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England-wide injury-severity analysis of e-scooter riders using a Bayesian spatial field model

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ABSTRACT

As electric scooter (e-scooter) use has expanded, understanding the factors associated with e-scooter rider injury severity has become increasingly important for road safety policy. This study analyses 2,128 crashes involving e-scooters and motor vehicles across England (2020–2023) to identify factors associated with severe and fatal injuries to e-scooter riders. Using the geographic coordinates of crashes, we developed a Bayesian spatial field model implemented via the Stochastic Partial Differential Equation (SPDE) approach for fast Bayesian estimation. Our approach accounts for spatial unobserved heterogeneity (area-level "context" effects) often overlooked in injury severity studies. Results indicate that severe or fatal injuries are more likely among older riders, male riders, and in crashes occurring in darkness, on single carriageways, on roads with speed limits of 40 mph or higher, involving heavy vehicles, at night or early morning, or with e-scooter skidding/overturning, frontal impacts, e-scooters entering main roads, or opponent vehicles moving straight. Conversely, motor vehicles performing moving-off manoeuvres are linked to lower odds of severe injuries. Importantly, the presence of authorised e-scooter trials was not found to be associated with rider injury severity outcomes. Our spatial analysis reveals higher odds of severe injury in parts of north-western and south-eastern England relative to the national average. Our research highlights the importance of vehicle kinematics, road environment, and spatial context in shaping injury severity and support targeted, evidence-based interventions, including infrastructure measures and vehicle-based safety technologies such as blind-spot detection.

1. Introduction

Electric scooters (e-scooters) have been a popular means of transport in recent years. They are well-suited for short-distance trips, especially last-mile trips (Baek et al., 2021). Following the implementation of regulations allowing and promoting the use of rental e-scooters in July 2020, rental e-scooter trials have been in place in 22 regions across England in 2024 (Department for Transport, 2024). Being a convenient supplementary mode, e-scooters possibly contribute to future transport equity (Sanders et al., 2020). Despite the numerous advantages discussed in previous research, the growing number of e-scooters has caused an increase in traffic injuries, raising traffic safety concerns.

Due to the lack of separate lanes, e-scooter riders mostly share the road with motorised vehicles. Gössling (2020) noted that e-scooters influence other road users, thereby increasing the complexity of the road transport system. In the UK, data collected by the Major Trauma Centre exhibits a rising trend in e-scooter injuries in 2020 (Ahluwalia et al., 2023). From the beginning of 2023 until the end of June, 1,269 e-scooter-related crashes have occurred in Great Britain, resulting in 1,355 casualties, with e-scooter riders accounting for approximately 80% of all injured individuals (Department for Transport, 2023b). The quantities of injuries in the first half of 2023 are significantly greater than the annual statistics record for 2020 (Department for Transport, 2021). In Austin, U.S., the injury rate for e-scooters is significantly higher than that for motor vehicles (Rix et al., 2021). Remarkably, the statistics on casualties in e-scooter crashes highlight the vulnerability of e-scooter users compared to other road users (Department for Transport, 2022b, 2023a). These calls for research to better understand e-scooter safety.

1.1. Current paper

This study aims to explore the England-wide determinants of e-scooter rider injury severities in crashes involving e-scooters and motorised vehicles, with the aim of providing insights to stakeholders (e.

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g., local authorities, transportation agencies, and e-scooter providers). We model crash severity conditional on a crash occurring, with crash-level covariates (standard in injury severity work). We include a continuous spatial random field at the crash point. That field can capture unobserved spatially structured factors: urbanicity, infrastructure, road user behaviour, enforcement, reporting differences, etc. We demonstrate the ease with which spatially varying coefficients can be incorporated into the analysis, even in a relatively computationally intensive setting. Finally, we note that our approach can reveal regional differences that are not known a priori, underscoring the value of the analysis in uncovering spatial patterns that warrant further investigation.

2. Literature review

2.1. Previous e-scooter safety studies

In studies on e-scooter safety, some research focuses on analysing injury rates and crash frequency (see, for example, Azimian and Jiao, 2022; Heydari et al., 2022; Rix et al., 2021). Most current studies on e-scooter crash injuries focus on understanding the characteristics of riders and crashes. Characteristics like age, gender, helmet usage, rider behaviour, crash details (location and time) and the cause of the crash were described (Bloom et al., 2021; Stigson et al., 2021; Uluk et al., 2022).

Concerning e-scooter injury severities, some previous studies provide only descriptive analyses based on severity (Trivedi et al., 2019; Yang et al., 2020). However, more recent research has introduced more systematic analyses. Asensio-Gil et al. (2024) applied a finite element analysis approach and a human body model to investigate rider injury severities in different numerical simulation scenarios. Using logistic regression models, Cicchino et al. (2021) and Osti et al. (2023) investigated the effects of rider characteristics and crash attributes on injuries resulting from e-scooter crashes. Specifically, focusing on injuries sustained by 105 e-scooter riders in Washington, DC (US), Cicchino et al. (2021) found that people who use e-scooters more frequently (ride at least once a week) and riders injured on the road were more likely to suffer severe injuries. Based on police-recorded data from Italy, Longo et al. (2024) adopted a binary logit model and found that a temporal factor (10p.m.-6 a.m.) increased the likelihood of injuries in e-scooter crashes. Similarly, based on the injury data from e-scooter-related crashes in the UK in 2021, Li et al. (2025) applied a binary logit model and found that the time between night and early morning was associated with a higher odds of severe injuries. They further noted that crashes involving older casualties and those occurring in rural areas increased the odds of severe injuries, whereas crashes involving female vehicle drivers reduced the risk. Dibaj et al. (2024) utilised an ordered logit model to explore the changes in the influence of certain variables before and after the e-scooter restriction policy was introduced. They noted that although people intoxicated were no longer significantly positively related to severe injuries after the policy implementation, people riding between 4p.m. to 9p.m. were associated with a higher likelihood of more severe injuries after that.

Some current e-scooter injury severity studies have further applied random parameter methods. For example, Gao and Zhang (2024) employed random parameters logit models with heterogeneity in means and variance, considering rider, driver, road, environment, vehicle and collision factors for a detailed analysis. In addition to discussing the effects of these variables, they highlighted the effects of the weekend and the second-party vehicle manoeuvre (moved off) vary across two-vehicle crashes, capturing the unobserved heterogeneity to some extent. However, they noted that spatial and temporal dependencies need to be addressed in future studies. Agheli et al. (2025) also built a random parameters logit model with heterogeneity in means and variance to analyse crash severity. Furthermore, they extended the statistical analytical method by applying a machine learning technique to identify important influencing factors, and subsequently compared the results from the two approaches. They noted that although some differences were observed, most of the determinants are aligned; for example, both methods identified that although female riders are generally less likely to sustain severe injuries, younger females and those involved in crashes at uncontrolled or give-way junctions face a higher risk. Based on several build environment characteristics of e-scooter crash locations, Abdi and O'Hern (2025) classified the e-scooter rider injury severity data into four clusters using an unsupervised machine learning approach, and then developed random parameters logit models for each cluster. Beyond analysing the determinants within each group, the effects were compared across clusters. For example, they found that younger rider (aged below 35 years), higher speed limit, and collisions involving car or heavy vehicles were consistently linked to more severe injuries in all identified clusters, while the effect of morning peak and afternoon peak were opposite in cluster 3 (intersection-dense areas) and 4 (residential and central areas) compared to injuries in cluster 1 (car-centric and mixed-use zones).

2.2. Factors affecting injury severity sustained by road users

Bicycles are perhaps most comparable to e-scooters in several ways. Based on the guidance of UK e-scooter trials (Department for Transport, 2024), e-scooters are allowed to share the same space on the road with bicycles. In addition, e-scooter riders are as vulnerable as cyclists due to the lack of protective gear and closer proximity to motor vehicles on roads. Given the similarity between these two modes and the scarcity of e-scooter injury severity research, this section of our literature review focuses on studies that investigate factors that affect injury severity sustained by cyclists in cyclist-vehicle crashes.

In these studies, age, gender, and road user behaviour are the most considered individual characteristics. Researchers generally found that males and older individuals often sustain more severe injuries (Behnood and Mannering, 2017a; Bíl et al., 2010; Gao and Zhang, 2024). Risky behaviours such as consuming alcohol before riding or driving and speeding increased the probability of cyclists sustaining severe injuries (Macioszek and Granà, 2021; Robartes and Chen, 2017). Environmental factors and roadway attributes are examined in several studies. For example, cyclists were found to be more likely to sustain serious and fatal injuries in darkness (Liu et al., 2022; Samerei et al., 2021). Crashes on two-way undivided roads can result in a higher risk of injury, and cyclists tend to be safer on rough road surfaces (Robartes and Chen, 2017). The posted speed limit can be positively associated with an increased risk of severe injury or fatality for cyclists (Chen and Shen, 2016). Regarding the vehicle and collision features, the type of motor vehicle (e.g., heavy goods vehicle) and crash details such as accident site location and temporal factors are commonly investigated. For example, crashes involving heavy vehicles such as buses or trucks were linked with an increased likelihood of more severe cyclist injuries (Kim et al., 2007; Macioszek and Granà, 2021; Yan et al., 2011). Crashes that occur at nighttime or in the early morning (22:00–6:00) tend to be more dangerous (Macioszek and Granà, 2021). Head-on collisions are more likely to result in more severe injuries (Macioszek and Granà, 2021; Yan et al., 2011).

2.3. A brief overview of analytical methods in injury severity analysis

Several statistical modelling methods have been applied in previous studies to identify and investigate the determinants of traffic-related injury severity sustained by road users. The level of injury severity considered in previous studies ranges from no injury to fatal injury. Binary logit models (Macioszek and Granà, 2021; Yan et al., 2011), multinomial logit models (Kim et al., 2007), ordered probit models (Abdel-Aty, 2003; Robartes and Chen, 2017) and ordered logit models (Rezapour et al., 2019) are commonly used.

Savolainen et al. (2011) and Mannering et al. (2016) highlighted the importance of accounting for unobserved heterogeneity in injury severity analysis. Unobserved heterogeneity arises due to unmeasured or unknown factors that affect injury severity sustained by road users. The conventional statistical approaches mentioned earlier have limitations in accounting for unobserved heterogeneity, resulting in biased parameter estimation. Therefore, more advanced methods are often employed, offering more detailed insights. Some examples include the latent class models (Samerei et al., 2021; Sasidharan et al., 2015; Yu et al., 2019) and random parameters models (Chang et al., 2016; Liu et al., 2022; Moore et al., 2011; Morgan and Mannering, 2011). The latent class approach allows the effect of covariates to vary across latent clusters to capture the heterogeneity within and between groups. For example, Sun et al. (2024) found three latent clusters in their analysis. The mixed logit model, also known as the random parameters multinomial logit model, extends the multinomial logit model by allowing parameters to vary across observations (or groups of observations) to capture unobserved factors. Some studies have utilised heterogeneity in means and variances approaches to better address unobserved heterogeneity and make more robust inferences (Behnood and Mannering, 2017a, 2017b; Chang et al., 2022; Kim et al., 2010; Liu et al., 2021). Some recent injury-severity studies have used deep learning techniques (e.g. see Seyfi et al., 2025).

The Bayesian approach is increasingly adopted in road safety research. The Bayesian framework is well suited for implementing complex and advanced approaches to account for unobserved heterogeneity. For example, it offers a flexible framework and can readily relax restrictive distributional assumptions (Heydari, 2018). Xie et al. (2009) estimated a Bayesian ordered probit model to explore factors affecting driver injury severity. Huang et al. (2008) developed a Bayesian two-level model for driver injury analysis based on hierarchical data, considering individual- and crash-level factors. Similarly, to analyse the injury severity of drivers, Chen et al. (2016) utilised driver-, vehicle- and crash-level factors to build a Bayesian hierarchical logit regression model.

Several studies have accounted for spatial dependence in crash or injury frequency analyses (Barua et al., 2016; Bhat et al., 2017; Chiou et al., 2014; Pervaz et al., 2025; Satria et al., 2021; Shoari et al., 2023; Singh et al., 2025). However, previous injury severity studies have made relatively limited attempts to address spatial dependence (Guadamuz and Aguero-Valverde, 2021). For example, Castro et al. (2013) investigated the severity of highway crash injuries using a spatial ordered-response probit model. Zeng et al. (2020) built a spatial ordered logit model to capture the spatial dependence among crashes in neighbouring road segments.

Based on the region-level crash severity data, Barmoudeh et al. (2022) developed a spatial multinomial structured additive regression model. Klassen et al. (2014) employed spatial mixed logit models to account for spatial variation at sites where cyclist-vehicle crashes occurred. Liu et al. (2020) constructed the geographically weighted ordinal logistic regression model using geographic location information to capture the spatial variations of influencing factors to account for spatial heterogeneity, and Xu et al. (2024) applied the same spatial approach to analyse police injury severity in traffic crashes. The geographically weighted regression is referred to as a limited approach and mostly exploratory compared to mainstream Bayesian spatial models that explicitly account for spatial dependence in the data (Haining and Li, 2020).

3. Data

The data used in this study were obtained from the UK STATS19 road safety database (Department for Transport, 2023c) that includes the crash, vehicle and casualty data sets. We combined these datasets obtaining crashes between e-scooters and motorised vehicles, focusing on injuries sustained by e-scooter riders. Note that the STATS19 data base records only injury crashes. As the number of fatal injuries was very small (see Fig. 1), serious and fatal injuries were combined into one category (against slight injuries). The final monthly data included 2,128 e-scooter-vehicle crashes (here, corresponding to rider injuries) in England from January 2020 to June 2023.

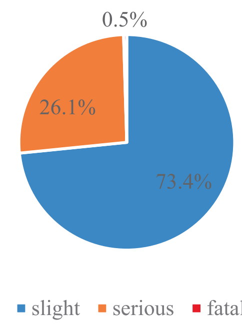

Fig. 1. Proportion of different injury severity categories.

A host of factors relating to rider, roadway, environmental, crash, and vehicle characteristics, together with an indicator for authorised e-scooter trial areas, were included in the analysis. Information on the e-scooter trial was compiled from the evaluation report, monitoring data, and guidance for users published by Department for Transport (2022a, 2025a, 2025b), and used to identify whether the rental e-scooter trials were implemented in each area. To examine whether there was an association between e-scooter trials and the severity of injuries sustained by riders, a value of one was assigned to crashes that occurred within a local authority where an authorised e-scooter trial was active at the time of the crash. Summary statistics of the data are reported in Table 1.

The spatial distribution of injuries in this study is presented in Fig. 2. This map is created using the crash location data. Each dot represents a rider injury in an e-scooter-vehicle crash, with red dots indicating those who sustained serious or fatal injuries, and blue dots representing those who were slightly injured. It can be observed that the spatial distribution of the two severity levels is uneven. Notably, a significant concentration of injuries (both slight and severe) is distributed in the Greater London area.

4. Methods

To account for the spatial dependence in the data, using geographic coordinates of e-scooter crashes, we adopted the Stochastic Partial Differential Equation (SPDE) approach together with the Integrated Nested Laplace Approximation (INLA), implemented via R-INLA (Chaudhuri et al., 2023; Konstantinoudis et al., 2020; Lindgren et al., 2011; Rue et al., 2009) which enables relatively fast inference. This is while employing the commonly used MCMC algorithms is not practical for such a computationally intensive problem (Belmont et al., 2024; Stipancic et al., 2020; Stipancic et al., 2021).

The SPDE representation requires a triangulated mesh over the spatial domain (Fig. A1 in Appendix). We constructed a two-dimensional constrained Delaunay triangulation covering England and a surrounding buffer region. The buffer (extending approximately 80 km beyond the boundary) reduces boundary artefacts by allowing locations near the national border to be influenced by triangles beyond the observation window. We used a mesh with a maximum triangle edge length of approximately 30 km inside England and 60 km in the outer buffer region. This design balances approximation accuracy over the study area with computational efficiency, while a minimum angle constraint prevents very thin triangles and improves numerical stability. The approach is powerful enough to allow us to estimate spatial confounding at any resolution we want across the country.

4.1. Bayesian binary logit model

We used a binary logistic regression model for our binary dependent

Table 1
Descriptive statistics of the data.

Variable	Injury severity Slight injury n = 1,562	Serious/fatal injury n = 566
Rental e-scooter trial		
Trial area	712 (45.58%)	237 (41.87%)
Non-trial area	*850 (54.42%)*	*329 (58.13%)*
Rider characteristics		
Age, years (mean [SD])	24.859 (11.145)	26.525 (11.915)
Gender of rider		
Male	1,206 (77.21%)	482 (85.16%)
Female	*356 (22.79%)*	*84 (14.84%)*
Environment factors		
Light conditions		
Darkness	404 (25.86%)	191 (33.75%)
Daylight	*1,158 (74.14%)*	*375 (66.25%)*
Weather conditions		
Fine weather	1,379 (88.28%)	483 (85.34%)
Adverse weather	*183 (11.72%)*	*83 (14.66%)*
Road attributes		
Road type		
Single carriageway	1,198 (76.70%)	460 (81.27%)
All other road types	*364 (23.30%)*	*106 (18.73%)*
Second road class		
Class A	162 (10.37%)	51 (9.01%)
Class B	56 (3.59%)	27 (4.77%)
Class C	72 (4.61%)	23 (4.06%)
Unclassified	938 (60.05%)	334 (59.01%)
Not at junction or within 20 m	*334 (21.38%)*	*131 (23.14%)*
Pedestrian crossing physical facilities		
Zebra	143 (9.15%)	35 (6.18%)
Pelican, puffin, toucan or similar non-junction pedestrian light crossing	152 (9.73%)	47 (8.30%)
Pedestrian phase at traffic signal junction	184 (11.78%)	77 (13.60%)
Central refuge	70 (4.48%)	21 (3.71%)
No physical crossing facilities within 50 m, Footbridge or subway	*1,013 (68.85%)*	*386 (68.20%)*
Road speed limit		
40 mph and over	64 (4.10%)	33 (5.83%)
30 mph or less	*1,498 (95.90%)*	*533 (94.17%)*
Junction detail		
Roundabout and mini-roundabout	182 (11.65%)	47 (8.30%)
T or staggered junction	599 (38.35%)	222 (39.22%)
Crossroad or more than 4 arms	233 (14.92%)	93 (16.43%)
Other junctions	162 (10.37%)	57 (10.07%)
Not at junction or within 20 m	*386 (24.71%)*	*147 (25.97%)*
Road surface conditions		
Dry surface	1,281 (82.01%)	461 (81.45%)
Other surface conditions (wet or damp, snow, frost or ice)	*281 (17.99%)*	*105 (18.55%)*
Vehicle characteristics		
Vehicle type		
Bus/coach/agricultural vehicle/goods over3.5 tonnes maximum gross weight (mgw)	44 (2.82%)	28 (4.95%)
Other vehicle types	*1,518 (97.18%)*	*538 (95.05%)*
Temporal factors		
Season		
Summer	431 (27.59%)	161 (28.45%)
Autumn	396 (25.35%)	138 (24.38%)
Winter	322 (20.61%)	110 (19.43%)
Spring	*413 (26.44%)*	*157 (27.74%)*
Week		
Weekend	361 (23.11%)	150 (26.50%)
Weekday	*1,201 (76.89%)*	*416 (73.50%)*
Time of day		
Nighttime and early morning (0:00–6:59)	67 (4.29%)	49 (8.66%)
Other times of day	*1,495 (95.71%)*	*517 (91.34%)*
Crash characteristics		
E-scooter skidding and overturning		
Skidding and/or overturning	117 (7.49%)	59 (10.42%)
None	*1,445 (92.51%)*	*507 (89.58%)*
E-scooter first point of impact		
Frontal impact	851 (54.48%)	366 (64.66%)
Other impact	*711 (45.52%)*	*200 (35.34%)*
Motor vehicle first point of impact		
Frontal impact	843 (53.97%)	302 (53.36%)
Other impact	*719 (46.03%)*	*264 (46.64%)*
Collision type		
Head on	383 (24.52%)	167 (29.51%)
Rear end –the end of e-scooter	92 (5.89%)	20 (3.53%)
Rear end-the end of motor vehicle	64 (4.10%)	28 (4.95%)
Side collision	175 (11.20%)	43 (7.60%)
Side with front of e-scooter	386 (24.71%)	161 (28.45%)
Side with front of motor vehicle	355 (22.73%)	111 (19.61%)
Other collision types	*107 (6.85%)*	*36 (6.36%)*
E-scooter junction location		
Entering main road	109 (6.98%)	55 (9.72%)
Other junction locations	*1,453 (93.02%)*	*511 (90.28%)*
Motor vehicle junction location		
Entering main road	114 (7.30%)	32 (5.65%)
Other junction locations	*1,448 (92.70%)*	*534 (94.35%)*
E-scooter manoeuvre		
Going ahead	1,204 (77.08%)	459 (81.10%)
Moving off	97 (6.21%)	31 (5.48%)
Other manoeuvres	*261 (16.71%)*	*76 (13.43%)*
Motor vehicle manoeuvre		
Going ahead	724 (46.35%)	300 (53.00%)
Moving off	173 (11.08%)	32 (5.65%)
Other manoeuvres	*665 (42.57%)*	*234 (41.34%)*

[a] Reference categories are indicated in italics.

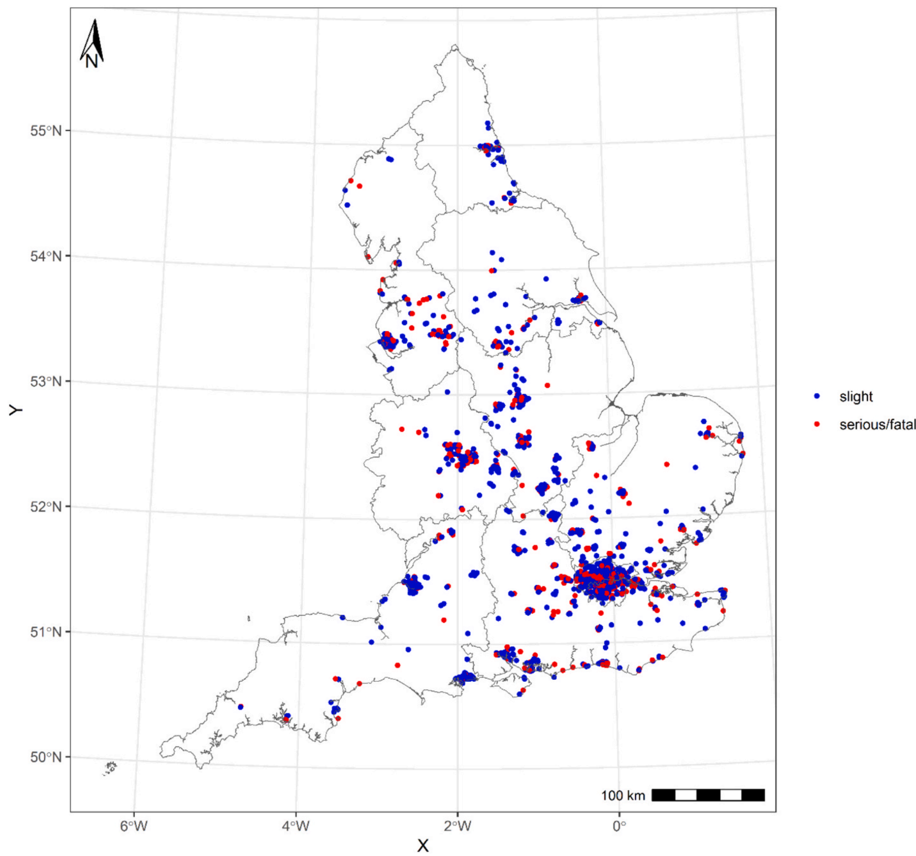

Fig. 2. Spatial distribution of e-scooter rider injury in England. See the electronic version for a colour view.

variable: slight injury vs. serious/fatal injury. A Bayesian binary logistic regression model is defined in Eq.1. Let *p(s)* represent the probability of an e-scooter rider suffering serious or fatal (severe) injuries in the point referenced location $s \in \mathbb{R}^2$; α_0 an intercept term; $\boldsymbol{X(s)}$ the predictor variables for the crash on the s-th location; and $\boldsymbol{\beta}$ a vector of regression coefficients associated with $\boldsymbol{X(s)}$.

$$y(s) \sim Bernoulli(p(s)) \quad logit(p(s)) = \alpha_0 + \boldsymbol{\beta X}(\boldsymbol{s}) \tag{1}$$

4.2. Bayesian spatial field model

We expand the model (1) to account for spatial correlation using spatial random effects. We modelled the spatial random effects using the Stochastic Partial Differential Equations (SPDE) approach (Lindgren et al., 2011). It can be specified as Eq. (2):

$$y(s) \sim Bernoulli(p(s)) \quad logit(p(s)) = \alpha_0 + \boldsymbol{\beta X}(\boldsymbol{s}) + u(s) \tag{2}$$

Where *u(s)* is the realisation of spatial Gaussian random field with a Matérn covariance (a continuous spatial field, also referred to as a Matérn process) at location *s*. The model parameters are estimated on the observed locations, but the SPDE approach allows the evaluation of the spatial field in the continuous space for $s \in \mathbb{R}^2$. The Matérn covariance function between locations can be defined as (Gómez-Rubio, 2020; Krainski et al., 2018):

$$Cov_M(u(s_m), u(s_n)) = \frac{\sigma^2}{2^{\nu-1}\Gamma(\nu)}(\kappa\|s_m - s_n\|)^{\nu} K_{\nu}(\kappa\|s_m - s_n\|) \tag{3}$$

Where σ^2 is a general scale parameter, representing the marginal variance of the Matérn process; $\Gamma()$ denotes the gamma function; ν and κ are the smoothness parameter and the scale parameter, respectively, and both are greater than 0; $\|\, s_m - s_n \,\|$ represents the Euclidean distance between locations s_m and s_n; and K_ν is the modified Bessel function of the second kind.

To set the SPDE, a two-dimensional mesh covering the study area is first generated using Constrained Refined Delaunay Triangulation. Subsequently, a projector matrix is constructed to link the spatial field specified at the mesh nodes (vertices in the triangulation) to the observed crash locations (Krainski et al., 2018).

We adopt a finite element representation of the Matérn field on the given two-dimensional mesh, where *J* denotes the total number of mesh nodes, w_j are random weights and $\{\phi_j\}$ is a set of piecewise linear basis functions that take the value 1 at the j-th mesh node and 0 at all other nodes (Konstantinoudis et al., 2020):

$$u(s) = \sum_{j=1}^{J} \phi_j(s) w_j \tag{4}$$

The Gaussian field with Matérn covariance is a solution of the following SPDE (Krainski et al., 2018):

$$(\kappa^2 - \Delta)^{\alpha/2} u(s) = W(s) \quad \alpha = \nu + d/2 \quad \kappa > 0, \nu > 0 \tag{5}$$

Where the locations $s \in \mathbb{R}^2$), Δ is the Laplacian operator, *W* represents a Gaussian spatial white noise process, *d* is the number of dimensions, where $d = 2$, and ν and κ are the smoothness and scale parameters respectively.

4.3. Bayesian spatial field model with spatially varying coefficients

An extension of the spatial model is to consider the spatially varying effects of covariates. Suppose the model includes an independent variable with spatially varying coefficients. In that case, the model is specified as in Eq. (6). Another Gaussian random field *v(s)* is generated and incorporated into the spatial model to allow the variable to have different impacts across various locations, thereby addressing spatial heterogeneity. In the model, Z represents the covariate with spatially varying coefficients.

$$y(s) \sim Bernoulli(p(s))$$

$$logit(p(s)) = \alpha_0 + \boldsymbol{\beta X}(\boldsymbol{s}) + v(s)Z(s) + u(s) \tag{6}$$

4.4. Prior specification

We assigned non-informative priors, normal (0, 1000), for fixed effect parameters. The prior of the intercept corresponds to an improper uniform prior on the real line (i.e., a flat prior implemented via infinite variance). For the Matérn process, the definition of range ρ and marginal variance σ^2 is given by Eq.7 (Lindgren et al., 2011). For the spatial models used in this study, we applied the penalised complexity (PC) priors for the Matérn covariance, where $\nu = 1$. PC priors are Bayesian priors that are constructed by explicitly penalising deviations from a simple, well-defined base model, so that more complex models are a priori less likely. Formally, they are built by placing an exponential prior on a measure of distance (Kullback–Leibler divergence) from the base model, yielding interpretable, weakly informative regularisation (Simpson et al., 2017; Sørbye and Rue, 2017). The probability of the ρ being smaller than 10 and the standard deviation σ exceeding 1 are assumed to be 0.1.

$$\rho = \sqrt{8\nu}/\kappa \tag{7}$$

$$\sigma^2 = \frac{\Gamma(\nu)}{\Gamma(\nu + d/2)(4\pi)^{d/2}\kappa^{2\nu}}$$

5. Results and discussion

The deviance information criterion (DIC) and the Watanabe-Akaike information criterion (WAIC) are used for model selection (Gelman et al., 2014), with lower values of DIC and WAIC indicating a better model fit. For detailed explanations of DIC and WAIC, see Spiegelhalter et al. (2002) and Watanabe and Opper (2010), respectively. It should be noted that in this study, we considered random parameter modelling and heterogeneity-in-means and heterogeneity-in-variance approaches, which are commonly used in the road crash literature; however, these did not improve the performance of our binary logit model. Interestingly, a Bayesian spatial field logit model improved the fit compared to the commonly used non-spatial logit model. The execution time for the Bayesian spatial field model (model 2) was only a few seconds, which is extremely fast for such a computationally intensive setting.

The spatially varying coefficient model has slightly lower DIC and WAIC values, but the difference is not considered substantial. Therefore, in this study we discuss the results of our Bayesian spatial field model, which captures spatial dependence via a spatially structured error term. The model incorporating the spatially varying coefficients is used to provide additional insights as we discuss in Section 5.2.1. With respect to model adequacy, we developed a simple binary logit model in Stata (StataCorp, 2025) and conducted a Pearson chi-squared goodness-of-fit test that indicated that the model fits the data well. Note that our extensions (i.e., the spatial models) further improved upon this baseline model.

It should also be noted that, to investigate temporal instability (Mannering, 2018), we included year indicators (2020–2023) as categorical variables in the model, as well as alternative groupings (e.g., 2020 as the COVID year vs. other years), and examined their interactions with other covariates. None of these interactions were statistically significant. Also, we considered various temporal RW1 and RW2 specifications to capture temporal dependence using temporally structured error terms and time–varying coefficients; however, this additional complexity was not needed and was not supported by the data (see Table A1 in the Appendix). Given that the addition of a temporal random effect did not improve model performance, we did not pursue more complex higher-order space–time interaction models. We therefore do not discuss temporal models further so as to avoid distracting from the main focus of the paper.

5.1. Model estimation results

The estimated results of the Bayesian non-spatial model, spatial model, and spatially varying coefficient model are provided in Table 2, Table 3 and Table 4. The results indicate that various rider, road, environmental, vehicle and crash characteristics are statistically significant in determining rider injury severity. We found that an increase in the age of riders increases the odds of serious or fatal injuries. This finding is in accordance with research on cyclists (Chen and Shen, 2016; Kim et al., 2007), and can be explained by the increased response time

Table 2
Posterior estimation summary − non-spatial Bayesian logit model (Model 1).

	Median	Std. Dev.	95% Credible Interval	
Intercept	−2.710	0.240	−3.181	−2.239
Rider characteristics				
Age	0.016	0.004	0.008	0.025
Gender of rider				
Male	0.452	0.136	0.187	0.718
Female	*reference category*			
Environment factors				
Light conditions				
Darkness	0.363	0.113	0.142	0.583
Daylight	*reference category*			
Road characteristics				
Road type				
Single carriageway	0.365	0.133	0.104	0.625
All other road types	*reference category*			
Road speed limit				
40 mph or above	0.634	0.234	0.175	1.093
30 mph or less	*reference category*			
Vehicle				
Vehicle type				
Bus/coach/agricultural vehicle/ goodsover3.5 tonnes mgw	0.599	0.254	0.101	1.097
Other vehicle types	*reference category*			
Time				
Time of day				
Nighttime and early morning (0:00–6:59)	0.578	0.206	0.175	0.981
Other times of day	*reference category*			
Crash characteristics				
E-scooter skidding and overturning				
Skidding and/or overturning	0.380	0.173	0.041	0.718
None	*reference category*			
E-scooter first point of impact				
Frontal impact	0.465	0.106	0.258	0.673
Other impact	*reference category*			
E-scooter junction location				
Entering main road	0.370	0.181	0.017	0.724
Other junction locations	*reference category*			
Motor vehicle manoeuvre				
Going ahead	0.247	0.108	0.035	0.460
Moving off	−0.585	0.213	−1.002	−0.168
Other manoeuvres	*reference category*			
DIC	2381.343			
WAIC	2381.677			

Table 3
Posterior estimation summary – Bayesian spatial logit model (Model 2).

	Median	Std. Dev.	95% Credible Interval	
Intercept	−2.657	0.257	−3.159	−2.153
Rider characteristics				
Age	0.018	0.005	0.009	0.027
Gender of rider				
Male	0.416	0.137	0.147	0.685
Female	*reference category*			
Environment factors				
Light conditions				
Darkness	0.361	0.114	0.138	0.583
Daylight	*reference category*			
Road characteristics				
Road type				
Single carriageway	0.349	0.135	0.084	0.614
All other road types	*reference category*			
Road speed limit				
40 mph or above	0.626	0.239	0.157	1.095
30 mph or less	reference category			
Vehicle				
Vehicle type				
Bus/coach/agricultural vehicle/ goodsover3.5 tonnes mgw	0.606	0.257	0.102	1.110
Other vehicle types	*reference category*			
Time				
Time of day				
Nighttime and early morning (0:00–6:59)	0.602	0.208	0.194	1.010
Other times of day	*reference category*			
Crash characteristics				
E-scooter skidding and overturning				
Skidding and/or overturning	0.373	0.176	0.027	0.718
None	*reference category*			
E-scooter first point of impact				
Frontal impact	0.460	0.107	0.250	0.669
Other impact	*reference category*			
E-scooter junction location				
Entering main road	0.406	0.183	0.047	0.765
Other junction locations	*reference category*			
Motor vehicle manoeuvre				
Going ahead	0.233	0.110	0.017	0.448
Moving off	−0.589	0.214	−1.009	−0.169
Other manoeuvres	*reference category*			
Standard deviation for spatial field (Spatially structured random intercepts)	0.389	0.110	0.221	0.651
DIC	2367.904			
WAIC	2368.299			

Table 4
Posterior estimation summary – Bayesian spatial logit model with a spatially varying coefficient (Model 3).

	Median	Std. Dev.	95% Credible Interval	
Intercept	−2.673	0.253	−3.168	−2.175
Rider characteristics				
Age	0.018	0.005	0.008	0.029
Gender of rider				
Male	0.417	0.137	0.148	0.687
Female	*reference category*			
Environment factors				
Light conditions				
Darkness	0.360	0.114	0.137	0.583
Daylight	*reference category*			
Road characteristics				
Road type				
Single carriageway	0.341	0.136	0.075	0.608
All other road types	*reference category*			
Road speed limit				
40 mph or above	0.642	0.241	0.170	1.113
30 mph or less	*reference category*			
Vehicle				
Vehicle type				
Bus/coach/agricultural vehicle/ goodsover3.5 tonnes mgw	0.596	0.257	0.091	1.101
Other vehicle types	*reference category*			
Time				
Time of day				
Nighttime and early morning (0:00–6:59)	0.597	0.208	0.188	1.006
Other times of day	*reference category*			
Crash characteristics				
E-scooter skidding and overturning				
Skidding and/or overturning	0.377	0.177	0.031	0.723
None	*reference category*			
E-scooter first point of impact				
Frontal impact	0.462	0.107	0.252	0.672
Other impact	*reference category*			
E-scooter junction location				
Entering main road	0.412	0.183	0.053	0.771
Other junction locations	*reference category*			
Motor vehicle manoeuvre				
Going ahead	0.236	0.110	0.020	0.452
Moving off	−0.589	0.215	−1.010	−0.168
Other manoeuvres	*reference category*			
Standard deviation for spatial field (Spatially structured random intercepts)	0.321	0.153	0.139	0.730
Standard deviation for spatial field (Coefficients of age of rider)	0.015	0.014	0.003	0.054
DIC	2366.044			
WAIC	2367.114			

and the generally more fragile physical condition of older individuals. Male riders experienced higher odds of fatal/serious injuries compared to female riders perhaps due to more risk taking behaviours. This finding is consistent with previous e-scooter injury studies (Agheli et al., 2025; Gao and Zhang, 2024). Gioldasis et al. (2021) indicated that risk taking behaviours, including consuming alcohol or drugs, are more common among male riders.

Our results illustrated that crashes that occurred in darkness increased the odds of fatal/serious injuries. This may be correlated with the limited visibility of both the rider and driver involved in the crashes under the dark conditions. The finding is consistent with the previous research findings (Abdi and O'Hern, 2025; Gao and Zhang, 2024), which demonstrated that the likelihood of serious and fatal injuries increase when a crash occurs in darkness. Kim et al. (2007) noted that the inadequate driver response due to poor visibility in darkness may lead to more severe injuries.

Regarding road attributes, we found that crashes that occurred on single-carriageways and roads with a speed limit of 40 mph or higher were associated with higher odds of more severe injuries. Car impact speed has been extensively studied as an important factor in traffic safety, with higher impact speeds increasing the risk of severe injuries among vulnerable road users (Heydari et al., 2020; Hussain et al., 2019). This finding is intuitive; one possible reason is that on roads with higher speed limits, collisions between e-scooters and vehicles tend to occur at higher speeds, increasing the odds of severe injuries. Previous e-scooter crash severity studies also noted the risk of riding on roads with higher speed limits (Abdi and O'Hern, 2025; Gao and Zhang, 2024).

We found that severe injuries are more likely to occur in collisions involving heavier or larger motor vehicles (buses, coaches, agricultural vehicles, and goods vehicles over 3.5 tonnes) compared to those involving smaller vehicles, such as cars, taxis and motorcycles. This finding is logical and aligns with previous cyclist injury studies (Kim et al., 2007; Macioszek and Granà, 2021; Yan et al., 2011). Based on our results, crashes between midnight and 7 a.m. were more likely to result in severe rider injuries. This is similar to the findings of previous e-scooter injury studies (Gao and Zhang, 2024; Longo et al., 2024). A possible explanation is that the traffic volume is relatively low at night, which may lead to dangerous behaviours such as speeding.

We found that an e-scooter skidding and/or overturning in a crash increases the odds of more severe rider injuries, which is expected due to the lack of sufficient protection for e-scooter riders. Also, we found that when the front of an e-scooter is the first point of impact in a crash with a motor vehicle, the odds of serious or fatal injuries increase. An e-scooter rider injury severity study has reported a correlation between head-on collisions and a higher likelihood of severe rider injuries (Abdi and O'Hern, 2025). The results in this study indicate that, in addition to head-on collisions, crashes involving the front of the e-scooter and other parts of a vehicle (back, offside, nearside), or crashes where the vehicle is not directly impacted (such as when a rider is injured while manoeuvring to avoid the motor vehicle), are also associated with an increased risk of serious or fatal injuries.

Our results show that the odds of severe injury increase when an e-scooter rider is at a junction and attempting to enter a main road. This can be explained by the fact that the main roads are typically associated with higher speed limits. As a result, riders may get involved in crashes with relatively high-speed vehicles, increasing the risk of severe injury.

Regarding the motor vehicle manoeuvre indicators, we found that compared to other manoeuvres (such as reversing, slowing or stopping, turning, and overtaking) immediately before the crash, the odds of a rider being seriously or fatally injured increases when the motor vehicle is going ahead and decreases when it is moving off. The latter finding is consistent with previous research (see; e.g., Gao and Zhang (2024)), which can be explained by the lower speed of the opponent vehicle during this kind of movement. We also explored the impact of e-scooter manoeuvres in our analysis and found that opponent vehicle manoeuvres have a more significant effect.

5.2. Policy implications

Table 5 represents the odds ratios computed based on the spatial model and the spatial model with spatially varying coefficients, providing a clear understanding of the effect of contributory factors on injury severity. Fig. 3 presents the posterior median values of odds ratios and their 95% credible intervals for the parameters of the Bayesian spatial model, with the variables arranged in ascending order. In this study, odds refer to the ratio of the probability of a rider being seriously or fatally injured to the probability of being slightly injured. Interestingly, we found that e-scooter trials did not have any statistically significant effect on injury severity sustained by e-scooter riders during the study period. However, issues of endogeneity may need to be addressed in order to draw a definitive conclusion. It shows that for each additional year of rider's age during the study period, the odds of a rider being seriously or fatally injured increased by 1.8%. The odds of suffering more severe injuries (versus being slightly injured) for males is 1.516 [1.158–1.984] times that of females. The odds of e-scooter riders being seriously or fatally injured in darkness is 1.434 [1.148–1.792] times higher than in daylight. The odds of serious and fatal injury is 1.418 [1.087–1.849] times higher when riding on a single carriageway compared to other roads. If riding on roads with a speed limit of 40 mph or higher, the odds of serious or fatal injury for individuals is 1.870 [1.169–2.991] times that of riding on roads with other speed limit requirements.

A collision between a heavy vehicle and an e-scooter is risky; the odds of severe injuries is 1.833 [1.107–3.035] times that of collision with other vehicles. The odds of being severely injured is 1.825 [1.214–2.745] times higher if crashes occur during nighttime and early morning. The odds of sustaining serious or fatal injuries is 1.452 [1.028–2.050] times higher for e-scooters skidding and/or overturning and 1.584 [1.284–1.953] times higher when the front of an e-scooter is the initial point of impact. When the e-scooter attempts to enter the main road, the odds of severe injury is 1.501 [1.048–2.150] times the odds of other situations. For the opponent motor vehicle, the odds of severe injuries is 1.262 [1.017–1.566] times higher if it is going ahead when the crash occurs. In contrast to the previously mentioned variables, the odds of serious or fatal injury is on average 44.5% [(0.555–1)*100] lower

Table 5
Posterior estimation summary of odds ratios for spatial logit models.

	Median	95% Credible Interval	
Bayesian spatial logit model with spatial error term (Model 2)			
Rider characteristics			
Age	1.018	1.009	1.027
Gender of rider			
Male	1.516	1.158	1.984
Female	*reference category*		
Environment factors			
Light conditions			
Darkness	1.434	1.148	1.792
Daylight	*reference category*		
Road characteristics			
Road type			
Single carriageway	1.418	1.087	1.849
All other road types	*reference category*		
Road speed limit			
40 mph or above	1.870	1.169	2.991
30 mph or less	*reference category*		
Vehicle			
Vehicle type			
Bus/coach/agricultural vehicle/goodsover3.5 tonnes mgw	1.833	1.107	3.035
Other vehicle types	*reference category*		
Time			
Time of day			
Nighttime and early morning (0:00–6:59)	1.825	1.214	2.745
Other times of day	*reference category*		
Crash characteristics			
E-scooter skidding and overturning			
Skidding and/or overturning	1.452	1.028	2.050
None	*reference category*		
E-scooter first point of impact			
Frontal impact	1.584	1.284	1.953
Other impact	*reference category*		
E-scooter junction location			
Entering main road	1.501	1.048	2.150
Other junction locations	*reference category*		
Motor vehicle manoeuvre			
Going ahead	1.262	1.017	1.566
Moving off	0.555	0.364	0.845
Other manoeuvres	*reference category*		
Bayesian spatial logit model with a spatially varying coefficient (Model 3)			
Rider characteristics			
Age	1.019	1.008	1.030
Gender of rider			
Male	1.518	1.159	1.987
Female	*reference category*		
Environment factors			
Light conditions			
Darkness	1.433	1.146	1.791
Daylight	*reference category*		
Road characteristics			
Road type			
Single carriageway	1.407	1.078	1.836
All other road types	*reference category*		
Road speed limit			
40 mph or above	1.899	1.186	3.045
30 mph or less	*reference category*		
Vehicle			
Vehicle type			
Bus/coach/agricultural vehicle/goodsover3.5 tonnes mgw	1.815	1.096	3.007
Other vehicle types	*reference category*		
Time			
Time of day			
Nighttime and early morning (0:00–6:59)	1.816	1.207	2.734
Other times of day	*reference category*		
Crash characteristics			
E-scooter skidding and overturning			

(*continued on next page*)

Table 5 (*continued*)

	Median	95% Credible Interval	
Bayesian spatial logit model with spatial error term (Model 2)			
Skidding and/or overturning	1.458	1.031	2.061
None	*reference category*		
E-scooter first point of impact			
Frontal impact	1.587	1.286	1.957
Other impact	*reference category*		
E-scooter junction location			
Entering main road	1.510	1.054	2.162
Other junction locations	*reference category*		
Motor vehicle manoeuvre			
Going ahead	1.266	1.020	1.571
Moving off	0.555	0.364	0.846
Other manoeuvres	*reference category*		

when the motor vehicle is moving off.

A considerable proportion of crashes over the study period occurred while a motor vehicle was initiating movement from a stationary position, with moving-off manoeuvres accounting for 205 crashes (around 10% of all crashes over the study period). Therefore, the moving-off phase is a critical point for targeted safety interventions. Moving-off conflicts are widely recognised to be driven by limitations in drivers' visual scanning and blind-spot coverage, particularly in urban environments where e-scooters and other vulnerable road users frequently approach from the rear or nearside of stationary vehicles. From a Safe System perspective, this combination of high exposure and clear perceptual failure mechanisms suggests that moving-off manoeuvres represent a high-leverage target for vehicle-based safety technologies.

In this context, Advanced Driver Assistance Systems, and Blind Spot Detection in particular, are directly relevant, as they are specifically designed to compensate for mirror and head-check limitations during manoeuvre initiation. Our findings therefore support the case for wider—and potentially mandatory—deployment of Blind Spot Detection and related sensing technologies within vehicle safety standards, especially in urban settings with high vulnerable road user activity. This is in accordance with previous research that discusses the importance of Blind Spot Detection in the context of cyclist safety when it comes to nearside collisions and lane changing (Gildea et al., 2021).

Our results indicate that crashes on roads with speed limits of 40 mph or higher and those involving heavy vehicles notably increased the probability of severe injuries. These findings highlight that on roads with higher speed limits and higher proportions of heavy vehicles, greater attention should be given to protecting e-scooter riders.

5.2.1. *Spatial inferences*

Our spatial model is exactly the kind of model that can absorb area-level "context" effects even when explicit area-level data are not available in the injury-severity data, a common attribute of most crash-level datasets. The spatial distribution of the posterior median of the exponential of random intercept is shown in Fig. 4. This can be interpreted as the relative odds ratio attributed to unknown spatial confounders. The colour gradient from deep blue to yellow illustrates an increasing odds ratio of serious or fatal injury. Both spatial dependence and spatial heterogeneity are illustrated in this map. It can be observed that in general the adjacent areas exhibit similar values, while in some areas, such as the northwestern and southeastern parts of England, e-scooter riders face a higher odds ratio of severe injury (versus slight injury) relative to the average odds ratio of injury across the country. This means that there are environmental factors or other factors that are missing in our model. These high-risk areas may require additional attention, such as the development of targeted traffic safety interventions, enforcement and policies.

While further in-depth investigation is required to understand the underlying causes of this elevated risk in certain areas, the higher risk observed in the Northwest and Southeast likely reflects different underlying contextual mechanisms rather than a single common cause. In the Northwest, higher concentrations of socio-economic deprivation, dense urban environments such as Greater Manchester, and above-average traffic volumes may contribute to elevated exposure and conflict risk, which could in turn increase injury severity when e-scooter crashes occur. Major trunk road and arterial corridors intersecting urban areas may further create complex traffic environments characterised by mixed vehicle flows and high interaction density, potentially increasing the severity of injuries sustained by e-scooter riders.

In contrast, the Southeast—while relatively less deprived on average—has the highest traffic volumes nationally, implying greater interaction between motor vehicles and micromobility users, particularly along arterial corridors and within urban–*peri*-urban transition zones. This region also accommodates relatively substantial heavy goods vehicle (HGV) traffic associated with major freight and logistics corridors, which may further shape the severity of vehicle–micromobility

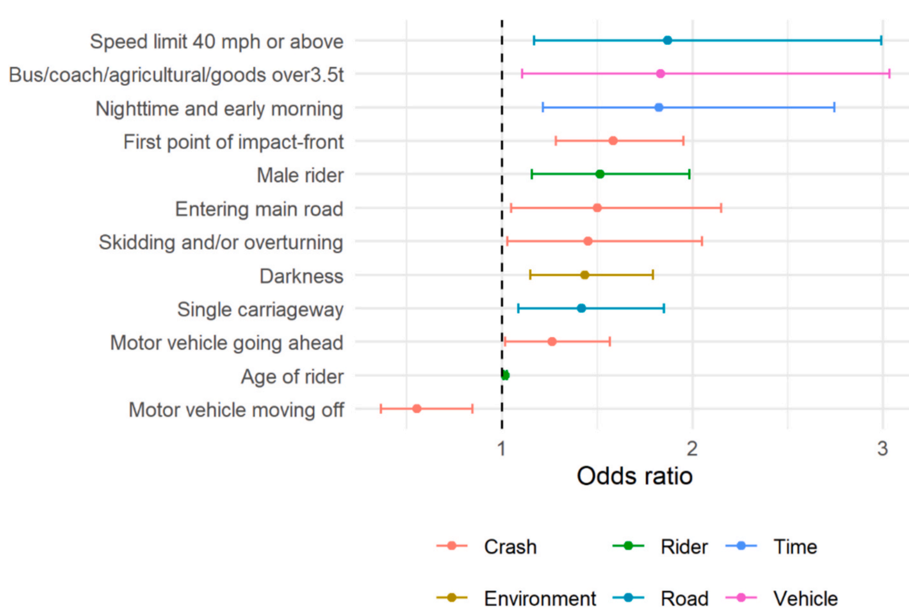

Fig. 3. Posterior median of odds ratios and their 95% credible intervals for spatial field model (Model 2).

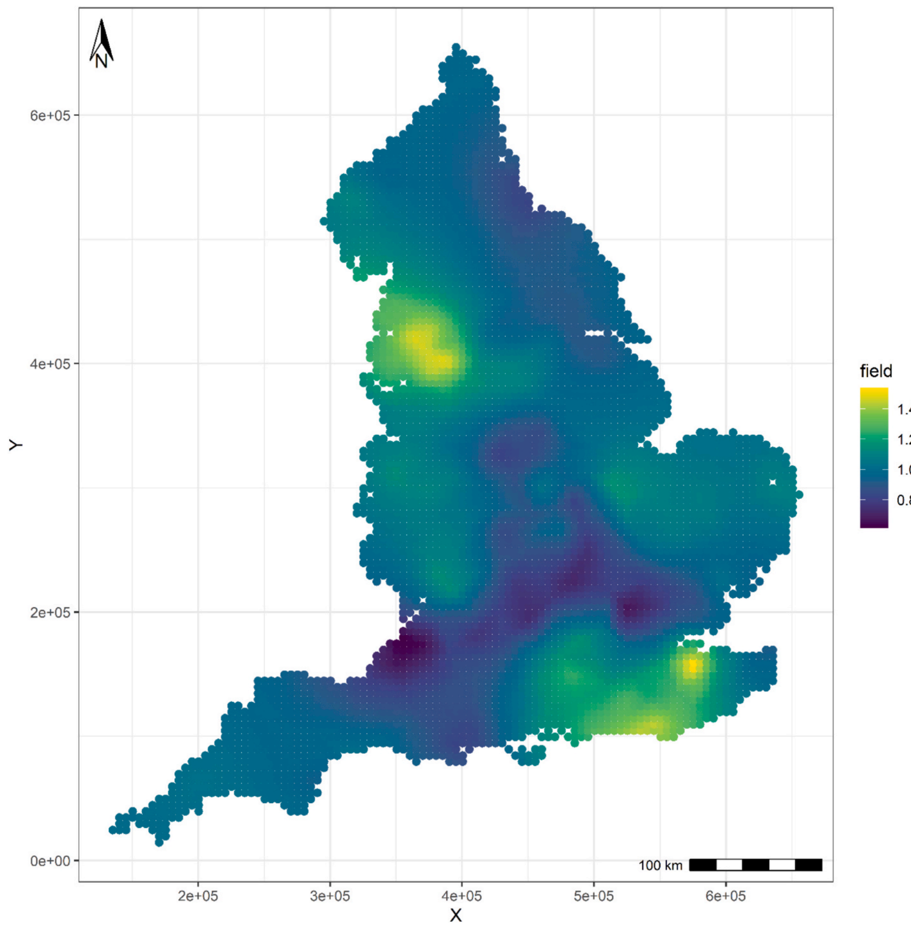

Fig. 4. Posterior median of the exponential of the spatial field (or spatially structured random intercept). See the electronic version for a colour view.

collisions given the greater mass and stopping distances of such vehicles. These transition areas, which form interfaces between dense urban centres and surrounding rural or commuter hinterlands, are often characterised by speed heterogeneity and unexpected interactions between road users, conditions that have been associated with higher injury severity for vulnerable road users. Notably, several of the high-risk areas identified in the South East are not part of the current DfT-approved e-scooter trial programme, suggesting that the observed elevated risk in these locations is unlikely to be driven by trial activity and may instead reflect broader traffic and network characteristics, as well as the presence of privately owned e-scooters operating outside formal trial schemes.

Broader urban context may also play a role; for example, previous work has reported a positive association between crime levels and e-scooter crash frequency (Heydari et al., 2022), indicating that crime-related activity may act as a proxy for urban intensity and social stressors relevant to micromobility risk. While these associations are ecological and cannot establish causality, they provide plausible context for the observed spatial heterogeneity and underscore the importance of region-specific safety strategies rather than uniform national approaches.

The posterior standard deviation of the spatial random field is displayed in Fig. 5. It represents the uncertainty of the spatial field. We observe an association between the spatial distribution of the standard deviation and the density of injuries in each location. Areas with a higher number of injuries, such as Greater London, tend to have lower standard deviations, indicating more reliable estimates. In contrast, relatively high values are observed in the far north and southwest corner of the map, suggesting greater uncertainty in these areas.

The significant variables in the spatial model with spatially varying coefficients are consistent with those in the spatial model, and their effects are similar. The impact of the age of the rider is found to vary across different locations. The variation might be related to the differences in unobserved or unmeasured contributory factors (e.g., road user behaviour, road infrastructure, etc.) across England. In Fig. 6, the left panel shows the median posterior of the relative odds ratio (relative to the average odds ratio across the region), highlighting that there are variables that are missing from the model in the northwest and southeast part of the country. These unknown factors have a bearing on the severity of injuries sustained by e-scooter riders. The panel on the right shows the median posterior effect of age of the driver on accidents across England. In other words, the right panel shows the spatial relative change of the slope, compared with the overall slope across England. There is relatively weak evidence of spatial variation, with the largest difference happening in the northwest part of England, where the effect of age of rider on the likelihood of severe injuries is 1% larger than the overall effect of age of rider across England.

6. Summary and conclusions

This research provides a detailed analysis of e-scooter rider injuries in England. We utilised a Bayesian spatial approach to identify and investigate the factors influencing the likelihood of severe injuries sustained by e-scooter riders during 2020–2023. Considering a wide variety of factors, we found that multiple variables are positively associated with an increased likelihood of severe injuries. A considerable proportion of crashes occurred during vehicle moving-off manoeuvres, identifying this manoeuvre as a critical point for targeted safety interventions. Given the role of blind-spot in these conflicts, particularly in urban settings with high e-scooter and vulnerable road user activity,

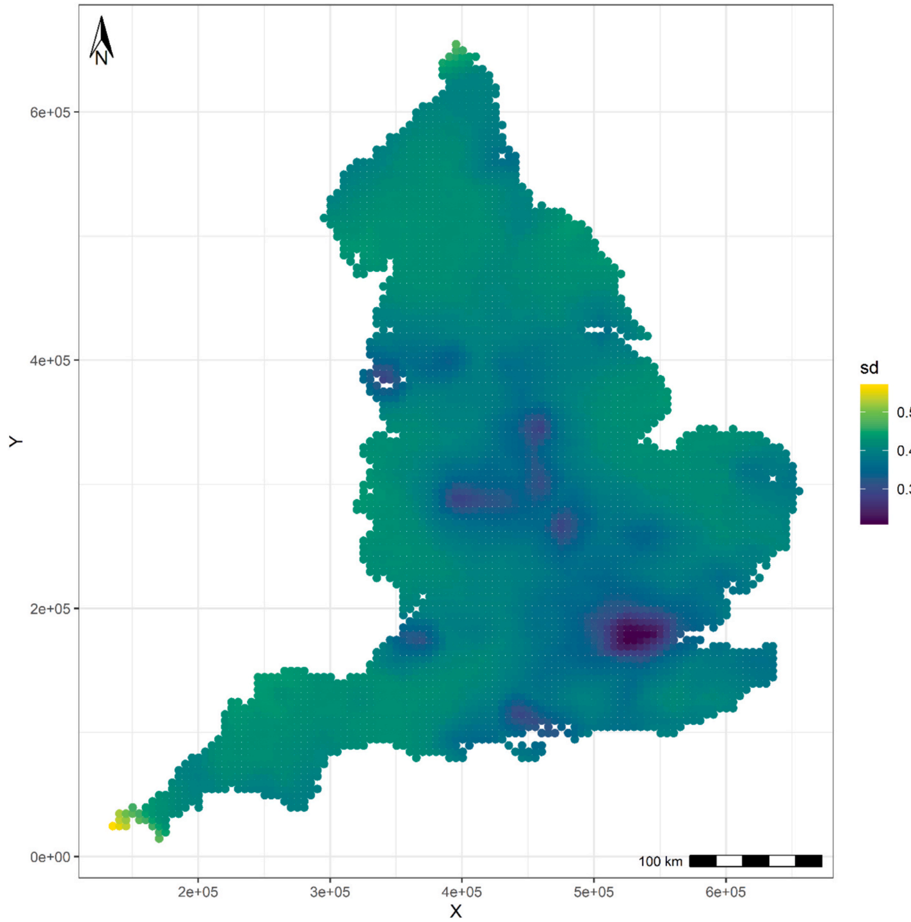

Fig. 5. Posterior standard deviation of the random intercepts. See the electronic version for a colour view.

the findings support wider—and potentially mandatory—deployment of Blind Spot Detection and related ADAS technologies within vehicle safety standards.

The modelling results indicate that accounting for spatial unobserved heterogeneity improved the model fit. The attempts to extend the spatial model suggest that investigating the variations in the impact of influencing factors across different crash locations has the potential for better addressing the unobserved heterogeneity issue.

Variables related to rider behaviour (e.g., riding under influence) and the type of e-scooters (shared or private) were not examined due to the lack of data. To better understand injury severity among e-scooter riders, stakeholders involved in collecting and reporting the data should consider including information on riding/driving under the influence, as well as the type of e-scooters (private vs. shared). Additionally, having a subscription with a shared e-scooter scheme may indicate more proficient riders, which could, in turn, influence safety outcomes. Capturing these key factors would provide valuable understanding of traffic safety in this context.

Moreover, as the regulations regarding e-scooters are refined, road users' familiarity with the presence of e-scooters on the road network increase, and the proficiency of e-scooter riders improves over time, the analysis results may also change. Therefore, it will be important to update the analysis as new data become available. While underreporting of e-scooter crashes remains a concern (Parliamentary Advisory Council for Transport Safety, 2024), caution should be exercised in interpreting the results. Nevertheless, the robustness of our findings is supported by the large sample of over 2,000 e-scooter crashes across the whole of England and a rigorous statistical analysis.

As discussed by Heydari et al. (2022), a wide range of stakeholders are involved in the design and implementation of safety interventions relevant to e-scooters. Educational initiatives and publicity campaigns typically fall under the remit of organisations such as e-scooter service operators, Local Authorities, the UK Department for Transport, and national safety bodies such as the Royal Society for the Prevention of Accidents. Enforcement activities involve police forces and the Driver and Vehicle Licensing Agency, with micromobility providers also playing a role in areas such as parking compliance, often in coordination with Local Authorities. Infrastructure-related measures, including traffic engineering interventions, are generally led by Local Authorities and the Department for Transport. These categories are not mutually exclusive, and responsibilities frequently overlap across agencies. Policy implications discussed in this paper provide valuable insights for stakeholders (e.g., local authorities, transportation agencies, and e-scooter providers) and can help improve road safety, particularly for e-scooter riders.

CRediT authorship contribution statement

Jingjing Zhao: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Garyfallos Konstantinoudis:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Shahram Heydari:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial

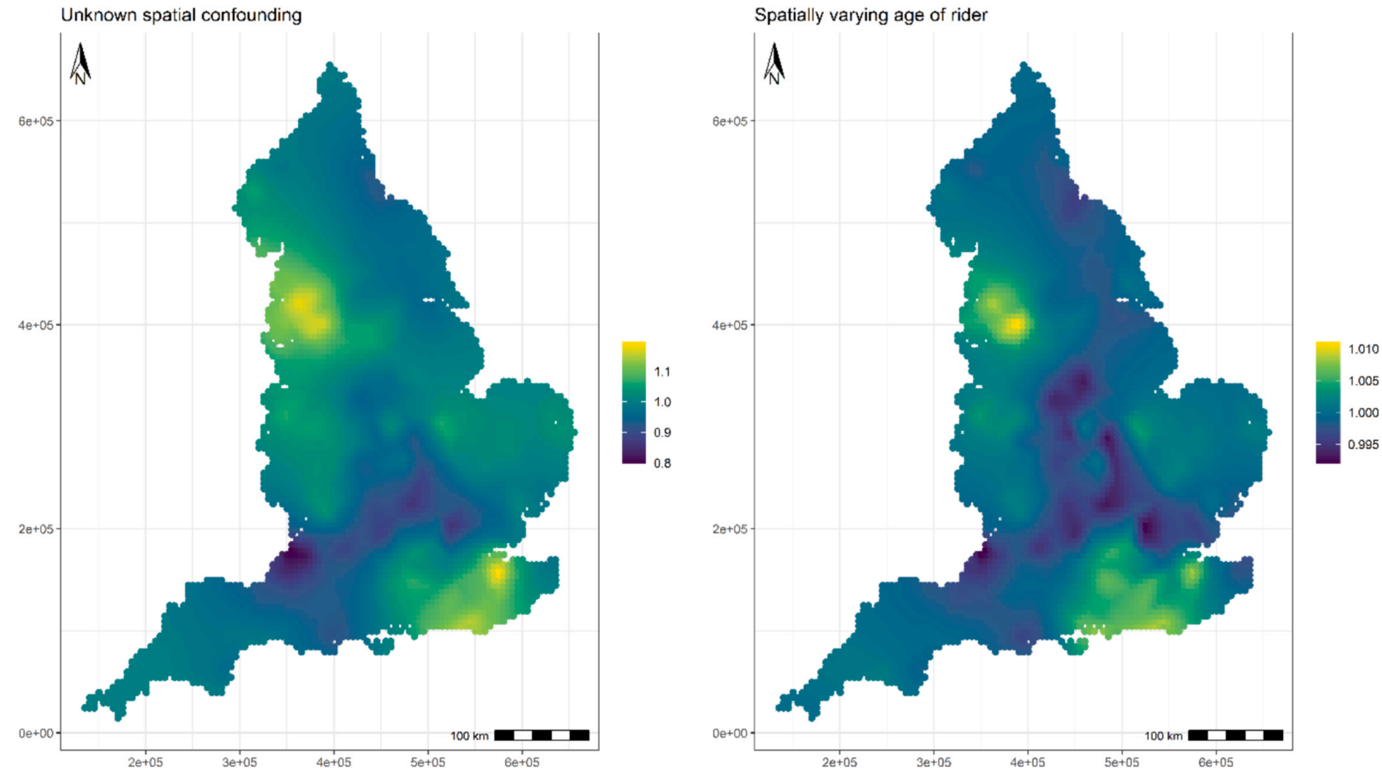

Fig. 6. Spatial distribution of posterior medians of the exponential of the random intercepts (left panel) and coefficients of the age of rider (right panel). See the electronic version for a colour view.

interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A

Table A1. Comparison of Bayesian model fit between models accounting for temporal effects and models in the paper

Model	Model Type	DIC	WAIC
Binary logit model	Non-spatial, non-temporal	2381.343	2381.677
Spatial field model	Spatial	2367.904	2368.299
RW1 model, RW1 on error term	Temporal	2381.969	2382.318
RW1 model, RW1 on coefficient of age of rider	Temporal	2382.673	2382.941
RW2 model, RW2 on error term	Temporal	2383.411	2383.819
RW2 model, RW2 on coefficient of age of rider	Temporal	2383.746	2384.184
Monthly random intercept model	Temporal	2381.868	2382.335
Monthly random parameters model with time varying coefficients of age of rider	Temporal	2383.097	2383.575
Spatial model with RW1 on error term	Spatial, temporal	2367.934	2368.711
Spatial model with RW1 on coefficient of age of rider	Spatial, temporal	2368.611	2369.402
Spatial model with RW2 on error term	Spatial, temporal	2369.356	2370.194
Spatial model with RW2 on coefficient of age of rider	Spatial, temporal	2369.939	2370.791
Spatial model with monthly random intercept	Spatial, temporal	2367.696	2368.509
Spatial model with monthly random parameters for age of rider	Spatial, temporal	2368.992	2369.807

Note: All temporal effects were specified on a monthly time scale (1–42) in this paper, RW1 = first-order random walk, RW2 = second-order random walk.

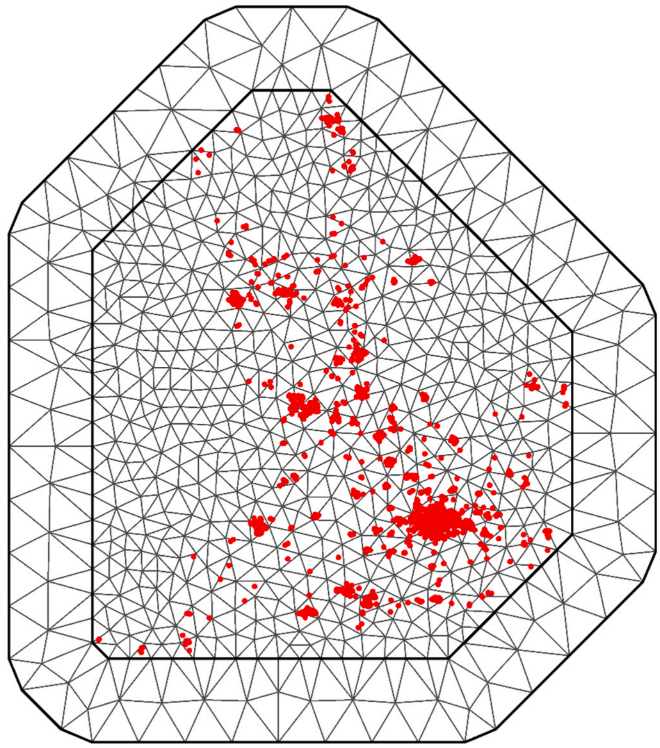

Fig. A1. Constrained refined Delaunay triangulation used for the spatial field model.

Data availability

Data is available from https://www.gov.uk/government/collections/road-accidents-and-safety-statistics

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