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MODELLING THE TEMPORAL DISTRIBUTION AND SEVERITY OF E-SCOOTER CRASHES IN SERBIA

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Abstract: The increasing use of electric scooters has created new road-safety challenges, particularly because crash occurrence and injury severity may follow different temporal patterns. This study examined the temporal distribution and severity of police-reported e-scooter crashes in Serbia. Data were included 282 crashes recorded between 22 July 2023 and 26 December 2025. The principal analysis was restricted to 243 crashes recorded during the complete calendar years 2024 and 2025. Hourly crash counts were analysed using Poisson regression with cyclic harmonic terms for daily and annual variation, while killed-or-seriously-injured (KSI) outcomes were examined using Firth penalised logistic regression. The severity model included year, weekend status, morning and night periods, site type and certainty of motor-vehicle involvement. Of the analysed crashes, 54 (22.2%) were classified as KSI. Adjusted crash intensity was higher in 2025 than in 2024 (IRR=1.32, 95% CI 1.03–1.69) and lower during weekend hours than weekdays (IRR=0.63, 95% CI 0.46–0.87). The fitted temporal distribution reached its daily maximum in the mid-afternoon and its annual maximum in late August. Morning crashes between 06:00 and 09:59 had significantly higher adjusted odds of a KSI outcome (aOR=2.63, 95% CI 1.20–5.76). Night-time, weekend, street-segment and motor-vehicle linkage estimates were imprecise and did not provide clear statistical evidence. The findings demonstrate that periods with the highest crash frequency differ from those associated with the most serious consequences. Prevention should combine time-targeted enforcement, speed management, continuous micromobility infrastructure and improved linkage of police, health and exposure data.

Keywords: Electric scooters; crash frequency; injury severity; temporal patterns; Firth logistic regression; Serbia

1. INTRODUCTION

Electric scooters have become a visible component of urban transport within a short period, but their safety performance is still difficult to describe consistently. Their low mass and modest operating speed may suggest limited kinetic risk, yet riders are unprotected and frequently share

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space with motor vehicles, cyclists and pedestrians. This places e-scooter users among vulnerable road users, a group that already bears more than half of global road deaths (World Health Organization, 2023). A harmonised global count of e-scooter casualties is not available because vehicle definitions, reporting thresholds and legal status differ between countries. Nevertheless, national statistics and the rapid growth of hospital case series show that the burden is no longer marginal. The International Transport Forum reported that motor vehicles are involved in around 80% of fatal crashes affecting cyclists and e-scooter riders, while the European Road Safety Observatory notes that head injuries and upper- and lower-limb fractures are among the most frequent outcomes (International Transport Forum, 2020; European Commission, 2026).

The first evidence on e-scooter injury was largely produced by emergency departments after shared fleets entered North American and European cities. These studies documented head trauma, fractures and hospital admission, together with low helmet use and a substantial share of falls without another vehicle (Badeau et al., 2019; Trivedi et al., 2019). Such records describe clinical burden well, but they do not always contain the road, traffic and temporal circumstances needed for prevention. Conversely, police databases provide crash location, time and involved road users, but miss many events that never reach the police. Comparisons of Swedish hospital and police records, and more recent linkage work in Norway, confirm that neither source alone captures the full problem (Stigson et al., 2021; Bjørnskau et al., 2025). The available numbers should therefore be interpreted as recorded crashes or treated injuries, rather than as the total incidence of e-scooter harm.

Countries have responded through combinations of speed limits, minimum-age rules, helmet requirements, restrictions on pavement riding, technical standards and parking controls. The main infrastructure recommendation is to treat e-scooters similarly to bicycles and reduce interaction with faster and heavier traffic where feasible (International Transport Forum, 2020). Reviews, however, find considerable variation in regulation and limited evidence that any single measure is sufficient across different operating environments (Kazemzadeh et al., 2023; Janikian et al., 2024; Mehranfar & Jones, 2024). This variation increases the importance of local evidence. The same rule may have different effects where private ownership dominates, cycling infrastructure is discontinuous, enforcement is uneven, or crash reporting practices differ.

The literature also differs methodologically. Hospital studies commonly use retrospective case series and logistic models to identify correlates of admission or injury severity. Police-based studies add roadway context and collision configuration; for example, Shah et al. (2021) applied a standardised crash typology to motor-vehicle-involved e-scooter crashes, whereas Cicchino et al. (2021) examined the association between trip characteristics and injury severity. Naturalistic riding studies can estimate exposure and observe precursors, but large trip samples may still contain few crashes. Pai and Dozza (2024), for instance, analysed 6,868 rental trips with 19 observed crashes. At an area level, zero-inflated Poisson and negative binomial models have been used to relate e-scooter injury counts to socioeconomic, transport and built-environment characteristics (Azimian & Jiao, 2022). Recent machine-learning studies offer flexible prediction of severity, but their practical interpretation depends on sample size, outcome balance and the quality of linked variables. Across these approaches, reviews repeatedly identify inconsistent denominators, under-reporting and weak comparability between police, hospital and operator data as central limitations (Kazemzadeh et al., 2023; Janikian et al., 2024).

Evidence from Serbia remains limited because e-scooters were only formally incorporated into the national road traffic framework through the 2023 amendments to the Road Traffic Safety Act (Republic of Serbia, 2023). The broader national road-safety record also remains demanding: Serbia reported 78 road deaths per million inhabitants in 2024, above the European Union average (European Commission, 2025). Earlier Serbian research established useful modelling

foundations without isolating e-scooters. Spatial count regression was used to examine urban crash frequency in Novi Sad (Pljakić et al., 2019), monthly national crash series were analysed with seasonal time-series models (Pljakić et al., 2021), and ARIMA and neural-network forecasts were compared for fatalities and injuries (Pljakić et al., 2022). They did not address the combination that is central to the present problem: high-resolution temporal variation in e-scooter crashes, the probability of killed-or-seriously-injured outcomes, and uncertainty in assigning the category of the other vehicle.

Based on the limitations identified in previous studies, this study aims to examine police-recorded e-scooter crashes in Serbia from three complementary perspectives: temporal variation in crash frequency, the severity of crash consequences, and the category of the other vehicle involved. More specifically, it seeks to identify daily, weekly, seasonal and annual patterns in recorded crash intensity, determine which temporal and road-related factors are associated with a killed-or-seriously-injured outcome, and assess whether motor-vehicle involvement contributes to crash severity while accounting for uncertainty in collision-partner linkage.

2. METHODOLOGY

2.1 Study design and data source

Crash data were obtained from the Road Traffic Safety Agency of the Republic of Serbia with institutional permission. The complete database contained 282 police-reported e-scooter crashes recorded between 22 July 2023 and 26 December 2025. Because 2023 represented an incomplete observation period, the principal analysis included 243 crashes recorded during the complete calendar years 2024 and 2025.

Two outcomes were examined. Temporal analysis was based on the number of crashes recorded within each of 17,544 one-hour intervals covering 2024–2025. Crash severity was defined as a killed-or-seriously-injured (KSI) crash, while slight-injury-only and property-damage-only crashes formed the comparison group.

The crash-level data were linked to an aggregated table containing other-vehicle categories using year, month and hour. Vehicle involvement was classified as confirmed, possible or not identified, depending on the reliability of the linkage. Because categories could not be assigned unambiguously when several crashes shared the same temporal key, a sensitivity analysis was also conducted on 118 crashes from single-crash temporal cells.

2.2 Harmonic Poisson model of crash occurrence

Hourly crash counts were analysed using Poisson regression with a logarithmic link, a standard framework for count and rate data (Frome, 1983). Daily and annual periodicity were represented by paired sine and cosine terms. This harmonic parameterisation preserves the continuity of cyclic time and avoids arbitrary cut-points between adjacent time categories (Stolwijk et al., 1999). Three harmonics were used for hour of day and two for day of year, providing sufficient flexibility without estimating a separate coefficient for every hour and month.

$$Y_t \sim \text{Poisson}(\mu_t).$$

$$\log(\mu_t) = \beta_0 + \beta_1 I_{2025,t} + \beta_2 W_t + H(h_t) + S(d_t).$$

$$H(h_t) = \sum_{k=1}^{3}\left[a_k \sin\left(\frac{2\pi k h_t}{24}\right) + b_k \cos\left(\frac{2\pi k h_t}{24}\right)\right].$$

$$S(d_t) = \sum_{j=1}^{2}\left[c_j \sin\left(\frac{2\pi j d_t}{365.25}\right) + e_j \cos\left(\frac{2\pi j d_t}{365.25}\right)\right].$$

In the equation, Y_t is the number of crashes in hourly interval t, ht is the hour of day, dt is the ordinal day of year, I 2025, t identifies intervals in 2025 and Wt identifies weekend intervals. Exponentiated coefficients are reported as incidence rate ratios (IRRs). Because adjacent hourly observations from the same date may be correlated, sandwich standard errors were clustered by calendar day, following the robust variance principles developed for correlated generalized linear-model observations (Liang & Zeger, 1986).

Nested models were compared using likelihood-ratio tests. Overall model parsimony was assessed using Akaike's information criterion (AIC), with smaller values indicating a preferable balance between fit and complexity (Akaike, 1974). A year-by-cycle interaction model tested whether daily and annual temporal shapes differed between 2024 and 2025. Pearson dispersion was used to assess whether a negative binomial model was required. The estimated dispersion was close to one; therefore, the Poisson specification was retained.

KSI severity was modelled conditional on a police-reported crash. Because only 54 KSI crashes were available and several predictor categories were sparse, Firth's bias-reduced logistic regression was used. The method maximises a penalised likelihood and reduces small-sample bias while producing finite estimates when ordinary logistic regression is affected by complete or quasi-complete separation (Firth, 1993; Heinze & Schemper, 2002):

$$\ell^*(\boldsymbol{\beta}) = \ell(\boldsymbol{\beta}) + \frac{1}{2}\log|I(\boldsymbol{\beta})|.$$

Predictors were specified before model estimation and included year, weekend, morning, night, street segment and other-vehicle linkage status. Daytime/evening hours, intersections/roads and no motor vehicle identified were the reference categories. Adjusted odds ratios (aORs) and 95% confidence intervals were calculated from the penalised estimates and their information matrix. The purpose of this model was explanatory and hypothesis-generating; no automated variable selection was used.

Categorical variables are presented as counts and percentages. KSI proportions are accompanied by Wilson 95% confidence intervals, which provide more reliable coverage than the normal approximation when categories are small (Wilson, 1927). Two-sided p values below 0.05 were treated as statistical evidence, but effect estimates and interval width were given priority over dichotomous significance decisions.

Data processing and statistical analysis were performed in Python 3.12.14 using pandas 2.2.3, NumPy 2.3.5 and SciPy 1.17.0. Figures were produced with Matplotlib 3.10.8. NumPy, SciPy and Matplotlib are established components of the scientific Python ecosystem (Harris et al., 2020; Hunter, 2007; Virtanen et al., 2020).

3. RESULTS

3.1. Sample characteristics

The principal 2024–2025 sample contained 243 police-reported e-scooter crashes: 105 in 2024 and 138 in 2025. 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. Street segments accounted for 130 crashes (53.5%), intersections for 106 (43.6%) and roads for seven (2.9%).

The temporal distribution was concentrated in the warmer and more active parts of the day. Overall, 176 crashes (72.4%) were recorded from May through October, 151 (62.1%) between 10:00 and 18:59 and 97 (39.9%) between 13:00 and 17:59. The hourly observation grid contained 17,544 cells. One crash occurred in 241 cells, two crashes occurred in one cell and the remaining 17,302 cells contained no crash.

3.2. Cyclic temporal model

Both cyclic components materially improved fit. Adding the daily harmonic terms to the baseline model reduced AIC from 2559.79 to 2452.29 (likelihood-ratio χ^2=119.50, df=6, p<0.001). Adding the annual cycle reduced AIC further to 2400.99 (χ^2=59.31, df=4, p<0.001). The Pearson dispersion statistic was 0.948, providing no evidence of overdispersion and no empirical justification for replacing the Poisson model with a negative binomial specification.

Table 1. Comparison of harmonic Poisson models

Model	Parameters	Log likelihood	AIC	Comparison
Baseline	3	-1276.90	2559.79	Year and weekend
Daily cycle	9	-1217.15	2452.29	LR χ^2=119.50; df=6; p<0.001
Daily and annual cycles	13	-1187.49	2400.99	Annual block: χ^2=59.31; df=4; p<0.001
Year interaction	23	-1181.51	2409.03	Interaction block: χ^2=11.96; df=10; p=0.288

After adjustment for daily and annual periodicity, the recorded crash intensity in 2025 was 31.6% higher than in 2024 (IRR=1.32, 95% CI 1.03–1.69). Weekend hours had a lower recorded crash intensity than weekday hours (IRR=0.63, 95% CI 0.46–0.87). This weekend estimate concerns the number of recorded crashes per calendar hour and must not be interpreted as exposure-adjusted rider risk.

The model with year-by-cycle interactions did not improve fit (χ^2=11.96, df=10, p=0.288) and had a higher AIC than the common-cycle model. The number of recorded crashes increased in 2025, but the data did not support a material change in the shape of the daily and seasonal patterns between the two years.

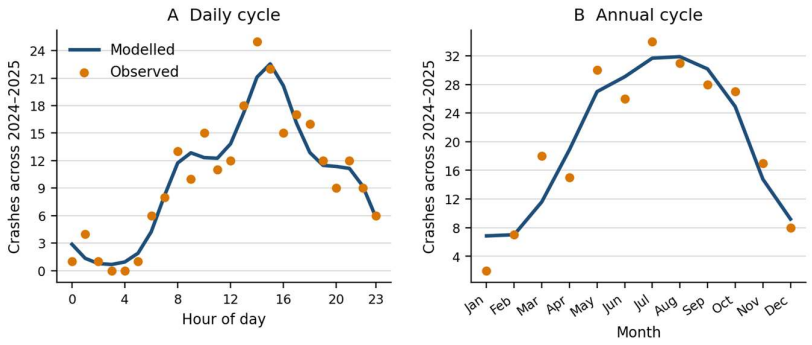


Figure 1. Observed and modelled temporal distributions of e-scooter crashes in Serbia, 2024–2025. Modelled values are aggregated predictions from the harmonic Poisson model.

The modelled daily curve reached its broad maximum around 15:00 and its minimum during the early-morning period. The estimated annual curve was highest in late August and lowest in the second half of January. The fitted peak-to-trough ratio was approximately 33.9 for the daily component and 4.9 for the annual component. These values describe the fitted curves rather than exact critical minutes or dates; the defensible interpretation is a mid-afternoon maximum and a late-summer seasonal maximum.

3.3. Factors associated with KSI severity

In the multivariable Firth model, the morning period was associated with higher odds of a KSI outcome after adjustment for year, weekend, night-time, site type and other-vehicle linkage status (aOR=2.63, 95% CI 1.20–5.76, p=0.016). The night-time estimate was also above one, but its interval was wide and included the null (aOR=2.19, 95% CI 0.81–5.88). Weekend crashes had an aOR of 1.60 (95% CI 0.76–3.34), while crashes on street segments had an aOR of 1.58 (95% CI 0.82–3.06). Neither estimate provided clear statistical evidence after simultaneous adjustment.

Table 2. Firth logistic regression of KSI crash severity

Predictor	Reference	aOR	95% CI	p
Year 2025	2024	1.20	0.63–2.27	0.580
Weekend	Weekday	1.60	0.76–3.34	0.215
Morning 06:00–09:59	Other hours	2.63	1.20–5.76	0.016
Night 22:00–05:59	Other hours	2.19	0.81–5.88	0.122
Street segment	Intersection or road	1.58	0.82–3.06	0.172
Confirmed motor vehicle	No motor vehicle identified	0.87	0.35–2.18	0.764
Possible motor vehicle	No motor vehicle identified	0.72	0.29–1.81	0.490

Note. KSI = killed-or-seriously-injured crash; aOR = adjusted odds ratio. n=243; KSI events=54.

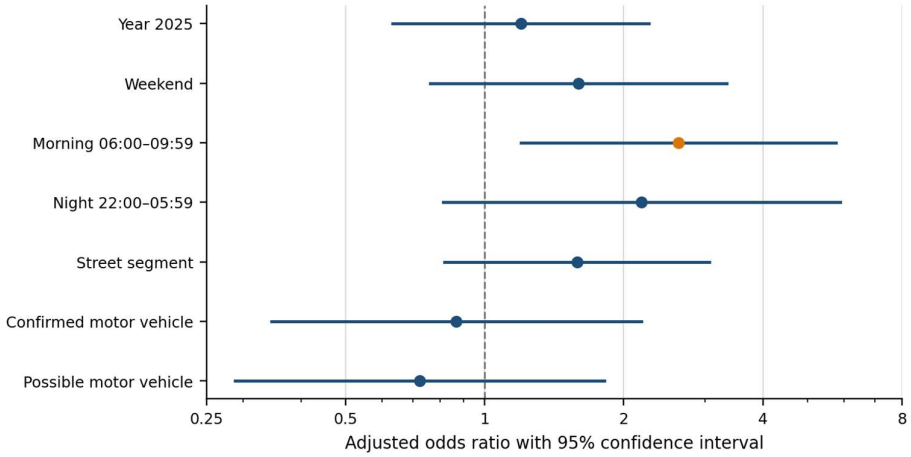


Figure 2. Adjusted odds ratios for KSI crash severity from the Firth logistic model. The vertical line indicates the null value of 1.

3.4. Other vehicle category and linkage uncertainty

A motor vehicle was confirmed for 90 crashes, possible but not uniquely assignable for 116 crashes and not identified for 37 crashes. The respective KSI proportions were 23.3%, 19.0% and 29.7%. In the adjusted Firth model, neither confirmed motor-vehicle linkage (aOR=0.87, 95% CI 0.35–2.18) nor possible linkage (aOR=0.72, 95% CI 0.29–1.81) was associated with KSI severity relative to no identified motor vehicle. These estimates do not establish a protective effect of motor-vehicle involvement; the wide intervals and uncertainty of the reference group preclude that interpretation.

Table 3. KSI outcomes according to motor-vehicle linkage status

Linkage status	Crashes	KSI n (%)	Wilson 95% CI (%)
Confirmed motor vehicle	90	21 (23.3%)	15.8–33.1
Possible motor vehicle	116	22 (19.0%)	12.9–27.0
No motor vehicle identified	37	11 (29.7%)	17.5–45.8

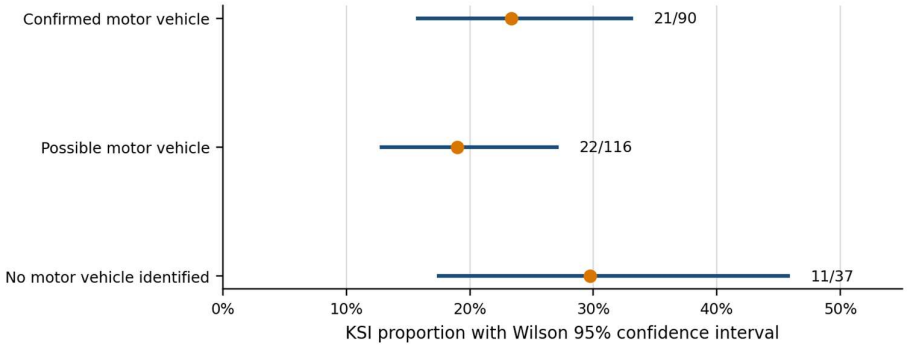


Figure 3. KSI proportions by motor-vehicle linkage status. Labels show KSI crashes divided by all crashes in each group.

Table 4. Deterministically linked other-vehicle categories in single-crash temporal cells

Other-vehicle category	Crashes	KSI n (%)
Passenger car present	83	19 (22.9%)
Goods vehicle	6	2 (33.3%)
Bus	1	0 (0.0%)
Bicycle	3	2 (66.7%)
No other category recorded	25	7 (28.0%)

The high-confidence sensitivity sample contained 118 crashes and 30 KSI outcomes. Within this subset, confirmed motor-vehicle involvement was not associated with KSI severity after adjustment for the same temporal and site variables (aOR=0.66, 95% CI 0.23–1.88). The sensitivity result was directionally consistent with the full-sample linkage-status model. However, individual categories were too sparse for reliable multivariable comparison: among deterministically linked crashes, passenger cars predominated, whereas goods vehicles, buses, bicycles, motorcycles and mopeds occurred in small numbers. Category-specific odds ratios were therefore not reported.

3.5. Integrated interpretation

The three analyses address different questions. The Poisson model identifies when e-scooter crashes were most frequently recorded, while the Firth model evaluates factors associated with KSI consequences conditional on a recorded crash. The linkage analysis evaluates whether the available category data support inference about the other vehicle. The observed increase in total crash intensity during 2025 did not correspond to a clear adjusted increase in KSI odds. Mid-afternoon and late-summer periods accounted for the highest recorded frequency, whereas the morning period showed the clearest severity association. These findings indicate that time windows with the greatest crash volume are not necessarily the same as those with the largest proportion of serious outcomes.

The available data did not show a stable association between motor-vehicle linkage status and KSI severity. This null result should be interpreted as insufficient evidence rather than evidence of no difference. Almost half of the principal sample belonged to ambiguous multi-crash temporal cells, and the source tables did not provide a common crash identifier. Future

data exchange should retain a shared event identifier and should separately record the collision partner, crash configuration and injured road-user role.

4. DISCUSSION AND CONCLUSION

The results reveal a pronounced temporal structure in police-recorded e-scooter crashes in Serbia, while showing that periods with the highest crash frequency do not necessarily have the most severe consequences. Of 243 crashes recorded in 2024–2025, 54 (22.2%) were classified as KSI. Adjusted crash intensity was 31.6% higher in 2025 than in 2024, whereas weekend hours had 37% lower intensity than weekdays. The temporal pattern remained stable across both years, with a mid-afternoon daily peak and an annual maximum in late August. Conversely, the strongest severity association occurred between 06:00 and 09:59, when the adjusted odds of KSI were 2.63 times higher than during the daytime/evening reference period. Prevention should therefore address both high-frequency periods and time intervals associated with more severe outcomes.

The increase in 2025 represents growth in recorded crash burden rather than necessarily higher risk per trip because data on trips, kilometres travelled and fleet size were unavailable. Increased e-scooter use, changes following their legal recognition in 2023, greater reporting awareness and changes in police recording may have contributed. Rix et al. (2024) demonstrated that hourly distributions of e-scooter use and injury incidence do not necessarily coincide, confirming the importance of exposure data. The mid-afternoon and late-summer peaks are nevertheless consistent with greater mobility, favourable weather and seasonal availability (Kazemzadeh et al., 2023; Rix et al., 2024). They also support earlier Serbian research treating road casualties as temporally structured observations (Pljakić et al., 2021, 2022). Cyclic harmonic terms were appropriate because they preserved continuity across midnight and calendar-year boundaries while remaining parsimonious for a short series containing many zero counts.

The morning KSI association may reflect commuter interaction with denser and faster traffic, speed differentials, arterial-road use, time pressure or visibility and surface conditions. These explanations remain hypotheses because the required variables were unavailable. Rix et al. (2024) also reported particularly high early-morning injury incidence per trip, while Dibaj et al. (2024) identified temporal severity variation and an important role of alcohol intoxication. The Serbian night-time estimate was elevated but imprecise (aOR=2.19), meaning that night riding cannot be considered unimportant. Similarly, weekends had lower crash intensity but an elevated, statistically uncertain KSI estimate (aOR=1.60). These findings demonstrate why crash occurrence and severity should be modelled separately. Differences from hospital studies may also reflect different samples, outcome definitions and under-reporting in official statistics (Bjørnskau et al., 2025; Stigson et al., 2021).

Street-segment crashes had higher estimated KSI odds than the intersection/road reference category (aOR=1.58), although the confidence interval included one. Uninterrupted segments may permit higher speeds and expose riders to overtaking, access-point and surface-related hazards. Cicchino et al. (2021) similarly found greater injury severity on roadways than on sidewalks, although the study designs and location classifications differ. Intersections also remain important because of crossing and turning conflicts. Prevention should consequently provide continuous protected routes and safe transitions through junctions rather than treating segments and intersections separately.

Motor-vehicle linkage status was not reliably associated with KSI severity. Confirmed and possible motor-vehicle involvement produced aORs of 0.87 and 0.72, respectively, compared with crashes in which no motor vehicle was identified. These estimates do not indicate a

protective effect. Motor vehicles play an important role in fatal micromobility crashes, particularly through turning and crossing conflicts (International Transport Forum, 2020; Shah et al., 2021). In this database, the other vehicle could only be assigned deterministically in single-crash temporal cells, while the reference category did not represent verified single-e-scooter crashes. The sensitivity analysis was similarly inconclusive (aOR=0.66, 95% CI 0.23–1.88), indicating insufficient information rather than absence of an effect.

The study is strengthened by national police data, a complete hourly grid, cyclic representation of daily and annual patterns, penalised logistic regression appropriate for 54 KSI outcomes, and explicit treatment of linkage uncertainty. Its limitations include under-reporting of falls and less severe injuries, absence of exposure data and incomplete information on rider age, sex, helmet use, alcohol, speed, weather, lighting, road surface and the identity of the injured participant. Only two complete years were analysed, limiting long-term inference. The observational models therefore describe associations conditional on a police-recorded crash and cannot establish causal effects.

The findings support a layered prevention programme. Enforcement, public communication and route inspections should be intensified during afternoon hours and before the late-summer peak, while morning interventions should focus on speed management, yielding and overtaking enforcement, sight-distance improvement and commuter conflict points. Continuous protected micromobility infrastructure, safe intersection design, adequate lighting and rapid surface repairs are needed on corridors with high traffic speeds and volumes. Rider measures should promote helmets, front and rear lighting and conspicuous clothing, while enforcing passenger, alcohol and speed restrictions. Where shared fleets operate, geofenced speed limits and targeted late-night restrictions may complement infrastructure measures. Helsinki evaluations found lower injury incidence following combined speed and night-time restrictions, although the reduction in severity was smaller (Dibaj et al., 2024; Pakarinen et al., 2023).

Future databases should retain a common crash identifier and record the collision partner, crash configuration, injured-person role, helmet use and alcohol status. Police–hospital linkage would improve identification of unreported events, while operator and mobility-survey data would provide exposure denominators. In conclusion, recorded e-scooter crashes increased in 2025 but retained stable daily and seasonal patterns. Crash frequency was greatest in the mid-afternoon and late summer, whereas morning crashes had the clearest association with KSI severity. Evidence regarding the other vehicle remained inconclusive. Reducing the burden therefore requires time-targeted enforcement, continuous safe infrastructure, speed and behaviour management, and improved linked data.

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