

# Cause-Based Unsupervised Risk Profiling of Injury-Involved Traffic Accidents with Post-Hoc Severity Validation

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## ABSTRACT

Understanding the heterogeneous nature of traffic accidents is significant for developing effective road safety policies and targeted preventive strategies. In this study, traffic accidents were examined independently of outcome variables, and an analytical framework based on accident-based risk profiling was proposed. The dataset used, consisting of official traffic accident records involving injuries, was converted into an accident-based structure using unique accident identifiers, yielding a more compact and interpretable representation for analysis. To enhance interpretability and reduce noise, the dataset was limited to summary variables related to road characteristics, environmental conditions, accident types, and vehicle and driver attributes. In addition, risk profiles were derived using the K-Means clustering method within an unsupervised learning framework. Only variables representing the structural conditions under which the accident occurred were included in the clustering process, while the number of deaths and injuries was excluded to prevent outcome leakage. Following clustering, a continuous severity score was defined, assigning a higher weight to accidents with fatalities, to compare the severity levels of the risk profiles. The results revealed the existence of four distinct and balanced risk profiles that were found to differ significantly in terms of accident severity, accident types, speed limits, and temporal distributions. The highest-risk profile was associated with run-off-road and rollover accidents occurring on roads with high speed limits, whereas lower-risk profiles were primarily characterized by contact-related accident types on roads with lower speed limits. These findings indicate that evaluating traffic accidents based on structural risk profiles, rather than solely on frequency or binary severity classes, provides more informative results. The proposed approach offers a practical methodological framework for developing decision support systems in traffic safety and for formulating targeted preventive policies.

*Keywords-traffic accidents; risk profiling; unsupervised learning; severity analysis*

## I. INTRODUCTION

Road traffic accidents are among the most crucial issues in transportation policy, causing injuries or even the loss of lives, while also resulting in several economic costs. The traffic safety literature shows that accidents cannot be attributed solely to driver error, but rather to multiple factors, including road geometry, environmental conditions, and traffic control infrastructure, which are associated with elevated accident risk [1, 2]. Therefore, data-driven approaches aimed at extracting risk patterns from accident records have become common [3].

Machine Learning (ML)-based methods have gained prominence in traffic accident analysis due to their ability to model the multidimensional and complex relationships of risk patterns [4]. In particular, accident severity (fatality/ injury levels) prediction, and quantitative assessment of risk factors are widely addressed within classification and regression frameworks [5]. However, studies focusing solely on prediction performance raise two fundamental issues from a public policy perspective: i) limited interpretability of the causes of heightened risk, and ii) limited ability to produce actionable profiles or segments suitable for intervention.

In this context, Explainable Artificial Intelligence (XAI) approaches are used to enhance decision-making in traffic safety applications [6], with their main advantage being their ability to quantify the conditions under which risk increases, thereby identifying potential intervention points [7]. Furthermore, interpretable modeling facilitates practical adoption by supporting trust and accountability [8].

The aim of this study is to construct an accident-level dataset by aggregating accident records based on Accident Identity (ID) and to derive risk profiles using only causal variables. An important aspect of this approach is that outcome variables, such as death and injury, are excluded from the profile generation stage and used only for post-hoc evaluation. This reduces the risk of outcome leakage and ensures that the resulting profiles represent condition-based segments suitable for policy development [9]. Next, the present work conducts post-hoc validation using severity metrics that provide an objective assessment of whether the profiles correspond to more severe outcomes, while the profiles themselves provide a basis for decision support by enabling interpretation of variables such as accident type, speed limit, and traffic control elements [10].

#### A. Literature Review

In the field of traffic accident severity modeling, gradient-based and tree-based methods have demonstrated strong predictive performance [4]; however, because model performance is sensitive to dataset structure and variable distributions, comparative studies are essential for model selection [11] and for assessing generalizability across different traffic contexts [12].

Beyond model selection, researchers must address inherent data complexities; for instance, the rarity of fatal or severe injury outcomes often creates class imbalance problems that complicate both model training and evaluation [13]. Additionally, the heterogeneous nature of accident records, which typically combine numerical and categorical fields, requires specialized preprocessing [14], including the use of recent transformer-based architectures designed specifically for such mixed-data scenarios [15].

The predictive accuracy of these frameworks is also deeply influenced by environmental and infrastructural variables. Studies at regional and national scales indicate that local road infrastructure and driving behaviors can significantly alter the relative importance of various risk factors. Specifically, road geometric characteristics, such as curve radius, superelevation, and section speed, are significant predictors of accident-prone zones when analyzed through ensemble and regression-based frameworks [2, 16]. The challenge of interpreting these contributing factors is often compounded by data quality issues and the high diversity of accident categories [17], suggesting that the overall comprehensiveness of the feature set is a primary determinant of model performance [18]. These complexities are further magnified by temporal and spatial dimensions, as intraday and seasonal variations introduce significant fluctuations in crash risk [19]. To capture this variability, dynamic modeling approaches have been proposed to replace fixed-coefficient models [20], while network-based

models incorporating road topology have further explained the spatial clustering tendencies of accidents [21].

Additionally, accident risk is viewed not as an isolated event, but as a continuous process shaped by the interaction between vehicle mobility, driver behavior, and existing infrastructure [22]. This perspective necessitates careful experimental design to ensure model robustness [23], alongside a commitment to methodological transparency regarding how evaluation metrics shape the interpretation of the results [24]. To bridge the gap between complex model outputs and practical safety interventions, XAI is used [6], offering interpretable insights to policymakers for specific actions such as implementing lower speed limits and adjusting lighting conditions or traffic control status [8]. Despite the utility of XAI, generating reliable explanations remains challenging in high-dimensional spaces with abundant categorical variables; consequently, researchers have proposed combining dimensionality reduction with XAI to enhance clarity [25].

Finally, recent efforts in severity prediction seek to improve not only predictive accuracy but also the "why" behind the data [26], often utilizing rule-based and hybrid designs to integrate domain expertise into the model [27]. Complementing these supervised approaches, clustering and profile-based analyses of group accidents under structurally similar conditions are conducted to provide segment-level safety insights [10]. This profiling approach is often more actionable than a single global risk score because it identifies specific combinations of conditions, such as the interaction between accident type and traffic control, which define a risk profile [28]. Such analyses can also reveal distinct risk patterns based on vehicle types or specific driver behaviors [29].

A key methodological gap in the existing profiling literature, however, is the frequent inclusion of outcome variables directly within the clustering process. When death or injury counts are used as clustering features, the resulting profiles are defined by their outcomes rather than the causal conditions that produced them, which is a form of "outcome leakage" that blurs the cause-and-effect distinction. A more methodologically sound approach involves generating profiles using only causal variables and reserving outcome metrics for post-hoc validation [9], while also considering the robustness and transferability of these profiles across different contexts [30].

## II. MATERIALS AND METHODS

### A. Data Source and Scope of Work

The dataset used in this study was obtained from official administrative traffic crash records provided by the General Directorate of Security of Türkiye, and covers the period between 2014 and 2023. The records include injury- and fatality-involved crashes reported under national traffic reporting regulations, which were accessed under formal institutional research permission granted by the relevant authority upon official request for academic purposes. Due to confidentiality and data protection policies, the dataset is not publicly available and cannot be shared.

The raw dataset consists of time information, road characteristics, environmental conditions, vehicle and driver-related variables, and outcome variables, including the number of fatalities and injuries. Since the raw data may contain multiple records for the same accident, an accident-level approach was adopted as the unit of analysis instead of individual rows, where each accident is represented by a unique Accident ID key (AccidentId). The general methodological flow of the study is summarized in Figure 1.

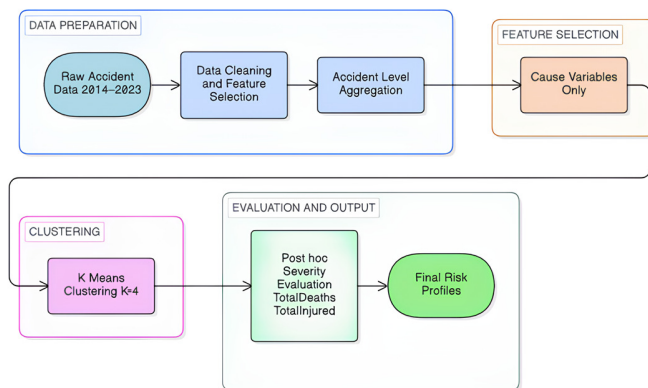


Fig. 1. Methodological workflow.

### B. Data Preprocessing and Variable Derivation

In the preprocessing stage, time information was standardized. For records lacking the AccidentHour variable, accident time was derived from the AccidentTime field to capture intraday temporal patterns. Moreover, outcome variables, TotalDeaths and TotalInjured, were converted to numerical format, as they appeared in different formats in the raw dataset, with missing or inconsistent values set to zero.

Furthermore, cause variables were divided into numerical and categorical groups. Numerical variables include accident time, road speed limit, number of lanes, and number of vehicles involved, while categorical variables include road type, road surface, weather and lighting conditions, traffic light status, accident type, point of first impact, vehicle type, and driver behavior.

### C. Accident-Level Aggregation

Raw records were grouped by AccidentId to construct an accident-level dataset, while aggregation strategies were applied according to variable type. Specifically, numerical cause variables were averaged to account for minor variations across sub-records, while categorical variables were summarized using the most frequent value (mode), representing the dominant condition. Outcome variables, such as fatalities and injuries, were aggregated to preserve the total impact of each accident. As a result, each row corresponds to a single accident, ensuring consistent event-level representation without duplication effects. Let  $i$  denote an accident identified by AccidentId and let  $j$  index its associated records. Accident-level numerical cause variables are computed as:

$$\bar{x}_i = \frac{1}{n_i} \sum_{j=1}^{n_i} x_{ij} \quad (1)$$

### D. Cause-Effect Separation and Severity Score

Only cause variables were used for risk profile derivation, while outcome variables (fatalities and injuries) were excluded from clustering. This approach aims to prevent profiles from being shaped directly by outcomes, thereby enabling a clearer analysis of the conditions under which risk is observed.

The outcome variables were used for evaluation purposes after the profiles were obtained. For the evaluation, an accident-level severity score is defined as a weighted linear combination of fatalities and injuries, assigning greater weight to fatalities. This score was used to interpret the relative risk levels of the profiles, but was not used as a clustering input at any stage:

$$SeverityScore_i = 5 \cdot TotalDeaths_i + TotalInjured_i \quad (2)$$

where  $TotalDeaths_i$  and  $TotalInjured_i$  represent the total number of fatalities and injuries associated with accident  $i$ , respectively.

Additionally, a sensitivity analysis was conducted to evaluate the impact of weight selection on the results. The profile ranking was recalculated under the fatality/injury weight scenarios (3:1) and (10:1), and it was observed that the profile ranking remained unchanged in both scenarios.

### E. Feature Transformation and Clustering

The cause variables in the accident-level table were transformed into a numerical feature space suitable for clustering. Numerical variables were standardized to account for scale differences, while categorical variables were encoded using one-hot encoding. Rare categories appearing in fewer than 1% of observations were identified across several features, including RoadClass (e.g., "Parking Area", "Forest Road"), RoadSurface (e.g., "Gravel", "Dirt"), WeatherCondition (e.g., "Blizzard", "Hail"), AccidentType (e.g., "Hit Animal", "Object Fell from Vehicle"), VehicleType (e.g., "Cart", "Train"), and DriverAlcoholTestResult (e.g., "Drunk", "Very High Blood Alcohol Concentration"). These categories were retained in the dataset but encoded using one-hot encoding with the handle\_unknown="ignore" parameter, which assigns a zero vector to any category not observed during training. This approach prevents rare or unseen categories from disproportionately influencing the clustering process.

Risk profiles were extracted using the K-Means algorithm. To objectively justify the selection of the number of clusters used, internal validation metrics were computed for K values ranging from 2 to 8, including silhouette score, Calinski-Harabasz index, Davies-Bouldin index, and inertia (elbow method). Although  $K = 2$  yielded the highest silhouette score, this solution resulted in overly coarse segmentation that masked structural differentiation between accident contexts. The elbow curve showed a diminishing marginal reduction in inertia beyond  $K = 4$ , indicating that additional clusters provided limited explanatory gain. Moreover, while internal indices varied slightly across K values, the  $K = 4$  configuration provided a balanced trade-off between cluster compactness, separation, and practical interpretability, and was selected as the most appropriate solution.

Given the feature matrix  $X = \{x_1, x_2, \dots, x_n\}$ , K-Means partitions the data into K clusters by minimizing the within-cluster sum of squares:

$$\min \sum_{k=1}^K \sum_{i \in C_k} (x_i - \mu_k)^2 \quad (3)$$

#### F. Ranking Profiles by Risk Level and Outputs

Since K-Means produces clusters with arbitrary labels, the resulting profiles were ranked based on their average *SeverityScore*. Clusters were relabeled in ascending order of average severity, where RiskProfile = 0 corresponds to the lowest risk and RiskProfile = 3 to the highest.

### III. RESULTS

The final dataset after the preprocessing and simplification steps contained 10,481 accident events, while the resulting risk profiles are presented in Table I. The extracted risk profiles are well balanced in terms of sample size and exhibit a progressively increasing average severity across reordered profile labels from Profile 0 to Profile 3. Profile 0, having the lowest average severity value, is characterized by relatively minor injuries, while Profile 3, having the highest average severity value, is characterized by a higher concentration of fatal accidents. Additionally, the evaluation of mean fatalities and injuries indicates that fatalities increase markedly in Profile 3, while Profile 2 is characterized by a relatively high number of injuries but a lower fatality rate, indicating that profiles differ not only in overall severity but also in severity composition (Figure 2).

TABLE I. SUMMARY STATISTICS OF THE EXTRACTED ACCIDENT-LEVEL RISK PROFILES, INCLUDING PROFILE SIZE AND AVERAGE SEVERITY INDICATORS

Risk profile	Number	Mean severity	Mean deaths	Mean injured
0	2,931	2.6288	0.0341	2.4582
1	1,972	3.4113	0.0492	3.1653
2	3,141	3.5985	0.036	3.4187
3	2,437	3.8826	0.1145	3.3102

To statistically assess whether the observed differences in severity across the profiles were significant, a Kruskal-Wallis H test was conducted on the severity score. The results revealed a statistically significant difference among clusters ( $H = 319.97$ ,  $p < 0.001$ ), with an effect size of  $\varepsilon^2 = 0.030$ , indicating a small-to-moderate practical difference in severity distributions across profiles.

#### A. Profile-Based Analysis of Severity Distributions

The severity score distributions associated with risk profiles are presented as boxplots in Figure 3. The results reveal that there are significant differences between the profiles not only in terms of average values but also in terms of distribution structure. Specifically, while the severity distributions in Profile 0 and Profile 1 were concentrated within a narrower range, Profile 3 exhibited a broader distribution, with accidents involving extreme values clustered under this profile. This finding indicates that Profile 3 is characterized not only by higher average severity but also by a more heterogeneous accident structure prone to extreme outcomes.

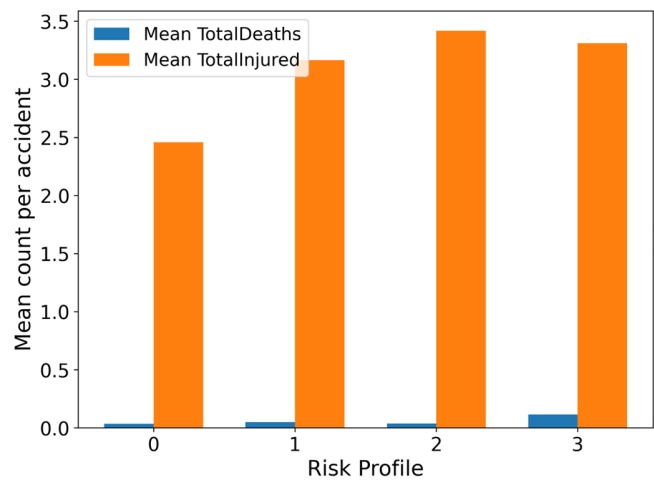


Fig. 2. Average fatalities and injuries by risk profile.

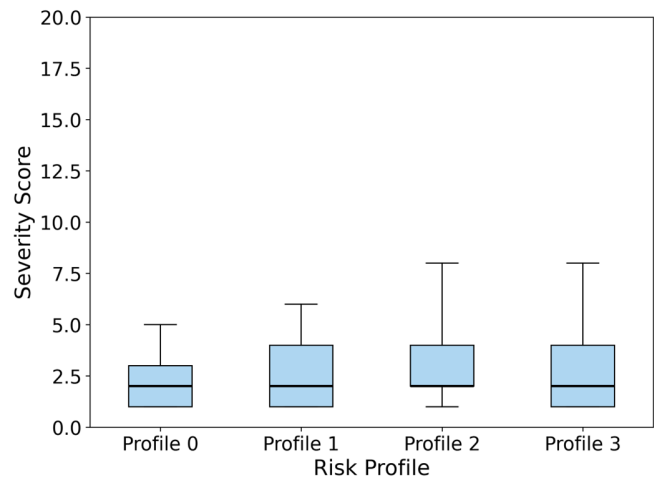


Fig. 3. Severity score boxplots by risk profile without outliers (whiskers: 10<sup>th</sup>-90<sup>th</sup> percentile).

#### B. Characterization of Risk Profiles According to Accident Types

Figure 4 presents the profile-based accident type distributions, showcasing that i) Profile 0 consisted mainly of pedestrian and side collisions; ii) Profiles 1 and 2 were characterized predominantly by side and rear-end collisions, which are more compatible with urban and medium-density traffic conditions; and iii) Profile 3 was distinctly characterized by off-road and rollover accidents, which are among the accident type scenarios associated with higher mortality risk in the literature. The last observation structurally explains why Profile 3 emerged as the highest-risk profile.

In addition, the association between accident type and risk profile was examined using a Chi-square test of independence. The test produced a statistically significant result ( $\chi^2 = 3,364.66$ ,  $p < 0.001$ ), while Cramér's V was calculated as 0.327, indicating a moderate association between accident type and risk profile classification.

C. The Relationship Between Speed Limits and Risk Profiles

Examination of the profile-based speed limit distributions showed that low- and medium-risk profiles (Profile 0-2) were largely concentrated on roads with a speed limit of 50 km/h, while roads with speed limits of 90 km/h and above were predominant in Profile 3. This result suggests that high speed limits are strongly associated with higher fatality rates. Furthermore, the distinction between speed limits and risk profiles indicates that the clustering process successfully captured speed-related structural risks. Figure 5 illustrates this relationship.

D. Timing Distribution and Intraday Patterns

The examination of the temporal distribution of risk profiles revealed distinct intraday patterns between profiles. According to the results presented in Figure 6, low-risk accidents were concentrated primarily during daytime and afternoon hours, while medium-risk profiles showed an increase toward evening hours. In contrast, accidents associated with Profile 3 were distributed across a wider time range, particularly during nighttime hours, which indicates that high-risk accidents occur more frequently during periods associated with low visibility conditions and higher-speed driving environments.

severity [1, 11, 16]. Furthermore, the temporal analysis revealed that high-risk accidents are concentrated during nighttime periods and distributed across a wider range of hours, likely reflecting the combined effects of reduced visibility, driver fatigue, and higher speeds [19, 20]. In contrast, the prevalence of low-risk profiles during daytime peak hours suggests that while interaction density is higher, the resulting outcomes are comparatively less severe.

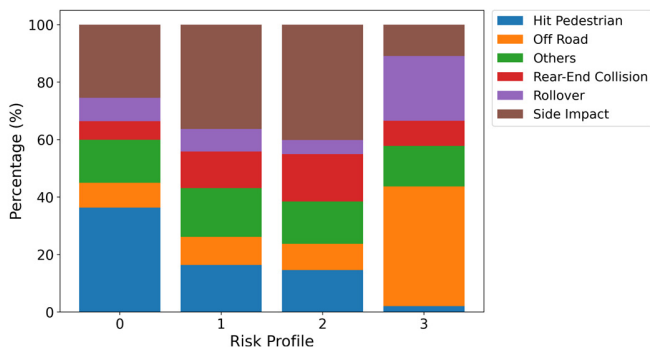


Fig. 4. Accident type by risk profile.

IV. DISCUSSION

A. Comparison with Previous Studies

The findings of the current study suggest that evaluating traffic accidents solely through outcome variables provides an incomplete picture of the underlying risk structure. By collectively considering road characteristics, environmental conditions, speed limits, accident types, and temporal variables, more meaningful risk profiles can be observed, emphasizing the necessity of holistic, structural assessments over one-dimensional, outcome-centered approaches. For instance, the association of high-risk profiles with run-off-road and rollover accidents on high-speed roads reinforces the established relationship between velocity and crash lethality. Conversely, the concentration of low- and medium-risk profiles within urban environments, characterized by lower speed limits and contact-dominant accidents, demonstrates how structural risk configurations shift according to the traffic context. These observations are consistent with broader literature emphasizing the role of contextual and infrastructural determinants in crash

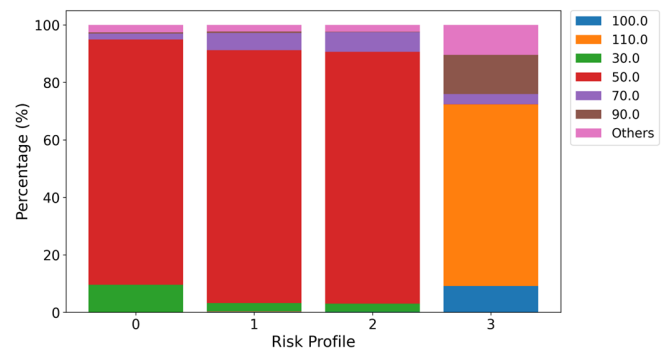


Fig. 5. Speed limits (km/h) by risk profile.

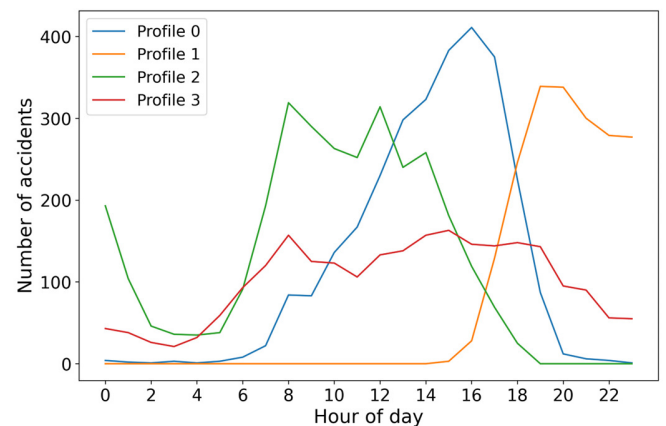


Fig. 6. Timing distribution by risk profile.

B. Policy Implications and Limitations

The extracted profiles provide an interpretable segmentation framework designed to support context-sensitive decision-making, with the structural differentiation observed between profiles suggesting that prevention strategies should be context-sensitive rather than uniformly applied. For example, profiles associated with higher speed limits and run-off-road or rollover patterns may require infrastructure-oriented interventions, enhanced roadside protection, or targeted enforcement strategies. In contrast, profiles characterized by contact-dominant urban accidents may benefit from intersection design improvements, traffic calming measures, and pedestrian-focused safety interventions.

Despite these contributions, several limitations should be acknowledged. Initially, the dataset is limited to injury- and fatality-involved crashes, meaning that the derived profiles represent structural differentiation within a severity-prone subset rather than the entire crash population. Second, while K-

Means was applied following standardization, clustering in high-dimensional sparse spaces can occasionally introduce distance distortions. Future research should explore alternative algorithms specifically designed for mixed-type data, such as K-Prototypes or Gower distance-based methods, to further test clustering robustness. Third, this study did not incorporate explicit spatial dependency modeling and given that road-network topology and regional heterogeneity significantly influence accident structures, future work should integrate spatial autocorrelation measures or network-based clustering. Finally, while internal validation was conducted, the proposed model has not undergone external validation across independent temporal or regional subsets. Subsequent studies should assess the stability of these clusters through cross-year segmentation or bootstrapped resampling procedures to ensure broader applicability.

## V. CONCLUSION

This study analyzed traffic accidents at the individual accident level to derive meaningful risk profiles based exclusively on the structural conditions present at the time of the event. By transforming complex, multi-line administrative records into a simplified and interpretable format, the proposed approach successfully identified multidimensional risk patterns that are often obscured in raw data. The findings underscore that traffic accidents are not homogeneous, but they form distinct risk profiles shaped by the specific interplay of traffic environments, speed limits, and accident types.

A key strength of this methodology lies in the intentional exclusion of severity variables from the clustering process. By reserving these metrics for post-hoc evaluation, the study ensures reliability and structural interpretation of risk that does not result from outcome leakage. Consequently, the resulting profiles provide a practical decision-support framework for policy development, preventive safety planning, and strategic resource allocation. To build upon these findings, future research should expand the scope of analysis to include property-damage-only accidents, explore alternative clustering algorithms, and integrate spatial dependencies to capture broader geographic and topological trends.

## DECLARATION OF COMPETING INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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## DATA AVAILABILITY

The dataset used in this study is not publicly available due to confidentiality and data protection policies. The data were obtained from official administrative records with institutional research permission.

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