



Building An E-Scooter Safety Culture: Temporal-Situational Crash Profiles And Data-System Readiness In Serbia

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ABSTRACT

E-scooter safety is framed as a problem of injury severity or infrastructure, although persistent risk-taking also reflects the norms and practices through which a new mode is integrated into traffic. This study examines what police-reported crash patterns can—and cannot—reveal about e-scooter safety culture in Serbia. The national database contained 282 crashes recorded between 22 July 2023 and 26 December 2025; the primary analysis used 243 crashes from the complete calendar years 2024–2025. Temporal, seasonal and site variables were analysed descriptively and by multiple correspondence analysis followed by Ward clustering. Crash severity and year were excluded from clustering and compared between profiles. The database was also audited against behaviour and compliance domains identified in the literature and Serbian regulation. Three profiles emerged: weekday warm-season mobility (50.6%), spring daytime mobility (27.2%) and weekend/night-time mobility (22.2%). KSI proportions ranged from 19.7% to 25.9% and did not differ between profiles. The audit found six directly available and two derivable indicators, while fourteen essential indicators—including helmet use, alcohol, speed, passenger carriage and vehicle conformity—were absent. Crash records can guide context-specific prevention, but direct monitoring of e-scooter safety culture requires standardised behavioural fields, exposure data, observational surveys and linkage with health records.

1. Introduction

Electric scooters have rapidly become a visible form of urban mobility. They can extend public transport and replace short car trips, but small wheels, an upright riding position and the absence of a protective structure leave riders vulnerable to surface defects, falls and conflicts with faster vehicles. Reviews consistently report head and facial injuries, fractures, alcohol involvement, low helmet use and underreporting, especially for single-vehicle falls (Janikian et al., 2024; Kazemzadeh et al., 2023; Mehranfar & Jones, 2024). E-scooter safety is therefore both an injury-prevention problem and a question of how a new mode is integrated into streets shared with pedestrians, bicycles and motor vehicles. Traffic safety culture describes the shared values, beliefs, attitudes, norms and behaviour through which road users and institutions understand and manage safety (Edwards et al., 2014; Nævestad & Bjørnskau, 2012; Nævestad et al., 2026).

It includes what riders believe others normally do, what they consider acceptable, how consistently rules are enforced, whether infrastructure supports expected conduct and whether authorities collect information needed to learn. Formal rules can change quickly, while everyday expectations develop through repeated interaction. A helmet requirement may therefore have limited effect if non-use is perceived as normal, enforcement is rare or a short trip is considered harmless. Behavioural evidence confirms the importance of these informal influences. Descriptive norms and perceived behavioural control predict willingness to speed, use a telephone, carry a passenger or ride without a helmet (George & Brown, 2025). Risky behaviour has also been linked to unsafe attitudes and rider confidence (Asgharpour et al., 2025). Among young adults, subjective norms can predict dangerous intentions, whereas legal knowledge alone appears insufficient to prevent illegal riding (Phipps & Hamilton, 2024; Ventsislavova et al., 2024).

Cross-national studies identify variation by crash history and permissive attitudes, while inconvenience and short-trip rationalisation help explain helmet non-use (Delavary et al., 2025; Haworth et al., 2024). Education should therefore address perceived norms and make safe behaviour visible, supported by credible enforcement and street design. E-scooter culture is also spatial and temporal. Weekday commuting, weekend evening use and intersection travel create different expectations and conflicts. Five-country surveys found disagreement between riders and pedestrians about appropriate riding space and recurrent sidewalk near-miss concerns (Drimlová et al., 2024; Šucha et al., 2023). Prevention must identify when and where these situations occur, even when crash records do not contain attitudes. Temporal-situational profiles can guide observation, communication and enforcement toward relevant contexts, but cannot establish the beliefs or intentions that produced a crash.

Serbia regulated light electric vehicles through the 2023 amendments to the Road Traffic Safety Act. Vehicles are limited to 0.6 kW, 25 km/h and 35 kg; riders younger than 14 are prohibited; helmets are mandatory; passengers may not be carried; and cycle infrastructure has priority. Carriageway use and visibility requirements depend on the context. Since 15 June 2024, only vehicles with the prescribed identification sticker may be used on public roads (Republic of Serbia, 2023; Road Traffic Safety Agency of the Republic of Serbia, 2024). These provisions define expected conduct, but culture assessment must also determine whether compliance is observed, socially supported and recorded. An obligation absent from the data system cannot be monitored through that system. Police data provide standardised time, location and consequence information, but only a selective view of e-scooter safety. Hospital and self-report comparisons show that many single-vehicle and less severe events are missed and that serious-injury definitions may differ (Bjørnskau et al., 2025; Department for Transport, 2023; European Commission, 2026). If helmet use, alcohol, speed, passenger carriage, riding surface and vehicle conformity are absent, changing norms or compliance cannot be connected with observed trends. Data quality is thus part of institutional safety culture: an informed system must identify both where harm occurred and which preventable practices were present. This study examines what police-reported crashes can—and cannot—contribute to e-scooter safety culture in Serbia. Its objectives are to: (i) describe temporal and situational patterns during the complete calendar years 2024–2025; (ii) identify recurring crash-context profiles without using injury severity to construct them; and (iii) audit the crash file against behavioural, compliance and institutional-learning domains. The dual framework joins operational targeting with data-system readiness: profiles indicate where culture-sensitive prevention should be directed, while the audit specifies what must be recorded before culture can be measured rather than inferred.

2. METHODOLOGY

2.1. Study design and data

A retrospective, crash-level study was conducted using records supplied by the Road Traffic Safety Agency of the Republic of Serbia. The source file contained all available police-reported crashes involving at least one e-scooter from 22 July 2023 to 26 December 2025.

Each row represented one crash and included date, local time, WGS 84 coordinates, settlement status, general site type, intersection configuration and crash-level numbers of fatalities, seriously injured and slightly injured persons. The full file contained 282 crashes. Because 2023 covered only part of the year, the primary analysis was restricted to the 243 crashes recorded during the complete calendar years 2024 and 2025. The 39 records from 2023 were retained only as contextual information and were not used to compare annual totals. A killed-or-seriously-injured (KSI) crash was defined as a crash in which at least one person was killed or seriously injured. The comparison group combined slight-injury and property-damage-only crashes. Casualties were aggregated at crash level, so the available file did not always identify whether the injured person was the e-scooter rider or another participant. KSI was therefore used as a description of crash consequence, not as an individual rider-injury outcome. The study estimates neither crash incidence nor rider risk because trip counts, distance travelled and riding time were unavailable.

2.2. Operational safety-culture framework

Traffic safety culture was operationalised at three analytically distinct levels. First, recorded temporal and road-context variables were used to identify situations in which safety-related norms and practices may be expressed. Second, KSI prevalence was compared across these profiles as a consequence indicator, but it was not used to create the profiles. Third, the source file was audited for its ability to observe culture-relevant behaviour and regulatory compliance. This structure prevents a common interpretive error: clustering crashes by time and place can reveal actionable contexts, but it does not directly measure attitudes, beliefs or norms. Direct culture measurement would require surveys, interviews or systematic observation. The audit instrument contained 22 indicators grouped into exposure/event, road context, rider, rider behaviour, rule compliance, vehicle/use, crash mechanism and outcome domains. An indicator was classified as available when directly present, derivable when reproducibly calculated from recorded variables, and absent when it could not be established from the supplied file. Selection of indicators was informed by behavioural studies and reviews, as well as by Serbian requirements concerning minimum age, helmet use, passenger carriage, permitted riding space, visibility and vehicle identification (George & Brown, 2025; Janikian et al., 2024; Republic of Serbia, 2023; Ventsislavova et al., 2024).

2.3. Variables and statistical analysis

Date and time were used to derive calendar month, season, weekday/weekend and four time periods: morning (06:00–09:59), daytime (10:00–15:59), evening (16:00–21:59) and night (22:00–05:59). Site type was harmonised as intersection, street segment or road. Solar elevation was calculated from date, time and crash coordinates using standard astronomical equations; observations were classified as daylight (solar elevation above 0°), civil twilight (−6° to 0°) or darkness (below −6°). Counts and proportions were calculated for all categories. KSI proportions are reported with Wilson 95% confidence intervals. Multiple correspondence analysis (MCA) was used to represent four categorical context variables—time period, day type, season and site type—in a continuous low-dimensional space.

If Z denotes the complete disjunctive indicator matrix for n crashes and Q variables, the correspondence matrix is $P = Z/(nQ)$. With row masses r and column masses c , the matrix subjected to singular-value decomposition was:

$$S = D_r^{-1/2}(P - rc^T)D_c^{-1/2}.$$

The first dimensions accounting for at least 70% of total inertia were retained. Ward hierarchical clustering was then applied to the retained crash coordinates. Candidate solutions with two to five clusters were compared using the silhouette coefficient, subject to a minimum cluster size of 20 crashes to avoid unstable, very small groups. The selected solution was described using category proportions and deviations from the overall sample. Injury severity and calendar year were excluded from MCA and clustering and compared between profiles only after the groups had been fixed. Pearson chi-square statistics were used for exploratory comparisons of KSI across recorded characteristics and profiles. Monte Carlo p-values were obtained from 20,000 permutations with a fixed random seed. Effect size was expressed as Cramér's V , and Benjamini–Hochberg false-discovery-rate correction was applied across the six univariate KSI comparisons (Benjamini & Hochberg, 1995). The analysis is descriptive and hypothesis-generating: p-values do not overcome the absence of exposure or behavioural variables, and profile labels are interpretive summaries rather than latent rider types. Data processing and statistical analysis were performed in Python 3.12 using pandas, NumPy, SciPy and scikit-learn; figures were produced with Matplotlib. MCA and Ward clustering follow established categorical data-analysis and hierarchical-grouping principles (Greenacre & Blasius, 2006; Ward, 1963).

3. RESULTS

3.1. Sample and temporal patterns

The complete file contained 282 crashes: 39 during the partial observation period in 2023, 105 in 2024 and 138 in 2025. The principal 2024–2025 sample comprised 243 crashes. One crash involved a fatality, 53 involved at least one seriously injured person without a fatality, 166 involved slight injuries only and 23 were property-damage-only events. Thus, 54 crashes (22.2%) met the KSI definition. Most crashes occurred inside settlements (238; 97.9%). Street segments accounted for 130 crashes (53.5%), intersections for 106 (43.6%) and roads for seven (2.9%). Table 1 shows that the data were strongly urban and settlement-centred, which limits inference about rural e-scooter use.

The annual counts should not be interpreted as a rate or a regulatory effect. The 31.4% increase from 105 crashes in 2024 to 138 in 2025 may reflect greater use, reporting changes, enforcement, exposure or a combination of these factors. The KSI proportion was 20.0% in 2024 and 23.9% in 2025, with overlapping confidence intervals. The monthly series was seasonal but not identical between years: activity was distributed across spring, summer and autumn, with few winter observations. The day-by-time heat map showed that reported crashes were present across the week rather than concentrated in a single commuting period (Figure 1).

Table 1. Distribution of crashes and KSI outcomes, Serbia, 2024–2025

Characteristic	Category	Crashes, n (%)	KSI, n (%)	KSI 95% CI, %
Year	2024	105 (43.2)	21 (20.0)	13.5–28.6
	2025	138 (56.8)	33 (23.9)	17.6–31.7
Day type	Weekday	196 (80.7)	40 (20.4)	15.4–26.6
	Weekend	47 (19.3)	14 (29.8)	18.7–44.0
Time of day	Morning, 06–09	37 (15.2)	13 (35.1)	21.8–51.2
	Daytime, 10–15	103 (42.4)	19 (18.4)	12.1–27.0
	Evening, 16–21	81 (33.3)	14 (17.3)	10.6–26.9
	Night, 22–05	22 (9.1)	8 (36.4)	19.7–57.0
Site type	Intersection	106 (43.6)	18 (17.0)	11.0–25.3
	Street segment	130 (53.5)	34 (26.2)	19.4–34.3
	Road	7 (2.9)	2 (28.6)	8.2–64.1
Lighting	Daylight	177 (72.8)	38 (21.5)	16.1–28.1
	Civil twilight	11 (4.5)	2 (18.2)	5.1–47.7
	Darkness	55 (22.6)	14 (25.5)	15.8–38.3

Note: $n=243$; KSI=killed or seriously injured crash. Percentages in the KSI column are within-category percentages; confidence intervals are Wilson intervals.

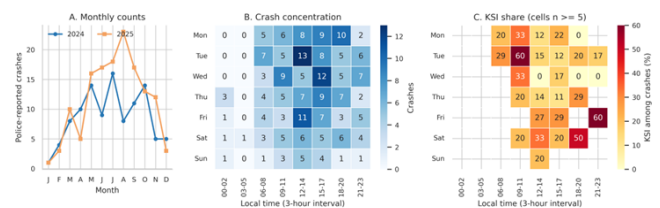


Figure 1. Temporal distribution of police-reported e-scooter crashes, 2024–2025. KSI percentages are displayed only for day–time cells with at least five crashes.

Daytime and evening accounted for 75.7% of the sample. Morning and night crashes were less frequent but had higher unadjusted KSI proportions: 35.1% and 36.4%, respectively, compared with 18.4% in daytime and 17.3% in the evening. The overall time-of-day comparison produced $\chi^2(3)=8.11$, Monte Carlo $p=0.046$ and Cramér's $V=0.183$. After correction across six comparisons, however, $q=0.278$; the pattern should therefore be treated as a targeted observation priority rather than confirmatory evidence. Weekend crashes had a KSI proportion of 29.8%, compared with 20.4% on weekdays ($p=0.243$; $V=0.077$). KSI was not robustly associated with year, season, site type or lighting. Wide intervals for night, winter and road categories reflect small denominators.

3.2. Temporal-situational profiles

Six MCA dimensions were retained and explained 72.1% of total inertia; the first two accounted for 14.6% and 13.2%. Among solutions satisfying the minimum-size rule, three clusters achieved the best silhouette coefficient (0.241). Four- and five-cluster solutions had slightly higher coefficients but each produced a group of only seven crashes and were rejected as operationally unstable. Figure 2 displays the first two MCA dimensions; bubble area represents the number of crashes sharing an identical categorical pattern, while crosses indicate profile centroids.

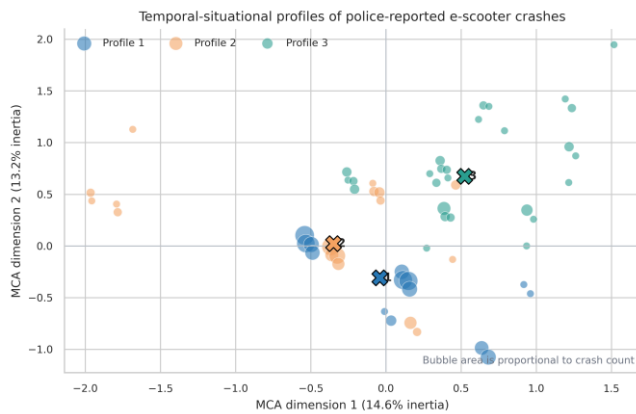


Figure 2. Multiple correspondence analysis of temporal-situational crash profiles. Bubble area is proportional to the number of crashes with the same categorical pattern; crosses show profile centroids.

Profile 1, labelled weekday warm-season mobility, contained 123 crashes (50.6%). Almost all occurred on weekdays (98.4%); 56.1% occurred in summer and 43.9% in autumn. Intersections represented 48.0%. Profile 2, spring daytime mobility, contained 66 crashes (27.2%); 93.9% occurred in spring, 50.0% during daytime and 81.8% on weekdays. It also contained all seven road-category crashes. Profile 3, weekend/night-time mobility, contained 54 crashes (22.2%); 61.1% occurred on weekends, 35.2% at night, 31.5% in winter and 59.3% on street segments. These groups describe combinations of circumstances, not persons or motives. A crash in Profile 3, for example, cannot be classified as recreational without information on trip purpose.

KSI proportions were 22.0% in Profile 1, 19.7% in Profile 2 and 25.9% in Profile 3 (Table 2; Figure 3). The difference was small ($\chi^2(2)=0.68$, $p=0.713$; $V=0.053$). The share of crashes recorded in 2025 ranged from 48.5% to 63.0% and also did not differ significantly between profiles ($p=0.241$; $V=0.108$). Consequently, the profiles are useful for segmenting preventive activity, but the data do not support describing one profile as inherently more dangerous than the others.

Table 2. Characteristics of the three temporal-situational profiles

Profile	n (%)	Interpretive label	Defining features	KSI, n (%); 95% CI
1	123 (50.6)	Weekday warm-season mobility	98.4% weekday; 56.1% summer; 43.9% autumn; 48.0% intersection	27 (22.0); 15.5–30.1
2	66 (27.2)	Spring daytime mobility	93.9% spring; 50.0% daytime; 81.8% weekday; 10.6% road	13 (19.7); 11.9–30.8
3	54 (22.2)	Weekend/night-time mobility	61.1% weekend; 35.2% night; 31.5% winter; 59.3% street segment	14 (25.9); 16.1–38.9

Note: Profile labels summarise combinations of recorded circumstances and do not identify rider motives or attitudes. Profile comparison: $\chi^2(2)=0.68$, $p=0.713$, Cramér's $V=0.053$.

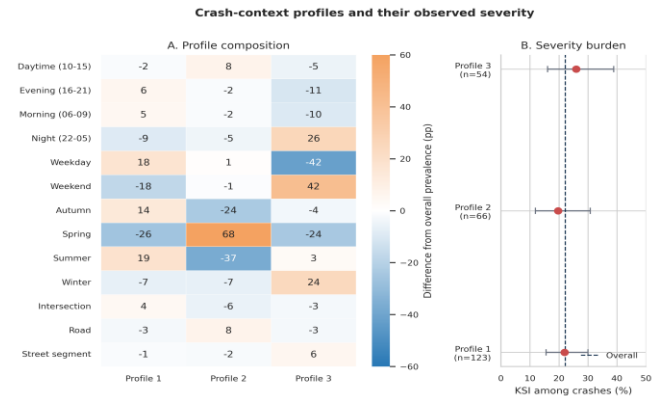


Figure 3. Composition and KSI proportions of the temporal-situational profiles. Error bars are Wilson 95% confidence intervals.

3.3. Safety-culture observability audit

The observability audit identified a substantial mismatch between the legal and behavioural content of e-scooter safety and the information captured by the crash file. Six of 22 indicators (27.3%) were directly available and two (9.1%) were derivable; fourteen (63.6%) were absent. Date, time, coordinates, settlement status, site type, intersection configuration and crash-level consequence support reliable temporal and situational description. By contrast, the file could not determine rider age or sex, helmet use, alcohol or psychoactive substances, speed, passenger carriage, distraction, actual riding surface, manoeuvre, collision partner, private/shared status or sticker and vehicle conformity (Table 3). The data can therefore identify contexts for fieldwork, but not the cultural mechanisms or rule-compliance patterns operating within those contexts.

Table 3. Readiness of the crash database for e-scooter safety-culture monitoring

Domain	Indicators audited	Status	Implication
Exposure and event	Date, time and coordinates	2 available; 2 derivable	Temporal targeting and lighting can be reconstructed
Road context	Settlement, site and intersection type	3 available; 2 absent	Actual riding surface and weather/surface condition are missing
Rider	Age and sex	2 absent	Minimum-age compliance and demographic targeting cannot be assessed
Rider behaviour	Helmet, alcohol/drugs, passenger, speed, distraction	5 absent	Core protective and risky behaviours cannot be assessed
Rule compliance	Vehicle sticker/conformity, manoeuvre	2 absent	Key post-2024 compliance cannot be evaluated
Vehicle and mechanism	Ownership model, collision partner/configuration	2 absent	Shared/private use and crash mechanism cannot be separated
Outcome and exposure	Crash severity, rider attribution, trips/distance	1 available; 2 absent	Severity is recorded, but rider-specific outcome and risk denominator are unavailable

Note: Across 22 indicators, six were directly available, two were derivable and fourteen were absent. Structurally inapplicable intersection fields were not treated as data-quality failures.

4. DISCUSSION AND CONCLUSIONS

Police-reported crashes provided two complementary forms of evidence: an operational context map and a test of institutional data readiness. Three temporal-situational profiles emerged, but their KSI proportions were similar and imprecise. Segmentation can therefore organise prevention without labelling one set of circumstances a verified high-risk culture. Safety culture concerns shared meanings and practices; the crash file records consequences. The bridge between them must remain explicit. The largest profile—weekday mobility in summer and autumn—supports treating e-scooters as routine urban transport, not only leisure devices. Prevention should become part of commuting policy: visible helmet use, predictable intersection behaviour, safe overtaking and clear facility expectations. Communication must address riders and other road users because culture is co-produced, while the Safe System distributes responsibility across users, authorities, operators and designers (Nævestad et al., 2026). The spring daytime profile offers a practical moment for refresher communication, retailer information and visible enforcement as seasonal use resumes. The weekend/night-time profile is behaviourally distinctive, but possible mechanisms—alcohol, social riding, conspicuity or passenger carriage—are unrecorded. They should be measured, not assumed. Stratified roadside observations and anonymous surveys should cover all profiles and oversample weekend nights. Survey items should include descriptive and injunctive norms, perceived control and risk, enforcement credibility and reasons for non-compliance, reflecting evidence that norms can predict dangerous intentions more consistently than legal knowledge alone (George & Brown, 2025; Phipps & Hamilton, 2024).

Higher unadjusted KSI proportions in morning and night crashes merit attention, not a causal claim: the association was modest and did not survive false-discovery-rate correction. Morning events may involve commuting interaction, while night events may involve visibility or impairment; exposure may also differ. Observation should record rider and motor-vehicle flows, helmet and passenger use, lighting, facility choice and distraction. Speed measurement and conflict-based video analysis, where lawful and ethically approved, would provide leading indicators independent of injury occurrence. The central finding is the data-system gap. Fourteen of 22 culture-relevant indicators were absent, including nearly all direct measures of behaviour and compliance. The supplied file cannot establish whether the rider met the age rule, wore a helmet, carried a passenger, used a compliant vehicle, displayed the sticker or travelled on a permitted surface. Nor can it separate private/shared use or identify manoeuvre and collision partner. Changes in reported crashes therefore cannot be connected to changing norms, enforcement or vehicle conformity. A minimum national module should record rider age and sex; helmet use; suspected alcohol or drugs; passenger carriage; speed; distraction; ownership model; sticker and technical conformity; actual riding surface; manoeuvre; collision partner; and person-level outcome. Explicit unknown and not-applicable categories should replace silent blanks. A privacy-preserving crash identifier should support linkage with emergency and hospital records because police systems miss many single-vehicle falls and may classify serious injury differently (Bjørnskau et al., 2025; Department for Transport, 2023). Trips, kilometres or riding minutes by place and time are also needed to distinguish growing exposure from worsening risk.

Prevention should combine normative, regulatory and environmental measures. Norm-based messages can correct beliefs that helmet non-use, sidewalk riding or passenger carriage are universal, but should use measured local prevalence. Fair and consistent enforcement can strengthen rule credibility in the identified contexts. Retailers, schools, universities, employers and operators can set expectations before travel. Continuous cycle routes, safe intersections, smooth surfaces and speed management must make the safe choice normal and convenient. The study is limited to police-reported crashes over a short period. The 2023 data are incomplete; use, enforcement and reporting may differ between 2024 and 2025; and no exposure denominator was available. Outcomes were aggregated at crash level and could not always be attributed to the rider. Small cells yielded wide intervals, and MCA and clustering depend on chosen variables and categories. No survey or observation was available, so the study neither measures safety culture directly nor shows that a norm caused a crash. In conclusion, the data identify three settings for targeted e-scooter prevention but no profile with a demonstrably different severity burden. Their immediate value is to guide culture-sensitive observation, communication and enforcement. Their deeper limitation is institutional: almost two thirds of the required behavioural and compliance indicators are absent. Standardised crash fields, hospital linkage, exposure measures and repeated observational and attitudinal surveys are needed to determine whether safe conduct is understood, expected and practised. These additions would turn a descriptive database into a learning system and support targeted, shared-responsibility prevention.

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