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No Street is an Island:
Street Network Morphologies and Traffic Safety

ABSTRACT

Network morphological analysis has emerged as a tool to quantify street network structures, providing a nuanced foundation for evaluating their impacts on traffic safety. Yet, there is a lack of disaggregate-level evidence on the spillover effects and spatial heterogeneity of these impacts. This research conducts a comprehensive, disaggregate-level, multi-scale examination on the overall impacts of street network morphologies on traffic safety. Our study focuses on the frequency of traffic injury collisions over a five-year period across more than 190,000 street links in Greater London. We characterise street-link morphologies at local (0 – 1 km), meso (0 – 3 km), and city (0 – 8 km) scales using a spatial design network analysis. For each spatial scale, we apply extended auto-negative binomial models to examine the overall impact of street-link morphological characteristics on the injury collision frequency, considering both the link being investigated and other surrounding links determined by the spatial scale.

We find significant spatial heterogeneity in the overall safety impacts of street-link morphologies. At the local scale, higher farness of a street link corresponds to an overall increase in injury collisions, whereas at the meso and city scales, it indicates an overall decrease. At the local and meso scales, higher betweenness of a street link is associated with an overall increase in injury collisions, but at the city scale, it correlates with an overall decrease. Independent of the spatial scale, a larger diversion ratio of a street link is linked to an overall decrease in injury collisions. These findings are similar to those on killed and seriously injured-only collisions. Our findings suggest that encouraging compact street network structures, which aligns well with New Urbanism and the Compact City policy, may *not* necessarily be effective for an overall reduction in injury collisions across an entire city.

KEYWORDS

Traffic safety; Collision; Street network; Morphology; Topology

Word count – main body of the manuscript: 8954

1. Introduction

Traffic collisions rank amongst the top ten killers worldwide. 1.3 million people are killed, and up to 50 million are injured as a result of traffic collisions each year (WHO 2018). Whereas 90% of road deaths transpire in low- and middle-income countries, high-income countries bear 60% of the economic losses stemming from traffic collisions (Chen et al. 2019). According to OECD's (2022) report, for example, there were 91,199 injuries and 1,516 fatalities resulting from traffic collisions in 2020 in the UK. Despite these figures being relatively low compared to other countries, the economic costs incurred were still substantial – a staggering 1.5% of the UK's GDP in 2020, equivalent to 40.6 billion US dollars. Creating a safer traffic environment has therefore become a global policy issue and was proposed in the form of two targets in the United Nations' Sustainable Development Goals (UN 2016).

Confronting the pressing challenge of traffic safety has profoundly shaped the evolution of planning philosophies. In particular, planning for safe street network structures has received substantial attention, since it potentially offers a long-term solution for traffic safety improvement over a wide population (Ewing and Dumbaugh 2009). In Europe, in response to the safety challenges arising from growing automobile use, the hierarchical street network gained popularity in the mid-20th century. This structure aims to separate through-traffic from local traffic to ensure safety in residential areas (MOT 1966). It organises streets into a hierarchy based on function, with local streets serving residential areas and higher-order roads connecting them to the broader urban network. The hierarchical street network thus features a tree-like structure, where arterial streets branch into collector streets, which further subdivide into local roads and cul-de-sacs. However, as the structure prioritises traffic efficiency in high-order streets and limits connectivity between residential areas, it has been criticised for promoting car dependency, which in turn, potentially increases traffic exposure and risks in the city (Urban Design Group 2018).

Amidst the critiques of the hierarchical street network, compact street network structures, which are integral to New Urbanism and the Compact City Policy, have been highlighted since the 1970s (Dieleman and Wegener 2004). Characterised by dense intersections and short block lengths, these structures aim to enhance network connectivity and prioritise active modes of transport. It is anticipated that by reducing individuals' exposure to motorised traffic, these compact networks can contribute to traffic safety improvements (Stevenson et al. 2016). Yet, evidence supporting this still remains inconclusive (Wang et al. 2013, Zhang et al. 2015), and a major critique is that the increased compactness can potentially lead to an uptick in risky conflicts between different road users (Marshall and Garrick 2011). Within this context, it is essential to generate robust empirical evidence concerning relationship between street network structures and traffic safety, thereby informing more effective planning of safer street networks.

Studies have been conducted to investigate the relationship between street network structures and traffic safety. Most of these studies are based on the visual classification of street networks (Gladhill and Monsere 2012, Marks 1957, Marshall et al. 2014). Through visual inspections, street networks in these studies were classified into non-overlapping patterns, such as the 'gridiron' and 'loops and lollipops' patterns. While such classifications seem to be straightforward, they are qualitative and subjective in nature; they tend to mask the disparities in network structures within the same pre-defined pattern and cannot effectively capture the complexity of street network structures. This challenges the generalisability and applicability of the findings.

Recognising the need for a deeper understanding of the intricacies of street network structures, several studies have sought to apply morphological analysis for network structure quantification (Guo et al. 2017, Wang et al. 2013, Wang et al. 2018, Cooper 2017). They used node-based morphological metrics to quantify how a specified street – represented as a node in a network graph – is topologically and geometrically connected with other streets via the network. Network morphological quantifications are not independent of visual inspection approaches; instead, they serve as an extension, which provides more detailed and objective characterisations of street network structures. In these studies, the morphological metrics were predominately aggregated at the area level to quantify street network structures in each unit of analysis, and on this basis, the relationship between street network morphologies and area-level collision frequency is examined.

Yet, existing studies on street network morphology-traffic safety relationships present three limitations. First, these studies segregate the entire street network into subnetworks by geographical units and compute morphological metrics based on these subnetworks. This overlooks the impact of cross-unit connections between streets at different spatial scales on traffic safety. Second, within a geographical unit, the collision frequency of each street and how each street is connected to other streets may differ. However, area-aggregated street morphologies and area-level collision frequency may obscure these differences. The applied aggregate-level analyses may thus be susceptible to ecological fallacy – the misassumption that a population-level average applies to each individual within the population (Portnov et al. 2007) – when investigating the safety impacts of street network morphologies. Third, these studies exclusively consider the direct impact of street network morphologies, focusing on their safety implications within each unit of analysis. However, the spillover impact, which refers to how the morphologies of a street network impact traffic safety in surrounding areas, have yet to be explored. This limits our understanding of street network structures' overall safety implications.

This research aims to conduct a disaggregate-level, multi-scale examination on the overall impacts of street network morphologies on traffic safety. We examine five-year injury collisions of more than 190,000 street links in Greater London, UK. A street link is defined as a segment of roadway between junctions or any change in the function of the roadway. We perform a spatial design network analysis (sDNA) to characterise the street network morphologies at the street-link level using three metrics (farness, betweenness, and diversion ratio) at three spatial scales (local, meso, and city scales). This allows for the quantification of street network structures at various spatial scales, and facilitates conducting disaggregate-level analyses to reduce ecological fallacy. We apply extended auto-negative binomial (EANB) models to examine the impact of street-link morphologies on the injury collision frequency of the link investigated and other surrounding links. This enables us to capture the direct, spillover, and overall impacts of street network structures on traffic safety. Our research findings and approaches help support the design of street network structures for improving traffic safety.

2. Traffic Safety Studies on Street Networks

2.1. Visual Inspection of Street Network Structures

Initial studies investigating the effects of street network structures on traffic safety date back to the 1950s. In his study, Marks (1957) utilised visual inspection to categorise the street network structures of subdivisions in Los Angeles, US, into two patterns: gridiron and limited access, he found that the frequency of total collisions was eight times higher in the gridded subdivisions. It is important to note that in our paper, the term 'total collision' encompasses both injury and non-injury collisions unless otherwise specified. In their seminal work, Southworth and Owens (1993) provided a more comprehensive view of such classifications. They categorised US community street networks into five patterns: gridiron, interrupted parallel, incremental infill, loops and lollipops, and hybrid patterns. Subsequently, similar classifications have been widely adopted in traffic safety studies through the visual inspection of street network structures. Results reported in the literature suggest that the 'gridiron' pattern may be associated with a greater frequency of total collisions than other patterns, particularly the 'loops and lollipops' pattern (Gladhill and Monsere 2012, Rifaat and Tay 2009, Sun and Lovegrove 2013). However, some studies indicate that gridiron patterns may mitigate the severity of collisions (Rifaat et al. 2012, 2011).

2.2. Morphological Quantifications of Street Network Structures

In recent decades, space syntax has emerged as a tool to quantify street network structures. Space syntax encompasses a range of techniques that leverage graph theory and morphological metrics to analyse spatial configurations of urban spaces. On this basis, traffic safety studies have sought to advance beyond the visual inspection approaches of network structures by investigating the extent to which road traffic safety is affected by street network morphologies. Amongst concepts developed in space syntax to characterise network morphologies, three – reachability, choice, and severance – have attracted notable attention in the existing traffic safety literature. Through the mediating roles of traffic exposure, traffic speed, and traffic conflicts, as we will discuss, street network morphologies characterised by these three concepts are potentially linked to traffic safety.

Reachability denotes the ease with which a given location can be reached from, or reach, other locations in a network. Greater reachability for a street link is indicative of a greater potential for frequent visitation and ease in accessing other links in the network. This concept is commonly quantified using the closeness metric (Zhang et al. 2015, Mi et al. 2020), which calculates the average (topological or geometrical) distance between a given street link and links along the network's shortest paths. Two other metrics, namely, the integration metric and clustering coefficient, have also been applied to measure reachability. The integration metric can be viewed as a metric similar to closeness standardised by the number of street links in the (sub)network where the focused link is located (see, Guo et al. (2017) for details); the clustering coefficient calculates the ratio of the number of connections a given street link has to the total number of street links in the network (Zhang et al. 2015).

The concept of reachability is intricately linked with traffic safety. First, street links with greater reachability at a large spatial scale (e.g., at a city scale) tend to attract more motorised traffic volume, which increases the exposure to traffic risks in such links (Jayasinghe et al. 2015). In contrast, street links with greater reachability at a small spatial scale (e.g., at a neighbourhood scale) may encourage the use of active transport to travel to and from those links (Kang 2018), thereby reducing traffic exposure. Second, an increase in the reachability of a street link increases the likelihood of conflicts amongst road users in their surrounding areas due to the rise in the number of junctions. This, in turn, can result in a higher incidence of collisions in these areas (Zhang et al. 2015). However, the need for frequent manoeuvres by drivers in these areas may result in lower driving speeds (Aarts and van Schagen 2006), thereby increasing reaction time in the event of a conflict, which helps reduce the occurrence and severity of collisions.

Choice refers to how likely a given location is to be traversed on the shortest paths between each location pair in a network (Hillier et al. 1986). Therefore, the concept of choice focuses on through-movement flow in a network (Sarkar et al. 2018); a higher level of choice indicates a more centralised role of the focused street link in connecting other links in a network. The concept is commonly quantified using betweenness (Sarkar et al. 2018, Wang et al. 2018, Cooper 2017), which calculates the number of shortest paths between all other pairs of locations in the network that pass through the street link investigated. The concept of choice has the potential to influence traffic safety through its intermediary effect on traffic exposure. For example, since individuals tend to seek short-cuts to save cognitive and physical efforts as well as reduce expenses in travelling, street links with higher betweenness may experience greater traffic volume (Cooper 2017, Serra and Hillier 2019), which in turn, contributes to greater exposure to the risk of collisions.

Severance characterises the extent to which between-location connections deviate from the shortest path. The concept can be quantified using the diversion ratio (Sarkar et al. 2018), which calculates the average ratio of the shortest path distance to the straight-line distance. There may be a complex relationship between street network severance and traffic safety. On the one hand, high levels of severance create barriers that limit travellers' ability to move directly between locations, requiring longer and more circuitous routes that lower travel efficiency. This, as a consequence, disrupts the concentration of traffic volume and human activities in streets with high-level severance and their surrounding areas (He et al. 2019), which may reduce collision occurrence. On the other hand, street links with a high level of severance tend to be associated with limited driving visibility around junctions in surrounding areas (Hills 1980), as a result of twisted connections between links in these areas. This potentially leads to the increased occurrence and severity of collisions (Das et al. 2018).

The metrics used to measure reachability, choice, and severance in the existing traffic safety literature are predominately node-based morphological metrics. Such metrics treat a given street link as a node in a network graph, and on this basis, assess how it is connected to other links in the network. In contrast, graph-based metrics focus on the structural properties of an entire network. In this regard, Wang et al. (2013) used the meshedness coefficient, which gauges the number of bounded faces in a network, to measure the overall reachability of street links in the network (Buhl et al. 2006).

2.3. Street Network Morphologies and Traffic Safety

Studies on the street network morphology-traffic safety relationships were predominately conducted ecologically, with an exclusive focus on the direct impact of street network morphologies within specific geographical areas. Zhang et al. (2015) investigated the correlation between street network structures and the census-tract level frequency of total non-motorist-involved collisions in California, US. They considered three morphological metrics: farness (the reciprocal of closeness), betweenness, and the clustering coefficient. To model census tract collisions, the authors used the average values of farness and the clustering coefficient of street links in each census tract. The betweenness metric was aggregated at the census tract level by calculating 'the average difference between the relative [betweenness] centrality of the most central street and that of all other streets' (p. 38). The results suggested that census tracts with street networks, which was associated with smaller farness (i.e., a higher level of reachability), higher betweenness (i.e., a higher level of choice), and a larger clustering coefficient (i.e., a higher level of reachability), tended to indicate fewer non-motorist-involved collisions. Guo et al. (2017) examined the relationship between street network reachability and the frequency of pedestrian-vehicle injury collisions at the TAZ level in Hong Kong, China. The street network reachability of each TAZ was measured using the average integration metric of the street links. The results indicated that TAZs with a higher level of street network reachability were associated with an increased frequency of pedestrian-vehicle injury collisions.

Three studies applied area-aggregate node-based metrics to distinguish area-level street network patterns. Wang et al. (2018) considered the average relative betweenness of street links in each TAZ, a metric similar to that used by Zhang et al. (2015). Using this metric, the authors categorised TAZ network patterns in Shanghai, China, into four types: grid, irregular grid, mixed, and tree-like. The classification approaches were similar to those of Li and Wang (2017) for characterising adjacent street network patterns of meso-level units (the combination of street links and intersections) in Shanghai. These two studies indicated that areas with grid-pattern street networks were associated with fewer total collisions. Wang et al. (2013) considered the average closeness, average relative betweenness, and meshedness coefficient at the TAZ level in Florida, US. They visually classified four types of street network patterns and verified their classifications using morphological metrics. Inconsistent with the findings of Wang et al. (2018) and Zhang et al. (2015), Wang et al. (2013) found that TAZs with a grid street network pattern exhibited the highest frequency of total collisions, followed by those with mixed, loops and lollipops, and sparse types street network patterns.

Two studies were conducted at the disaggregate street-link level. Cooper (2017) used the model constructed based on street-link betweenness to predict street-link traffic flows and traffic safety performance in Cardiff, UK. The study showed that betweenness highly correlated with both motorised ($R = 0.90$) and cycling ($R = 0.78$) annual average daily traffic. The model accurately predicted high-risk and low-risk links with success rates of 75% and 73%, respectively. In Sarkar et al.'s (2018) study, the authors examined the relation between street-link morphologies and the severity of injury collisions in Greater London, UK. The results suggested that an increase in the betweenness of a street link may elevate the severity of injury collisions in that link, whilst an increase in the street-link diversion ratio tended to reduce the severity. While the use of disaggregate-level analyses in these studies helps reduce ecological fallacy, the lack of analyses on collision frequency and network morphologies' spillover impacts impedes a comprehensive understanding of the safety implications of street network structures.

3. Research Design

3.1. Data

We focused on street-link level injury collisions in Greater London over the period 2015–2019. We applied three types of data sets: (1) injury collision, (2) street network, and (3) neighbourhood socioeconomic and land use data sets. We extracted 2015–2019 injury collision data from STATS19, an open-access official database of road traffic collisions that resulted in injuries in Greater Britain. The data from STATS19, such as the geographical coordinates and severity of collisions, were initially obtained by the police at the scene of an accident or when the public reports an accident to a police station (DfT 2013). Local authorities validate the data obtained by the police before they are passed on to the UK Department for Transport for the final data integration. Similar to other national police-recorded databases, the number of injury collisions in STATS19 may be under-reported (Ward et al. 2002, Iacono and Levinson 2016). However, this database remains the most reliable and complete source of traffic accident statistics for Greater Britain (DfT 2022a). From 2015 to 2019, 126,347 collisions occurred in Greater London (**Figure 1- A**), which accounts for more than one-fourth of the total number in England. Among the recorded collisions, 12% resulted in severe injuries and fatalities. Our research focuses on the frequency of both total injury and killed and seriously injured (KSI) collisions at the street-link level.

We acquired data on the 2017 street network in Greater London from Ordnance Survey (OS) OpenRoads, which contains a detailed street network of Great Britain. The dataset consisted of 198,880 street links within the Greater London boundary in 2017, only a proportion of private roads and short cul-de-sacs with limited motorised traffic were not included in OS OpenRoads (OS 2017). Given its comprehensiveness and high quality, this dataset has been widely used in the existing literature exploring street network structures in Great Britain (Venerandi et al. 2022, Beecham et al. 2022).

We also considered street links (n = 62,159) situated outside Greater London but within an 8 km network distance (**Figure 1-B**) – the largest radius threshold we considered for measuring the morphological metrics – from each focused street link, for two reasons. First, we measured the morphological characteristics of a street link based on its connections with other links within specified radii. Including the street links located outside Greater London allowed for precise measurements of street-link morphologies. Second, we investigated three types of impacts of street-link morphologies on the frequency of total injury and KSI collisions: direct, spillover, and overall impacts. The direct impact refers to the impact of a street link's morphologies on the collision frequency of the link investigated; the spillover impact refers to the impact of a street link's morphologies on all other links situated within a given network radius surrounding the link. The overall impact corresponds to the sum of direct and spillover impacts. As detailed in subsection 3.4.2, calculating the spillover and overall impacts required the inclusion of morphological characteristics of street links outside Greater London in our models.

We obtained the neighbourhood socioeconomic characteristics, such as population density, population age composition, and average household income, at the super output area level from the 2011 UK Census. Neighbourhood land use data from 2017 were obtained from Geomni UKLand. This data set comprises nine categories of land use, including both man-made and natural landscapes. We used the middle super output area (MSOA; n = 964)-level data for our main analysis and conducted sensitivity analyses using the lower super output area (LSOA; n = 2,252)-level data. The neighbourhood-level variables were used as covariates in estimating the safety impacts of street-link morphologies. The estimation, however, may be susceptible to the modifiable area unit problem (MAUP), which occurs when the aggregation of the covariates at different geographic scales affects the results. Using both MSOA- and LOSA-level data thus allowed us to examine the robustness of our results against the MAUP.

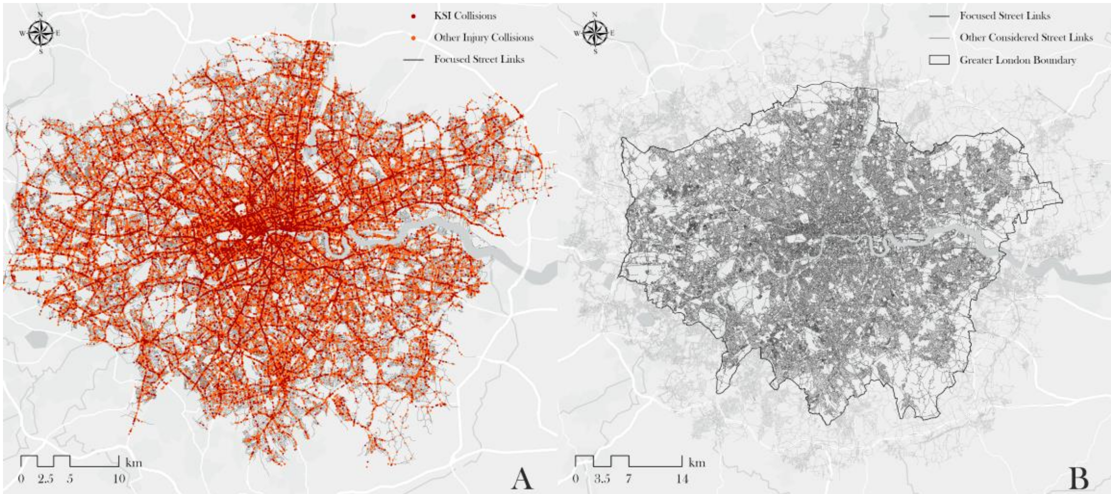

Figure 1 The distributions of (A) injury collisions and (B) considered street links in Greater London.

3.2. Street Network Morphologies

We performed an sDNA to characterise street network morphologies at the street-link level (Cooper and Chiaradia 2020). In sDNA, street links are the unit of analysis for the theoretical planar graph model of a city. Unlike conventional space syntax and network analyses, sDNA enables the joint characterisation of topological and geometrical features of a network at various spatial scales, rendering it more relevant for planning practices. Owing to these features, sDNA has been applied in various fields, such as public health, transport, and housing studies, to better understand the role of street networks in shaping society (Donald et al. 2014, Grimaldi et al. 2019). In light of the multiplicity of street network morphologies, we considered three concepts in sDNA, namely, unreachability, choice, and severance, to determine the applied morphological metrics, following our literature review.

First, we measured the opposite of the concept of reachability, i.e., unreachability, using the farness metric. This metric is defined as the average shortest distance between a street link and other links within a defined network radius. We did not use a measure of the reachability concept, namely the closeness metric. The reason is that the closeness metric is calculated using the reciprocal of the farness metric, and thus it has an exponential distribution, which is difficult to handle statistically (Cooper et al. 2021). A higher farness value indicates that the street link investigated contains farther and fewer connections with other links (Zhang et al. 2015). Second, we quantified the concept of choice using the betweenness metric, which is determined by the weighted number of times a street link lies on the shortest path between other pairs of links within a defined network radius. A higher betweenness value suggests a more centralised role for a street link in connecting other links. Third, to measure the concept of severance, we used the diversion ratio, which is defined as the mean ratio of the shortest length to the crow flight distance between a street link and other links within the radius. A larger diversion ratio suggests that a street link contains more twisted connections with other links. We refer our readers to **Appendix A** for detailed mathematical calculations of the morphological metrics.

We considered different spatial scales for calculating street morphological metrics. We applied three radii based on the Euclidean network distance: 0–1, 0–3, and 0–8 km. Following studies on street morphologies (Sarkar et al. (2018); Xiao et al. (2017)), we determined the size of these radius parameters based on the trip distance made by different modes of transport. According to the 2017 National Travel Survey for Great Britain, 1, 3, and 8 km correspond to the median distances of trips traversed by walking, cycling/bus, and car in Greater London, respectively (DfT 2022b). Therefore, the radii of 0–1, 0–3, and 0–8 km reflect the distance ranges of individuals' daily travels at spatial scales of '*local*,' '*meso*,' and '*city*', respectively.

We considered street links located within 8 km of Greater London when computing the morphological metrics to avoid spillover bias. In our main analyses, the shortest path for measuring the morphological metrics was determined based on the Euclidean distance (also known as the metric distance) along the network. The measured farness, betweenness and diversion ratio of street links are displayed in **Figure 2**, **Figure 3**, and **Figure 4**, respectively. We also used morphological metrics calculated based on angular distance for the sensitivity analysis, since some studies have suggested that these metrics may explain traffic volume better than metrics calculated based on Euclidean distance (Serra and Hillier 2019, Ciscal-Terry et al. 2016, Jayasinghe 2017).

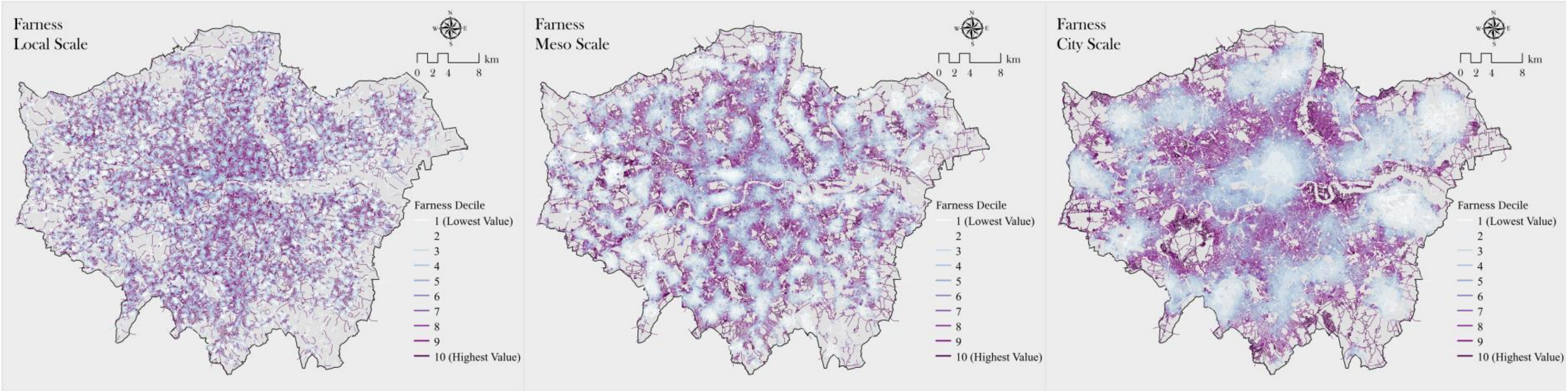

Figure 2 Farness of street networks at the link level.

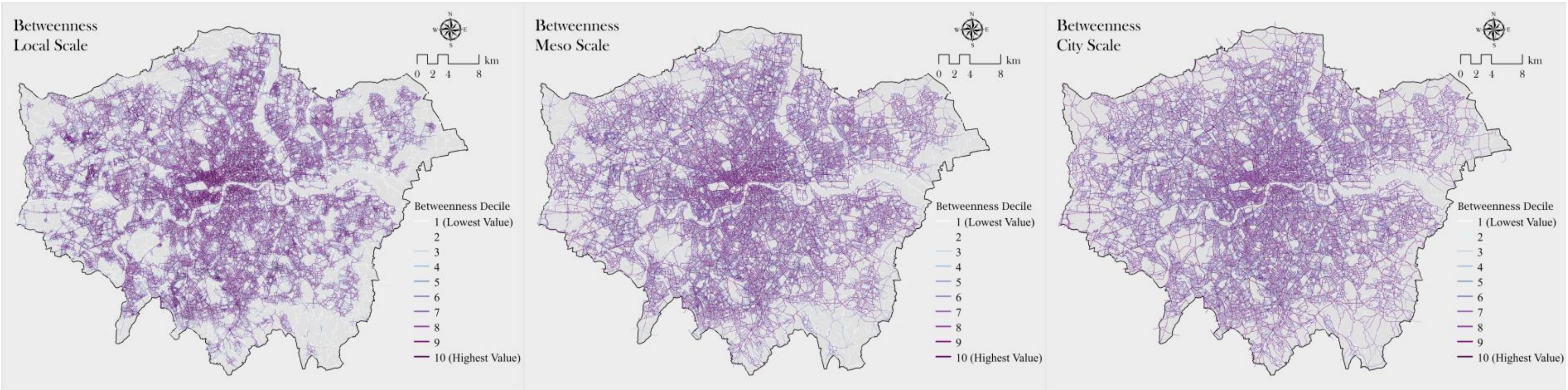

Figure 3 Betweenness of street networks at the link level.

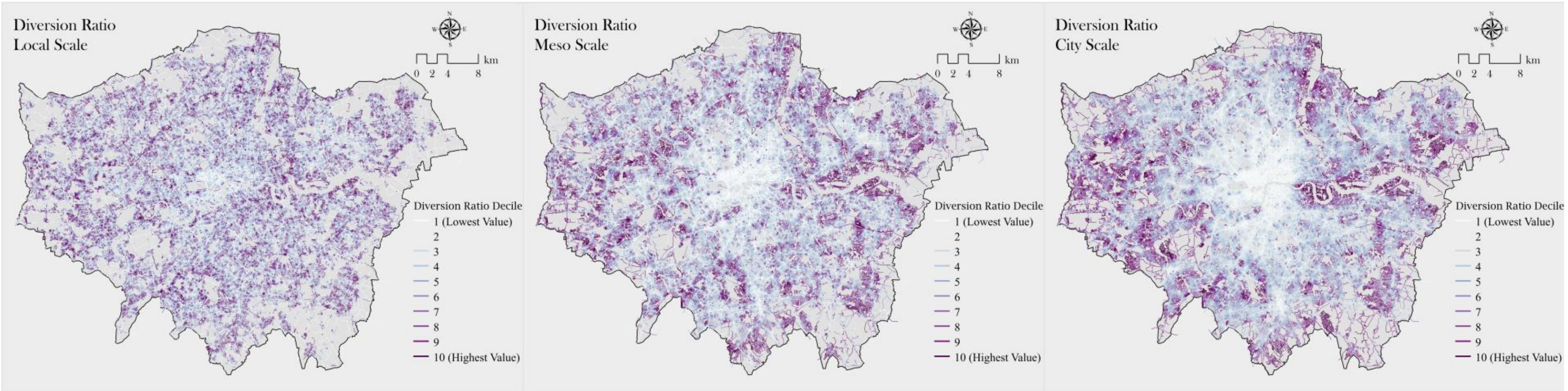

Figure 4 The diversion ratio of street networks at the link level

3.3. Covariates

We used two street-link-level covariates, namely, the length and function of street links. The function of street links was categorised into four types: (1) motorway/A road[1]; (2) B road[2]; (3) minor road; and (4) local roads (OS 2017), which respectively constituted 12%, 3%, 10%, and 75% of street links in Greater London.

The neighbourhood-level covariates were considered as follows (see **Table 1** for a summary of the statistics). These covariates have been revealed as determinants of traffic safety and of the generation/attraction of traffic volume.

- Socioeconomics: Population density, average household income, and percentage of households with children, work-age population, and white population (e.g., Kocatepe et al. (2017); Lee et al. (2014); Lee and Abdel-Aty (2018); Lee et al. (2018); Quddus (2008); Wang et al. (2016); Albalate and Fageda (2021)).
- Land use: The total land area and the proportion of business/commercial, industrial, and recreational land uses (e.g., Pulugurtha et al. (2013); Xie et al. (2019a); Chen and Lym (2021)).

We did not include traffic volume in our model estimation due to the influential role street network morphologies play in shaping trip generation and attraction (Kang 2017, Serra and Hillier 2019). Considering the potential mediating role of traffic volume in the relationship between street network morphologies and traffic safety, controlling for this variable may lead to an underestimation of street network morphologies' safety impacts. Instead, our analyses included a rich set of covariates that were closely related to trip generation and attraction. This approach allows for a more accurate assessment of the overall contribution of street network morphologies to traffic safety, thereby reducing the confounding effects of traffic volume.

In Greater London, 13% of street links cross through more than one MSOA. We merged all the MSOAs crossed by a street and recalculated the neighbourhood-level covariates for the street link investigated. The size of the merged MSOAs may not significantly affect our results, as we controlled the total land area of the merged areas and used variables that measured densities and percentages. The same argument held when LOSA-level covariates were used.

[1] A roads refer to major roads designed to facilitate large-scale transport within or between areas (OS 2017).

[2] B roads refer to roads designed to connect different areas and provide traffic distribution between higher- and lower-level roads in the network (OS 2017).

Table 1 Neighbourhood-level covariates.

Neighbourhood-level covariates	MSOA				LSOA			
	Min	Max	Mean	SD	Min	Max	Mean	SD
Land area (ha)	29.38	3520.10	231.55	278.81	1.00	3160.00	66.41	152.22
Population density (n/ha)	2.86	248.67	69.39	43.24	1.16	1089.00	74.94	52.06
Working-age population (%)	57.46	87.27	68.31	57.46	48.64	94.68	68.39	6.34
White population (%)	6.14	96.19	62.52	6.14	3.54	98.16	62.62	20.00
Households with children (%)	4.57	32.16	18.78	4.57	2.34	39.88	18.75	5.95
Average household income (n)	22367	141363	46319	15410	20110	140661	46649	15850
Business/commercial area (%)	0.00	88.97	10.19	0.00	0.00	41.38	5.58	0.02
Industrial area (%)	0.00	41.81	3.51	0.00	0.00	80.00	3.12	8.10
Recreational area (%)	0.00	51.42	10.01	8.82	0.00	69.74	8.51	12.07

3.4. Model

We proposed an EANB model to examine the direct, spillover, and overall impact of street-link morphologies on the frequency of total injury and KSI collisions at different spatial scales. The EANB model is an extension of the auto-negative binomial (ANB) model. This section elaborates on the rationale and the specifications of the ANB and EANB model.

3.4.1. ANB Model

An ANB model, developed by Besag (1974), can be established as follows (**Eqs (1)-(3)**):

$$y_{Si} = Negbin\left(u_{Si}, r\right) \tag{1}$$

$$\begin{gathered} \log\left(\boldsymbol{u}_S\right) = \rho \boldsymbol{W} \boldsymbol{y}_A + \boldsymbol{X}_S \boldsymbol{\beta} + \boldsymbol{C}\boldsymbol{\kappa} + \boldsymbol{\varepsilon}; \\ \boldsymbol{y}_A = \left[\boldsymbol{y}_S{}^{\mathbf{T}}, \boldsymbol{y}_O{}^{\mathbf{T}}\right]^{\mathbf{T}} \end{gathered} . \tag{2}$$

$$\begin{gathered} \boldsymbol{W} = \left[w_{ij}\right]; \\ w_{ij} = 1/d_{ij}, \text{ if } i \neq j \text{ and } d_{ij} \leq d_0; \\ w_{ij} = 0, \text{ otherwise} \end{gathered} \tag{3}$$

Here, $\boldsymbol{y}_S$ is a 198,880×1 vector of the collision frequency of street links in our study area. y_{Si} is assumed to exhibit a negative binomial distribution with an expected value u_{Si} and a dispersion parameter r. $\boldsymbol{X}_S$ denotes a 198,880×3 matrix of morphological metrics at a given scale of each street link in our study area; $\boldsymbol{\beta}$ is a vector of corresponding coefficients. $\boldsymbol{C}$ is a 198,880×14 matrix of one and covariates, and $\boldsymbol{\kappa}$ is a vector of the coefficients. $\boldsymbol{\varepsilon}$ is a vector of the residuals.

The ANB model allows accounting for the potential global network autocorrelation via the introduction of a spatially lagged term $\rho \boldsymbol{W} \boldsymbol{y}_A$. Here, ρ is the global autocorrelation parameter. $\boldsymbol{y}_A$ refers to a 261,039×1 vector of collision frequency of all considered street links that involve not only the links in Greater London (the 198,880×1 vector $\boldsymbol{y}_S$) but also those located outside Greater London but within an 8 km network distance from the links investigated (the 62,159×1 vector $\boldsymbol{y}_O$). $\boldsymbol{W}$ is a 198,880×261,039 network distance-based weight matrix with the diagonal elements set as zero. The non-diagonal element of $\boldsymbol{W}$ (w_{ij}; $i \neq j$) was determined by the inverse Euclidean distance ($1/d_{ij}$) through the shortest path between street links i and j, if d_{ij} is smaller than a cut-off value d_0. We set up d_0 in accordance with the spatial scale considered in the model (i.e., 1 km, 3 km, or 8 km). Otherwise, w_{ij} was set as zero. At each spatial scale, we evaluated the network global autocorrelation of street-link total injury and KSI collision frequency, using Moran's I index with the introduced weight matrix. Independent of types of collisions and spatial scales, we found positive network global autocorrelations (i.e., Moran's I > 0) of street-link collision frequency at the level of $p < 0.001$. This highlights the importance of accounting for the network global autocorrelation to reduce estimation bias.

There was high-level multicollinearity between $\boldsymbol{W}\boldsymbol{y}_A$ and the explanatory variables. Therefore, we first regressed $\boldsymbol{X}_S$ and $\boldsymbol{C}$ on $\boldsymbol{W}\boldsymbol{y}_A$ (**Eq. (4)**) and extracted the residual vector $\boldsymbol{\nu}$, based on the method of García et al. (2020). We then replaced $\boldsymbol{W}\boldsymbol{y}_A$ in **Eq. (2)** with $\boldsymbol{\nu}$ (**Eq. (5)**). Therefore, $\boldsymbol{\nu}$ is orthogonal to $\boldsymbol{X}_S$ and $\boldsymbol{C}$.

$$\boldsymbol{W}\boldsymbol{y}_A = \boldsymbol{X}_S\boldsymbol{\lambda} + \boldsymbol{C}\boldsymbol{\zeta} + \boldsymbol{\nu} \tag{4}$$

$$\log\left(\boldsymbol{u}_S\right) = \rho^*\boldsymbol{\nu} + \boldsymbol{X}_S\boldsymbol{\beta}^* + \boldsymbol{C}\boldsymbol{\kappa}^* + \boldsymbol{\varepsilon}^* \tag{5}$$

Glaser (2017) reviewed existing approaches for modelling spatial autocorrelation for count data. She classified these approaches into three categories: (1) autocorrelation models; (2) Bayesian autoregressive error models; and (3) models with lagged covariates. The ANB model falls into the first category and offers two advantages to our study. First, the ANB model, compared with Bayesian autoregressive error models that model global autocorrelation in the error terms, is more suitable when the dimension of the weight matrix $\boldsymbol{W}$ is large (also known as the 'Big m' problem, see Banerjee et al. (2003)). Few traffic safety studies explicitly considered the network global autocorrelation. The exceptional studies have predominately applied Bayesian autoregressive error models (Zeng and Huang 2014, Li and Wang 2017). However, these studies focused only on small-scale networks with a limited number of street links (n < 420). A key methodological barrier is that Bayesian inference may fail to converge owing to the large dimension and dense nature of matrix $\boldsymbol{W}$ (Musenge et al. 2013). By contrast, the ANB model allows us to partition $\boldsymbol{W}$ and then use linear algebra methods to obtain $\boldsymbol{W}\boldsymbol{y}_A$ prior to estimation, instead of using $\boldsymbol{W}$ directly. Second, introducing a spatially autocorrelated term of the dependent variable allows the ANB model to capture the autocorrelation effect of unobserved variables. By contrast, models with lagged covariates consider only the observed variables, which renders such models more susceptible to endogeneity.

3.4.2. EANB Model

Despite its computational flexibility, the ANB model centres on only the direct impact of each street-link morphological metric on collision frequency. The direct impact refers to the impact of a street link's morphologies on the collision frequency of the link investigated. However, the indirect impact, also known as the spillover impact, is overlooked in the ANB model. The spillover impact refers to the impact of a street link's morphologies on all other links situated within a network radius surrounding the link. To address both direct and spillover impacts, we proposed the EANB model by introducing a spatially lagged term of a morphological metric as follows:

$$\log\left(\boldsymbol{u}_s\right) = \alpha\boldsymbol{\sigma}_k + \varphi_k\boldsymbol{x}_{Sk} + \delta_k\boldsymbol{W}\boldsymbol{x}_{Ak} + \boldsymbol{X}_{S(-k)}\xi_k + \boldsymbol{C}\boldsymbol{\omega}_k + \tau_k; \quad \boldsymbol{x}_{Ak} = \left[\boldsymbol{x}_{Sk}{}^{\mathbf{T}}, \boldsymbol{x}_{Ok}{}^{\mathbf{T}}\right]^{\mathbf{T}} \tag{6}$$

Here, for a given spatial scale, $\boldsymbol{W}\boldsymbol{x}_{Ak}$ is the spatially lagged term of the kth morphological metric. $\boldsymbol{x}_{Ak}$ is a 261,039×1 vector of morphological metric k for street links that involve not only the links in our study area (the 198,880×3 matrix $\boldsymbol{x}_{Sk}$) but also those located outside Greater London but within an 8 km network distance from the links investigated (the 62,159×1 matrix $\boldsymbol{x}_{Ok}$). $\boldsymbol{X}_{S(-k)}$ is the matrix obtained after eliminating column k (i.e., $\boldsymbol{x}_{Sk}$) from matrix $\boldsymbol{X}_S$. $\boldsymbol{\sigma}_k$ is the residuals for the model where we regressed all explanatory variables in **Eq. (6)** on $\boldsymbol{W}\boldsymbol{y}_A$, following **Eqs.(4)**-**(5)**. α, φ_k, δ_k, ξ_k, and $\boldsymbol{\omega}_k$ are parameters (coefficients) to be estimated; $\boldsymbol{\tau}_k$ denotes residuals. In each EANB model, our parameters of focus were φ_k and δ_k, which were used in calculating the direct and spillover impact of morphological metric k on collision frequency; all variables but such a metric and its spatially lagged term were treated as controlled variables. Therefore, we estimated 18 EANB models, as we considered three morphological metrics, three spatial scales, and two types of collisions.

The average direct and spillover impact of morphological metric k of street link i (x_{Ski}) on collision frequency at a given spatial scale are given by **Eq. (7)** and **Eq. (8)**, respectively.

$$\frac{1}{n}\sum_{i=1}^{n}\frac{\partial\left(\mathrm{E}\left(y_{Si}\right)\right)}{\partial\left(x_{Sik}\right)} = \frac{1}{n}\sum_{i=1}^{n}\varphi_k\exp\left(\alpha\sigma_{ki} + \varphi_k x_{Ski} + \delta_k\left(\boldsymbol{W}\right)_{i*}\boldsymbol{x}_{Ak} + \left(\boldsymbol{X}_{S(-k)}\right)_{i*}\xi_k + \left(\boldsymbol{C}\right)_{i*}\boldsymbol{\omega}_k\right) \tag{7}$$

$$\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{\partial\left(\mathrm{E}\left(y_{Sj}\right)\right)}{\partial\left(x_{Sik}\right)} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n}\delta_k w_{ji}\exp\left(\alpha\sigma_{kj} + \varphi_k x_{Skj} + \delta_k\left(\boldsymbol{W}\right)_{j*}\boldsymbol{x}_{Ak} + \left(\boldsymbol{X}_{S(-k)}\right)_{j*}\xi_k + \left(\boldsymbol{C}\right)_{j*}\boldsymbol{\omega}_k\right) \tag{8}$$

In these two equations, n=198,880 is the number of street links investigated. $(\boldsymbol{W})_{n*}$, $(\boldsymbol{C})_{n*}$, and $(\boldsymbol{X}_{S(-k)})_{*n}$ respectively denote the nth row of matrix $\boldsymbol{W}$, $\boldsymbol{C}$, and $\boldsymbol{X}_{S(-k)}$. w_{ij} is the element of the ith row and jth column of the weight matrix $\boldsymbol{W}$. The direction of the direct impact of the morphological metric k is therefore determined by the direction of the coefficient φ_k associated with $\boldsymbol{x}_{Sk}$, whereas the direction of the spillover impact is determined by the direction of the coefficient δ_k associated with the spatially lagged term $\boldsymbol{W}\boldsymbol{x}_{Ak}$. On this basis, we calculated the overall impact of a street-link morphological metric on the overall frequency of collisions by summing the direct and spillover impact of the corresponding metric.

We tested the potential multicollinearity of EANB models through the variance inflation factor (VIF; best if < 5), and found no high-level multicollinearity, which could have comprised our statistical inferences. We adopted the White HC1 robust standard error to manage potential heteroscedasticities (MacKinnon and White 1985). Two sensitivity analyses were conducted.

First, we applied angular distance-based metrics to street network morphologies. Second, we used LOSA-level contextual covariates to examine the robustness of our estimations against the potential modifiable area unit problem.

4. Results

We first examined the ANB model for total injury collision frequency (**Table 2**). For model fitness, McFadden's R-squared values ranged from 0.368 to 0.384, while a McFadden's R-squared value exceeding 0.2 indicates good model fitness (McFadden 1979).

For the estimation of the input variables, the global network autocorrelation parameter exceeded zero (range: 0.08 to 0.14) at a significance level of 0.0001, regardless of the models. This indicates that the effect of street-link features on total injury collision frequency may be positively autocorrelated along the network.

The EANB models revealed significant correlations between street-link morphologies and total injury collision frequency (**Table 2**). Street-link farness at the local and meso scales presented a positive correlation with the total injury collision frequency of the link investigated. In contrast, no significant correlation was found between street-link farness at the city scale and the total injury collision frequency of the link investigated. This means that the direct impact of street-link farness on the total injury collision frequency of the link itself presents spatial heterogeneity (**Table 3** and **Figure 5)**. The coefficients for the spatially lagged terms of street-link farness were negative, suggesting that the increased farness of a street link at a given scale may have a spillover impact that contributes to fewer total injury collisions in other surrounding links determined by the same spatial scale (the same network radius) (**Table 3** and **Figure 5**). At each considered spatial scale, street-link betweenness was positively associated with the total injury collision frequency of the link investigated, whereas the coefficients for spatially lagged terms of betweenness were negative. These results indicate that, at a given spatial scale, an increase in a street link's betweenness may have a direct impact leading to more total injury collisions in the link investigated, but a spillover impact contributing to fewer total injury collisions in other surrounding links determined by the same spatial scale. Independent of the spatial scale, the street-link diversion ratio was negatively correlated with the total injury collision frequency of the link investigated, and the coefficients for its spatially lagged terms were negative. This indicates that, regardless of the spatial scale at which the diversion ratio was measured, its direct and spillover impacts may decrease the total injury collision frequency of the street link investigated and other surrounding links determined by the same spatial scale, respectively (**Table 3** and **Figure 5**).

We computed the overall impact of street-link morphologies measured at a given scale on total injury collision frequency, taking into account both the link being investigated and its surrounding links determined by the same spatial scale (**Table 3** and **Figure 5**). At the local scale, higher farness of a street link corresponded to an overall increase in the frequency of total injury collisions, whereas at the meso and city scales, it was associated with an overall decrease. At the local and meso scales, higher betweenness of a street link was associated with an overall increase in the frequency of total injury collisions, but at the city scale, it correlated with an overall decrease. Independent of the spatial scale, a larger diversion ratio of a street link was linked to an overall decrease in the frequency of total injury collisions.

Next, we investigated the EANB models for the KSI collision frequency (**Table 4**). The McFadden R-squared value (range: 0.424 to 0.431) suggested good model fitness. The global network autocorrelation parameter was significantly greater than zero (range: 0.57 to 0.97). The estimation results of the morphological metrics and their spatially lagged terms showed a pattern similar to those of the total injury collision frequency model. However, inconsistent with the findings reported previously, at the meso scale, higher street-link farness was associated with an overall increase in KSI collision frequency (**Table 5** and **Figure 6**).

For our sensitivity analyses using the angular distance-based morphological metrics, each metric's direction of direct and spillover impacts remained unchanged, and the model fitness remained highly similar (the McFadden R-squared ranged from 0.342 to 0.377 for the model of total injury collision frequency, and ranged from 0.449 to 0.455 for the model of KSI collision frequency). However, we found that the overall impact of meso-scale farness was no longer negative (**Appendix B**). When we used LSOA-level neighbourhood covariates, our estimation results remained fairly consistent with the direction and significance of the street-link morphological metrics and their spatially lagged terms (results are not shown for brevity). This suggests that our findings are relatively robust against the MAUP.

Table 2 Results of the EANB models on total injury collision frequency.

Focused Variables	Spatial Scale		
	Local (1 km)	Meso (3 km)	City (8 km)
	Coef. (Robust SE)	Coef. (Robust SE.)	Coef. (Robust SE)
Global Network Autocorrelation	1.376E-1 (3.661E-3) ***	1.097E-1 (2.996E-3) ***	7.812E-2 (2.983E-3) ***
Farness	4.634E-3 (1.332E-4) ***	2.103E-4 (5.132E-5) ***	-2.645E-5 (2.945E-5)
Spatially Lagged Farness	-6.515E-4 (3.491E-5) ***	-1.052E-4 (5.594E-6) ***	-2.710E-5 (1.107E-6) ***
McFadden R-squared	0.384	0.379	0.368
Global Network Autocorrelation	1.121E-1 (2.779E-3) ***	1.018E-1 (2.559E-3) ***	1.059E-1 (2.887E-3) ***
Betweenness	6.344E-5 (1.764E-6) ***	2.016E-6 (3.487E-8) ***	7.301E-8 (1.242E-9) ***
Spatially Lagged Betweenness	-6.616E-5 (2.778E-6) ***	-5.830E-7 (4.607E-8) ***	-3.159E-8 (1.570E-9) ***
McFadden R-squared	0.383	0.379	0.367
Global Network Autocorrelation	1.330E-1 (3.416E-3) ***	1.049E-1 (2.982E-3) ***	6.950E-2 (3.061E-3) ***
Diversion Ratio	-1.326E+0 (4.124E-2) ***	-2.965E+0 (6.193E-2) ***	-1.062E+1 (1.383E-1) ***
Spatially Lagged Diversion Ratio	-3.098E-1 (1.599E-2) ***	-1.692E-1 (8.789E-3) ***	-1.094E-1 (4.946E-3) ***
McFadden R-squared	0.384	0.379	0.368

Note. * p<0.01, ** p<0.001, *** p<0.0001.

Table 3 Impacts of street-link morphologies on total injury collision frequency.

	Direct Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	2.944E-3 (2.943E-3, 2.944E-3)	1.336E-4 (1.336E-4, 1.336E-4)	-1.680E-5 (-1.680E-5, -1.680E-5)
Betweenness	4.030E-5 (4.030E-5, 4.030E-5)	1.281E-6 (1.281E-6, 1.281E-6)	4.638E-8 (4.638E-8, 4.638E-8)
Diversion Ratio	-8.426E-1 (-8.150E-1, -8.701E-1)	-1.883E+0 (-1.632E+0, -2.135E+0)	-6.746E+0 (-4.997E+0, -8.495E+0)
	Spillover Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	-3.101E-4 (-3.101E-4, -3.101E-4)	-1.395E-4 (-1.395E-4, -1.395E-4)	-9.361E-5 (-9.361E-5, -9.361E-5)
Betweenness	-3.163E-5 (-3.163E-5, -3.163E-5)	-7.762E-7 (-7.762E-7, -7.762E-7)	-1.093E-7 (-1.093E-7, -1.093E-7)
Diversion Ratio	-1.477E-1 (-1.464E-1, -1.489E-1)	-2.244E-1 (-2.235E-1, -2.253E-1)	-3.787E-1 (-3.781E-1, -3.792E-1)
	Overall Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	2.634E-3 (2.633E-3, 2.634E-3)	-5.898E-6 (-5.896E-6, -5.899E-6)	-1.104E-4 (-1.104E-4, -1.104E-4)
Betweenness	8.677E-6 (8.677E-6, 8.677E-6)	5.046E-7 (5.046E-7, 5.046E-7)	-6.295E-8 (-6.295E-8, -6.295E-8)
Diversion Ratio	-9.902E-1 (-9.575E-1, -1.023E+0)	-2.108E+0 (-1.850E+0, -2.366E+0)	-7.125E+0 (-5.361E+0, -8.889E+0)

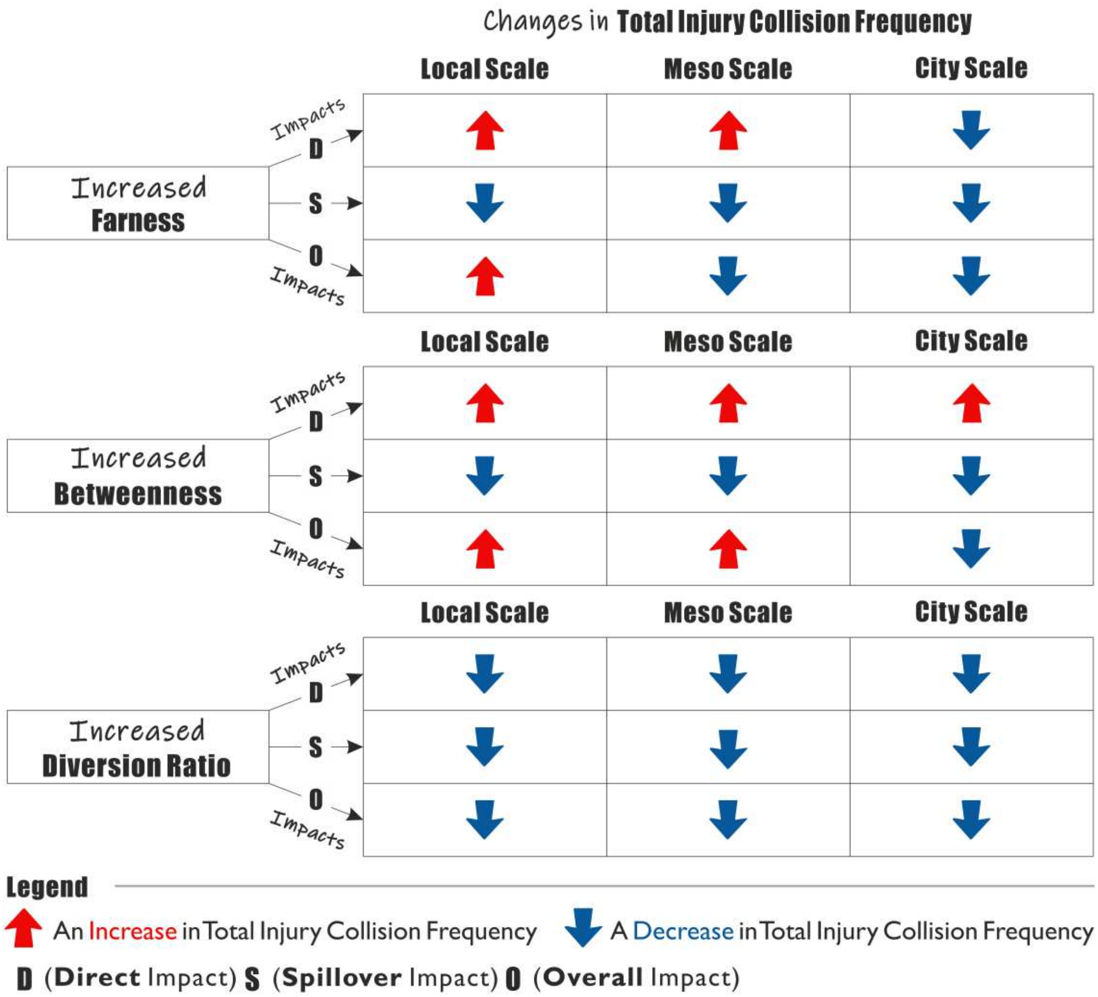

Figure 5 Summary of street-link morphologies' impacts on total injury collision frequency.

Table 4 Results of the EANB models on KSI collision frequency.

Focused Variables	Spatial Scale		
	Local (1 km)	Meso (3 km)	City (8 km)
	Coef. (Robust SE)	Coef. (Robust SE.)	Coef. (Robust SE)
Global Network Autocorrelation	9.665E-1 (4.085E-2) ***	8.567E-1 (3.767E-2) ***	6.081E-1 (3.679E-2) ***
Farness	4.672E-3 (2.160E-4) ***	2.771E-4 (9.729E-5) **	4.191E-5 (5.802E-5)
Spatially Lagged Farness	-7.687E-4 (5.698E-5) ***	-1.102E-4 (1.063E-5) ***	-2.191E-5 (2.168E-6) ***
McFadden R-squared	0.431	0.429	0.424
Global Network Autocorrelation	7.921E-1 (3.403E-2) ***	8.287E-1 (3.605E-2) ***	7.486E-1 (3.771E-2) ***
Betweenness	6.683E-5 (2.950E-6) ***	2.027E-6 (6.493E-8) ***	7.371E-8 (2.368E-9) ***
Spatially Lagged Betweenness	-6.820E-5 (4.676E-6) ***	-3.778E-7 (8.504E-8) ***	-1.894E-8 (3.032E-9) ***
McFadden R-squared	0.431	0.429	0.424
Global Network Autocorrelation	9.433E-1 (3.936E-2) ***	8.405E-1 (3.779E-2) ***	5.679E-1 (3.729E-2) ***
Diversion Ratio	-1.262E+0 (6.918E-2) ***	-2.717E+0 (1.154E-1) ***	-9.557E+0 (2.668E-1) ***
Spatially Lagged Diversion Ratio	-3.786E-1 (2.700E-2) ***	-1.903E-1 (1.680E-2) ***	-9.036E-2 (9.674E-3) ***
McFadden R-squared	0.431	0.429	0.424

Note. * p<0.01, ** p<0.001, *** p<0.0001.

Table 5 Impacts of street-link morphologies on KSI frequency.

	Direct Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	3.682E-4 (3.682E-4, 3.682E-4)	2.184E-5 (2.184E-5, 2.184E-5)	3.303E-6 (3.303E-6, 3.303E-6)
Betweenness	5.267E-6 (5.267E-6, 5.267E-6)	1.598E-7 (1.598E-7, 1.598E-7)	5.810E-9 (5.810E-9, 5.810E-9)
Diversion Ratio	-9.945E-2 (-9.909E-2, -9.982E-2)	-2.141E-1 (-2.107E-1, -2.176E-1)	-7.532E-1 (-7.289E-1, -7.775E-1)
	Spillover Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	-4.561E-5 (-4.561E-5, -4.561E-5)	-1.832E-5 (-1.832E-5, -1.832E-5)	-9.513E-6 (-9.513E-6, -9.513E-6)
Betweenness	-4.080E-6 (-4.080E-6, -4.080E-6)	-6.321E-8 (-6.321E-8, -6.321E-8)	-3.247E-9 (-8.247E-9, -8.247E-9)
Diversion Ratio	-2.247E-2 (-2.244E-2, -2.249E-2)	-3.163E-2 (-3.161E-2, -3.165E-2)	-3.929E-2 (-3.928E-2, -3.929E-2)
	Overall Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	3.226E-4 (3.226E-4, 3.226E-4)	3.523E-6 (3.523E-6, 3.523E-6)	-6.210E-6 (-6.210E-6, -6.210E-6)
Betweenness	1.187E-6 (1.187E-6, 1.187E-6)	9.656E-8 (9.656E-8, 9.656E-8)	-2.437E-9 (-2.437E-9, -2.437E-9)
Diversion Ratio	-1.219E-1 (-1.215E-1, -1.223E-1)	-2.458E-1 (-2.422E-1, -2.493E-1)	-7.925E-1 (-7.680E-1, -8.170E-1)

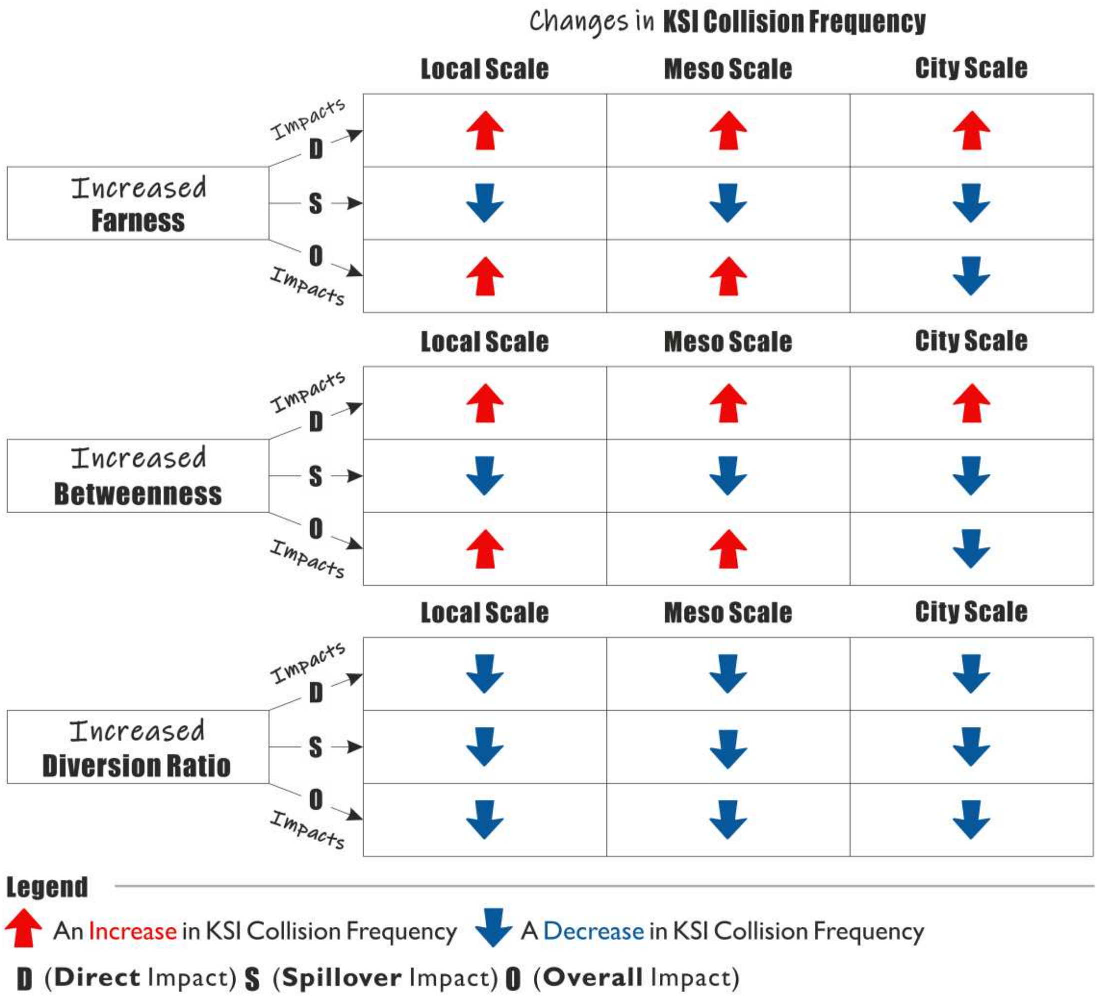

Figure 6 Summary of street-link morphologies' impacts on KSI collision frequency.

5. Discussions

5.1. Discussions on Principal Findings

This research investigated the extent to which street network morphologies at the link level may affect traffic safety. Our findings reveal that at a specified spatial scale, street-link morphologies, including street-link farness, betweenness, and the diversion ratio, are significantly correlated with the overall frequency of total injury and KSI collisions, considering both the link being investigated and its surrounding links determined by the same spatial scale.

First, for total injury and KSI collisions, higher farness of a street link at the local scale corresponded to an overall increase in collision frequency at the same scale. However, higher farness at the city scale had the opposite impact, resulting in an overall decrease in collisions at that scale. At the meso scale, the overall safety impact of street-link farness depended on the severity of collisions. Higher farness of a street link at the meso scale was associated with an overall decrease in the frequency of total injury collisions at that scale, but an overall increase in the frequency of KSI collisions. Existing studies conducted at the area level and an exclusive spatial scale presented mixed findings regarding the relationship between street network farness/closeness and traffic safety (Zhang et al. 2015, Guo et al. 2017). Our findings provide a broader picture of this issue by uncovering the spatial heterogeneity of such a relationship. Our findings show that this identified spatial heterogeneity can be largely ascribed to the disparity in the direct impact of street-link farness across spatial scales. The reason is that, independent of spatial scale, an increase in the street-link farness had a spillover impact that contributed to fewer collisions in the street links surrounding the investigated link. By contrast, increased street-link farness at the local and meso scales might have a direct impact leading to more collisions of the link investigated, whereas there was no significant relation between city-scale street-link farness and the collision frequency of the link investigated.

The positive spillover impact of higher street-link farness on traffic safety may be because there tend to be fewer junctions in areas surrounding street links with higher farness, which reduces the potential for conflicts between road users in these areas (Zhang et al. 2015). The negative direct impact of higher street-link farness on traffic safety may be attributable to the fact that the intensity to which street-link farness moderates motorised and non-motorised traffic volumes varies by the spatial scale. The farness metric reflects the difficulty with which a street can be reached via a network. The local and meso scales (0 – 3 km) correspond to the median distance of trips made on foot and by cycling. Therefore, higher farness of a given street at these two scales may increase physical barriers to walking and cycling to this street (Kang 2017, Kang 2018, Helbich 2017). As a consequence, there may be more motorised traffic conditions in street links with higher farness, thereby resulting in the less satisfactory traffic safety performance of such links. Compared with these two scales, motorised modes may account for larger shares of trips at the city scale (i.e., 0 – 8 km). While as destinations, street links with higher city-scale farness obstruct the use of non-motorised modes in short-distance trips, such links may also be less attractive to motorised long-distance trips due to the increased travelling time and costs (Jayasinghe et al. (2015), which contributes to less hazardous traffic conditions in these street links.

Our results suggest that, overall, smaller farness of a street link indicates a safer traffic environment at the local scale, but a riskier traffic environment at the city scale. Therefore, changing farness of a given street link or the average farness of links in a network, which can be achieved by modifying street network compactness, may be useful for improving traffic safety. For example, planners can decrease street-link farness by de-densifying street networks near a target street link, which would increase the distance between the link and the other links to which it connects. In recent decades, promoting street network compactness, which aligns well with the New Urbanism and the Compact City policy, has been seen as a proactive solution to improving traffic safety. However, we argue that such a street network structure may *not* necessarily be effective for an overall reduction in injury collisions across an entire city. While, according to our findings, a more compact street network structure may indeed help mitigate traffic risk at a small local spatial scale, it contributes to increased traffic risks overall when considering large spatial scales. Our argument is partially aligned with that of Ewing and Hamidi (2015), which suggests that increasing urban compactness may lead to more total injury collisions at the county level. Nevertheless, considering the benefits of compact street networks for public health and the quality of life (Xie et al. 2019b, Remali et al. 2015), it may be too hasty to conclude that street networks need to be largely de-densified. Instead, we highlight that a comprehensive assessment should be conducted ex-ante for planning projects involving the change in street farness.

Second, higher betweenness of a street link at the local and meso scales was associated with an overall increase in total injury/KSI collision frequency at the corresponding scale. In contrast, higher betweenness of a street link at the city scale correlated with an overall decrease in total injury collision/KSI frequency at the same scale. Inconsistent with the existing literature (Wang et al. 2018, Guo et al. 2017, Mukherjee and Jain 2021, Zhang et al. 2015), our findings reveal a spatial heterogeneity in the overall impact of street-link betweenness on traffic safety. By definition, the betweenness metric quantifies the extent to which a street is passed through via the shortest paths between street pairs in a network. Hence, street-link betweenness is positively associated with traffic volumes in the street investigated (Jayasinghe et al. 2015, Serra and Hillier 2019), as travelling via links with higher betweenness provides travellers with more possibilities to take shortcuts, thereby increasing the expected utility for the route choice (Henry et al. 2019, Sevtsuk 2021). Street links with higher betweenness may thus result in greater exposure to motorised traffic and the risk of collisions; this explains our results regarding the negative direct impact of increased street-link betweenness on traffic safety. Along the same line, holding total traffic volumes in a network constant, street links with lower betweenness may experience fewer traffic volumes, which helps explain the observed positive spillover impact of increased street-link betweenness on traffic safety.

However, it is unclear why there are differences in the direction of overall impacts of street-link betweenness across spatial scales. We speculate that this may be attributable to the non-linear relationship between traffic volumes and collision frequency (Qin et al. 2006). Qin et al. (2006) reveal that as traffic volumes increase, the number of collisions increases sharply but then slows down to reach a stable level. Street links with high betweenness at the city scale are typically urban arterials with heavy traffic (**Figure 3**). Therefore, compared to the other scales, an increase in street-link betweenness at the city scale may contribute to a smaller direct impact, due to the saturation effect of traffic volumes on collision frequency. This may explain the underlying reason for the observed overall impact of higher street-link betweenness at the city scale, which contributes to an overall decrease in the frequency of injury collisions at the same scale.

Our findings suggest that *ceteris paribus*, an increase in the average betweenness of street links may benefit overall traffic safety at the city scale. To achieve this, it is important to focus on the entire (sub)network, as an increase in the betweenness of one street link may come at the expense of a decrease for others in the (sub)network. Within this context, a city-scale street network structure with more links parallel to arterials with high-level betweenness helps achieve an increase in the average betweenness of street links in the network, and may thus be desirable for its traffic safety performance. This can be achieved through reconfiguring existing street links or building new ones. For new construction projects, questions for the planners are how to ensure the safety benefits derived from increased betweenness are not cancelled out by the decrease in average city-scale farness of street links, which had a negative overall safety impact at the city scale.

Third, at each considered spatial scale, an increased diversion ratio of a street link presented direct and spillover impacts contributing to fewer total injury/KSI collisions of the investigated street link and other surrounding links determined by the spatial scale. As a result, an increase in the diversion ratio of a street link at a given spatial scale was associated with a reduced overall number of injury/KSI collisions at the same spatial scale. This suggests that a street link with more twisted connections in the network may contribute to a safer traffic environment. One explanation for our finding is that a larger diversion ratio reflects a higher level to which street links deviate from the most direct path, thereby decreasing the travelling efficiency. *Ceteris paribus*, street links with a larger diversion ratio tend to be less attractive to travellers as a destination, thus resulting in less traffic in such links. The twisted local network surrounding a street link with a large diversion ratio may also increase cognitive difficulties in route navigation (Donald et al. 2014). Consequently, this disrupts the concentration of economic activities and traffic volume, as well as high-speed driving in these areas (Kang 2017, He et al. 2019), rendering these areas less exposed to a risky traffic environment.

Fourth, Euclidean distance-based and angular distance-based morphological metrics exhibited similar results and performance in explaining the frequency of total injury and KSI collisions. While some studies indicate that angular distance-based metrics outperform Euclidean distance-based ones in explaining traffic volume (Serra and Hillier 2019, Jayasinghe 2017), our findings suggest that this may not apply to their traffic safety implications. A plausible reason, as we previously outlined, is that traffic exposure is not the only influential factor linking street network morphologies and traffic safety; traffic speed and traffic conflicts also play crucial mediating roles in this relationship. Given the dominance of physical distance-based approaches in current planning practices, it is notable that Euclidean distance-based morphological metrics, with their robust explanatory power on injury collision frequency, could continue to play a pivotal role in street network planning for traffic safety improvement.

5.2. Discussions on Methodologies

Apart from our empirical findings, we believe that the EANB model employed is of wide applicability in understanding the relationship between street network patterns and traffic safety. In general, applying large-scale street networks is desirable for investigating such a topic, as it increases data representativeness, thus ensuring the transferability of the results. Nevertheless, these networks pose significant challenges in modelling global network autocorrelations and spillover impacts using classical Bayesian autoregressive approaches owing to the 'Big m' problem. As demonstrated in our study, for a network comprising over 190,000 street links, the EANB model can still estimate the autocorrelation effect and spillover impacts of street-link features in an acceptable time frame, whilst simultaneously yielding a desirable model fitness.

We also notice that the integrated nested Laplace approximation approach (Illian et al. 2012) allows the researchers to use the popular Bayesian analysis framework in the estimation of network autocorrelations and spillover impacts for a relatively large network (see, Gómez-Rubio et al. (2021)). While this approach has garnered increasing attention in recent years for big-data modelling, it focuses on models that can be expressed as latent Gaussian Markov random fields. It is thus limited by the use of a dense network weight matrix (Gómez-Rubio 2020). By contrast, EANB models provide a more flexible manner for constructing network weights, for example, using inverse distance squared decay functions. Against this backdrop, the EANB model allows location-specific distance decay functions identified using real-world travel data (Chen and Fractals, 2015) to be applied in future studies to establish network weights.

5.3. Strength and Limitations

We used high-quality data, applied innovative statistical approaches, and conducted sensitivity analyses to examine the relationship between street network morphology and traffic safety. To the best of our knowledge, our research is the first to conduct a comprehensive disaggregate-level assessment on the direct, spillover, and overall impacts of street network morphologies on injury collision frequency across spatial scales. The empirical findings, as we have discussed, offer in-depth insights into the relationship between street network structures and traffic safety, especially in high-income European cities characterised by dense street networks and large motorised traffic volumes. While the generalisability of our findings to other contexts is uncertain, the proposed methods and analytical framework allow for more robust and comprehensive analyses for such a relationship.

Nevertheless, our research presents several limitations. First, similar to most existing studies, we did not consider graph-based morphological metrics, such as the robustness of street networks, which may affect traffic safety-related elements (e.g., traffic volume, see Scott et al. (2006)). Future studies could benefit from applying multilevel analyses to combine both node- and graph-based metrics in their models. Nevertheless, the modifiable area unit problem must be prioritised owing to the involvement of graph-based metrics. Second, we partially explained our findings based on the moderating role of street network morphologies in shaping traffic volumes. In the absence of high-resolution traffic volume data at the street-link level, we cannot confirm the hypothesised mechanisms. As such, a multistage estimation strategy (see, e.g., An et al. (2021)) could be applied in future studies to compare the change in the effect of street network characteristics on traffic safety in models with and without traffic volume variables; the results could help understand the interrelationship between street network morphologies, traffic volume, and traffic safety. Thirdly, our EANB models lacked control for temporal covariates, such as weather conditions, potentially introducing endogeneity concerns, notwithstanding the satisfactory goodness of fit in our estimations. To tackle this concern, future studies should highlight the development of statistical models capable of managing both network and temporal autocorrelation within a big data context.

6. Concluding Remarks

We conducted a comprehensive, disaggregate-level, multi-scale examination on the impacts of street network morphologies on traffic safety. We focused on five-year traffic injury collision frequencies of more than 190,000 street links in Greater London. We characterised street-link morphologies at local (0 – 1 km), meso (0 – 3 km), and city (0 – 8 km) scales using a spatial design network analysis. For each spatial scale, we applied extended auto-negative binomial models to examine the overall impact of street-link morphological characteristics on the injury collision frequency, taking into account both the link being investigated and other surrounding links determined by the spatial scale. We found significant spatial heterogeneity in the overall safety impacts of street-link morphologies. At the local scale, higher farness of a street link corresponded to an overall increase in total injury collisions, whereas at the meso and city scales, it indicated an overall decrease. At the local and meso scales, higher betweenness of a street link was associated with an overall increase in total injury collisions, but at the city scale, it correlated with an overall decrease. Independent of the spatial scale, a larger diversion ratio of a street link was linked to an overall decrease in total injury collisions. These findings were similar to those on KSI-only collisions. We suggest that encouraging compact street network structures, which aligns well with New Urbanism and the Compact City policy, may *not* necessarily be effective for an overall reduction in injury collisions across an entire city.

Appendix A

We used three metrics, namely, farness, betweenness, and the diversion ratio to measure street network morphologies at the street-link level.

Farness for a given street link x is defined as:

$$\text{Farness}(x) = \left(\sum\nolimits_{y \in R_x} d(x,y)\right) \Big/ n \tag{1}$$

where R_x denotes the set of street links in the network radius from link x, and y represents a street link within R_x. n denotes the total number of street links within the network radius from link x. $d(x,y)$ represents the shortest distance along the network between links x and y.

Betweenness for a given street link x is defined as:

$$\text{Betweenness}(x) = \sum\nolimits_{y \in N} \sum\nolimits_{z \in R_x} OD(y,z,x) \tag{2}$$

where N is the set of street links in the global network system (see, Figure 1-B), and y denotes a street link within N. R_y denotes the set of street links in the network radius from link y, and z represents a street link within R_y. In sDNA, the function $OD()$ is set to 1 if x is on the first shortest path between y and z, set to 1/2 if $x = y \neq z$ or $x = z \neq y$, set to 1/3 if $x = y = z$, and set to 0 otherwise. According to sDNA's user manual (Cooper 2021), the contributions of 1/2 to $OD(y,z,x)$ reflect the end links of shortest paths which are traversed half as often on average, as journeys begin and end in the link centre on average. The contributions of 1/3 represent origin self-betweenness.

The diversion ratio for a given street link x is defined as:

$$\text{Div}(x) = \left(\sum\nolimits_{y \in R_x} d(x,y) / CFD(x,y)\right) \Big/ n \tag{3}$$

where R_x denotes the set of street links in the network radius from link x, and y represents a street link within R_x. n denotes the total number of street links within the network radius from link x. $d(x,y)$ represents the shortest distance along the network between links x and y, whereas $CFD(x,y)$ represents the crow flight distance (straight-line distance) between links x and y.

Appendix B

Impacts of angular-distance based morphological metrics on total injury collision frequency.

	Direct Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	1.341E-3 (1.341E-3, 1.341E-3)	7.739E-4 (7.739E-4, 7.738E-4)	7.570E-4 (7.570E-4, 7.570E-4)
Betweenness	3.787E-5 (3.154E-5, 3.154E-5)	6.410E-7 (6.410E-7, 6.410E-7)	4.516E-8 (4.516E-8, 4.516E-8)
Diversion Ratio	-1.010E+0 (-9.662E-1, -1.054E+0)	-1.717E+0 (-1.533E+0, -1.901E+0)	-4.652E+0 (-3.864E+0, -5.439E+0)
	Spillover Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	-1.573E-4 (-1.573E-4, -1.573E-4)	-2.726E-5 (-2.726E-5, -2.726E-5)	-1.370E-1 (-1.369E-1, -1.371E-1)
Betweenness	-3.154E-5 (-3.787E-5, -3.787E-5)	-1.690E-7 (-1.690E-7, -1.690E-7)	-4.522E-2 (-4.521E-2, -4.523E-2)
Diversion Ratio	-1.591E-5 (-1.591E-5, -1.591E-5)	-7.551E-8 (-7.551E-8, -7.551E-8)	-5.014E-2 (-5.013E-2, -5.015E-2)
	Overall Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	1.184E-3 (1.184E-3, 1.184E-3)	7.466E-4 (7.467E-4, 7.466E-4)	-1.362E-1 (-1.361E-1, -1.363E-1)
Betweenness	6.327E-6 (-6.327E-6, -6.327E-6)	4.719E-7 (4.719E-7, 4.719E-7)	-4.522E-2 (-4.521E-2, -4.523E-2)
Diversion Ratio	-1.010E+0 (-9.662E-1, -1.054E+0)	-1.717E+0 (-1.533E+0, -1.901E+0)	-4.702E+0 (-3.914E+0, -5.490E+0)

Impacts of angular-distance based morphological metrics on KSI collision frequency.

	Direct Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	2.825E-4 (2.825E-4, 2.825E-4)	1.006E-4 (1.006E-4, 1.006E-4)	8.645E-5 (8.645E-5, 8.645E-5)
Betweenness	6.136E-6 (4.194E-6, 4.194E-6)	8.279E-8 (8.279E-8, 8.279E-8)	5.793E-9 (5.793E-9, 5.793E-9)
Diversion Ratio	-1.175E-1 (-1.169E-1, -1.180E-1)	-1.994E-1 (-1.968E-1, -2.020E-1)	-5.339E-1 (-5.226E-1, -5.453E-1)
	Spillover Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	-4.305E-5 (-4.305E-5, -4.305E-5)	-3.585E-6 (-3.585E-6, -3.585E-6)	-2.086E-2 (-2.086E-2, -2.086E-2)
Betweenness	4.184E-6 (-6.136E-6, -6.136E-6)	-7.322E-9 (-7.322E-9, -7.322E-9)	-9.169E-3 (-9.169E-3, -9.170E-3)
Diversion Ratio	-9.610E-7 (-9.610E-7, -9.610E-7)	-5.082E-10 (-5.082E-10, -5.082E-10)	-1.566E-3 (-1.566E-3, -1.566E-3)
	Overall Impact		
	Local (95% CI)	Meso (95% CI)	City (95% CI)
Farness	2.394E-4 (2.395E-4, 2.394E-4)	9.700E-5 (9.700E-5, 9.700E-5)	-2.077E-2 (-2.077E-2, -2.078E-2)
Betweenness	1.942E-6 (-1.942E-6, -1.942E-6)	7.547E-8 (7.547E-8, 7.547E-8)	-9.169E-3 (-9.169E-3, -9.170E-3)
Diversion Ratio	-1.175E-1 (-1.169E-1, -1.180E-1)	-1.994E-1 (-1.968E-1, -2.020E-1)	-5.355E-1 (-5.241E-1, -5.469E-1)

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