pedestrians' and cyclists' road crashes that occurred over the five-year period 2014-2018. The Province of Brescia is the second province in the Lombardy Region (the most populated Italian region) in terms of number of pedestrians and cyclists involved in a road crash, after that of Milan. Specifically, for this study the framework described above has been implemented through the open-source R software.

According to **step 1**, the raw road crash data was collected from the official Italian National Statistical Institute (ISTAT), provided by Polis-Lombardia. Then, some pre-processing was performed to prepare data for the next step. First, as the raw data consisted of all type of road crashes, some filters were used to extract the road crashes occurred in the Province of Brescia (geographical filter) involving at least one VRU (user filter). The resulting database consisted of 4,006 observations. Two databases were created, one for pedestrians' road crashes (1,681 observations), and another for cyclists' road crashes (2,359 observations). Note that for some road crashes, both pedestrians and cyclists are simultaneously involved. In such cases, the associated observation was added to both databases. Next, from a total of 169 attributes, just crash general characteristics (e.g. time attributes, type of crash, number and role of people involved, road type, etc.), and the ones related to the infrastructural and environmental patterns were kept, according to the scope of the analysis. Next, attributes showing too many missing values were removed, and some data aggregation/disaggregation was also performed. All non-numerical attributes were transformed into numerical ones using a binary expansion. More precisely, every non-numerical attribute with *k* distinct values was replaced by *k* binary attributes. For each observation, the *i-th* binary attribute takes value 1 if and only if the original attribute takes the *i-th* value (*i=1,…,k*). Finally, to avoid that attributes taking large values have a high impact on the distance measure, the values taken by each attribute have been standardized by using the R function *scale()*.

Next, according to **step 2**, cluster analysis was performed for both databases. A dissimilarity matrix comprising the dissimilarity measures computed by using the distance function introduced above has been produced by using the R function *dist()*. Such dissimilarity measure is then fed into the *hclust()* function to carry out the aggregative h-clustering method. One critical requirement for cluster analysis is the determination of the number of clusters to be created. To determine such number, we proceeded as follows. By means of the R function *silhouette(),* we first computed the average silhouette value for different numbers of clusters. Then, we selected, as the optimal number of clusters, the one that maximized the average silhouette value. Some clusters were detected, and several infrastructural patterns were found to be relevant in their definition. Specifically, three clusters were identified for pedestrians and five clusters were detected for cyclists, which are presented in detail in the following paragraphs.

According to **step 3**, based on the infrastructural and environmental patterns typifying the several clusters, some risk factors were derived. Then, a list of suitable solutions was created, comprising both infrastructural and road-management measures aimed at improving road safety for VRUs. Such solutions were mainly derived by technical knowledge and expertise of the authors, as well as national and international best practices. Hence, each cluster is associated with the set of specific safety solutions, which can help in mitigating crash occurrence or severity, depending on the crash patterns detected and the corresponding risk factors. The results of the application of this step are presented in what follows for pedestrians and cyclists, respectively.

3.1. Pedestrians' clusters

The framework grouped the pedestrians' road crashes into 3 clusters. A thorough analysis of each cluster revealed that the month, the time of the day, and the driving violations of vehicles (e.g., missed right of way) are the main patterns that differentiate the 3 clusters, whereas the infrastructural and environmental patterns are rather similar across the 3 clusters. More precisely, the presence of non-protected pedestrian crossing, two-way undivided carriageways, and dry paved straight roads were found to be common among clusters. Table 1 reports, for each cluster, the cluster-specific patterns (the former), as well as the common patterns (the latter). Then, for each common pattern, we identified the associated risk factors and proposed suitable solutions.

Table 1. Risk factors and solutions for pedestrians' road crashes

Cluster (% observations)	Cluster-specific patterns	Common patterns	Risk factors	Solutions
CP3 (51,94%)	November Morning Missed right of way	Non-protected pedestrian crossing	Miss right of way to pedestrians	Remove all sight obstacles from the roadside area. Create sidewalks extension at crossings to enhance pedestrian visibility. Install traffic light with automated pedestrian detection systems.
CP2 (31,05%)	December Afternoon Missed right of way	Two-way undivided carriageway	Unsafe crossing phase for pedestrians.	Create raised crossing to extend the level of the sidewalk or create sidewalk extensions to reduce crossing distance. Introduce pedestrian refugee islands to split crossing stages and enhance pedestrians' safety.
		Presence of road signs (both vertical and horizontal)	Inadequateness of existing road signs	Maintain better horizontal road signs (e.g., zebra crossings) or introduce floor colouring to make them more visible. Replace discoloured vertical road signs to improve their perception.
CP1 (17,01%)	January Afternoon Vehicle was driving regularly	Dry paved straight road	Passing vehicles at high speeds	Introduce 30kph zones on minor urban road Introduce traffic calming elements (e.g. vertical deflection, horizontal shift, and roadway narrowing, etc.)
		Winter months	Lighting problems and low visibility	Install advanced lightings system to enhance pedestrian's visibility during dark hours such as "air crosswalk" or special luminescent floorings.

3.2. Cyclists' clusters

The framework grouped the cyclists' road crashes into 5 clusters (see Table 2). Compared to the pedestrians' case, the cyclists' clusters are more heterogeneous and infrastructural and environmental patterns contributed significantly in typifying such clusters. Due to space limitation, Table 2 reports for each cluster the typifying infrastructural and environmental patterns, the related risk factors, and the proposed suitable solutions.

Table 2. Risk factors and solutions for cyclists' road crashes

Cluster (% observations)	Patterns	Risk factors	Solutions
CC1 (79,53%)	Road intersections and/or roundabouts	Hit between a vehicle and cyclist	Provide intersection with cycle boxes ahead stop lines to advance cyclists over vehicles.
		Missed right of way	Create protected cycle facilities at intersection by extending kerbs to separate cyclists' manoeuvres from the ones of vehicles.
	Presence of road signs (both vertical and horizontal)	Inadequateness of existing road signs	Better maintain road signs (e.g. crossing signs) or substitute them where necessary Introduce different floor colouring to improve visibility
CC2 (17,63%)	Dry roads	Possible road surface decay	Better maintain road surface to avoid holes Create dedicated cycle paths with specific flooring materials
	Straight segments	Passing vehicles at high speeds	Separate cycle traffic from motor-vehicle traffic by creating protected cycle paths.

Cluster (% observations)	Patterns	Risk factors	Solutions
	Absence of road signs or presence of horizontal-only sings	Low road readability	Install readable cycling road signs and all advices needed to advice cyclists of possible hazards.
			Introduce different colouring to improve road signs perceptions.
CC3 (1,02%)	Wet roads	Possibility to fall on or off the road and collide with other vehicles	Maintain road surface especially where cyclists are admitted and keep manhole coverings free and the road surface levelled.
			Create protected cycle path along major roads and use smoothed kerbs, which can forgive hazardous manoeuvres.
	Absence of road signs	Low road readability	Install readable cycling road signs and all advices needed to advice cyclists of possible hazards.
			Introduce different colourings to improve road signs perceptions.
CC4 (0,72%)	Non-urban roads	Vehicles high speed	Separate cycle traffic from motor-vehicle traffic by creating protected cycle paths.
		Collision with other vehicles	
	Straight segments	Passing vehicles at high speeds	Create protected cycle paths along non-urban road segments and use smoothed kerbs, which can forgive hazardous manoeuvres.
	Presence of slope	Difficulties while cycling	Identify possible alternative itineraries with lower slope to facilitate cycling.
	Ruined flooring	Possibility to fall on or off the road	Maintain road surface especially where cyclists are admitted and level manhole coverings to the road surface.
	Presence of obstacles on the road	Possibility to collide	Verify visibility of cycle paths along roads.
			Keep cycle paths and roadside nearby free from obstacles.
	Absence of road signs	Low road readability	Specific road signs must be installed along non-urban roads to advise drivers of cyclists' presence nearby.
			At intersection, install specific crossing signs and use coloured flooring materials to enhance visibility.
CC5 (1,10%)	Straight segments	Passing vehicles at high speeds	Separate cycle traffic from motor-vehicle traffic by creating protected cycle paths.
	Road intersections and/or roundabouts	Hit between a vehicle and cyclist	Provide intersection with cycle boxes ahead of stop lines to advance cyclists over vehicles.
		Missed right of way	Create protected cycle facilities at intersection by extending kerbs to separate cyclists' manoeuvres from those of vehicles.
	Afternoon hours	Lighting problems and low visibility	Install advanced lighting system to enhance pedestrians visibility during dark hours such as "air crosswalk" or special luminescent floorings.
	Presence of road signs (both vertical and horizontal)	Inadequateness of existing road signs	Better maintain road signs (e.g. crossing signs) to make them more visible or introduce different colourings to improve road signs perceptions.

4. Conclusions

This paper proposed a framework to detect crash patterns and to define specific solutions to improve road safety. Specifically, it was tested on a real case study, by focusing on pedestrians' and cyclists' road crashes, mainly in urban areas. Road infrastructure and environmental patterns were found to be relevant for the definition of road crash clusters. Therefore, specific solutions were suggested accordingly, to mitigate pedestrians' and cyclists' crash occurrences. Although the framework did not enable detecting significantly different clusters for pedestrians, nonetheless it enabled highlighting the main infrastructural criticalities, which should be addressed with more attention to improve road safety for them. Instead, interesting different patterns were detected for cyclists' crashes.

A possible extension of the present research is to link the site-specific spatial dimension to the clustering analysis, so that further elements can be considered for the identification of critical sites for VRUs, i.e. "*black spots"*. An analysis of the risk of crashes, encompassing statistical models for the occurrence, the severity of crashes, and the exposure variables, would be an important research topic. The goal would be to better understand which interventions may reduce and/or eliminate specific risks and to identify the paths where pedestrians' and cyclists' could circulate, as already done in public transport (Porcu *et al.*, (2020), Barabino *et al.,* 2021).

5. Acknowledgment

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