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1 **No Street is an Island:**
2 **Street Network Morphologies and Traffic Safety**

3
4 **ABSTRACT**

5
6 Network morphological analysis has emerged as a tool to quantify street network structures,
7 providing a nuanced foundation for evaluating their impacts on traffic safety. Yet, there is a
8 lack of disaggregate-level evidence on the spillover effects and spatial heterogeneity of these
9 impacts. This research conducts a comprehensive, disaggregate-level, multi-scale examination
10 on the overall impacts of street network morphologies on traffic safety. Our study focuses on
11 the frequency of traffic injury collisions over a five-year period across more than 190,000 street
12 links in Greater London. We characterise street-link morphologies at local (0 – 1 km), meso (0
13 – 3 km), and city (0 – 8 km) scales using a spatial design network analysis. For each spatial
14 scale, we apply extended auto-negative binomial models to examine the overall impact of
15 street-link morphological characteristics on the injury collision frequency, considering both the
16 link being investigated and other surrounding links determined by the spatial scale.

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

27
28 **KEYWORDS**

29 Traffic safety; Collision; Street network; Morphology; Topology

30

31 Word count – main body of the manuscript: 8954

32

33 **1. Introduction**

34 Traffic collisions rank amongst the top ten killers worldwide. 1.3 million people are killed, and
35 up to 50 million are injured as a result of traffic collisions each year (WHO 2018). Whereas 90%
36 of road deaths transpire in low- and middle-income countries, high-income countries bear 60%
37 of the economic losses stemming from traffic collisions (Chen et al. 2019). According to
38 OECD's (2022) report, for example, there were 91,199 injuries and 1,516 fatalities resulting

39 from traffic collisions in 2020 in the UK. Despite these figures being relatively low compared
40 to other countries, the economic costs incurred were still substantial – a staggering 1.5% of the
41 UK's GDP in 2020, equivalent to 40.6 billion US dollars. Creating a safer traffic environment
42 has therefore become a global policy issue and was proposed in the form of two targets in the
43 United Nations' Sustainable Development Goals (UN 2016).

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

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

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

78 Recognising the need for a deeper understanding of the intricacies of street network
79 structures, several studies have sought to apply morphological analysis for network structure
80 quantification (Guo et al. 2017, Wang et al. 2013, Wang et al. 2018, Cooper 2017). They used

81 node-based morphological metrics to quantify how a specified street – represented as a node in
82 a network graph – is topologically and geometrically connected with other streets via the
83 network. Network morphological quantifications are not independent of visual inspection
84 approaches; instead, they serve as an extension, which provides more detailed and objective
85 characterisations of street network structures. In these studies, the morphological metrics were
86 predominately aggregated at the area level to quantify street network structures in each unit of
87 analysis, and on this basis, the relationship between street network morphologies and area-level
88 collision frequency is examined.

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

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

116 **2. Traffic Safety Studies on Street Networks**

117 **2.1. Visual Inspection of Street Network Structures**

118 Initial studies investigating the effects of street network structures on traffic safety date back to
119 the 1950s. In his study, Marks (1957) utilised visual inspection to categorise the street network
120 structures of subdivisions in Los Angeles, US, into two patterns: gridiron and limited access,

121 he found that the frequency of total collisions was eight times higher in the gridded subdivisions.
122 It is important to note that in our paper, the term 'total collision' encompasses both injury and
123 non-injury collisions unless otherwise specified. In their seminal work, Southworth and Owens
124 (1993) provided a more comprehensive view of such classifications. They categorised US
125 community street networks into five patterns: gridiron, interrupted parallel, incremental infill,
126 loops and lollipops, and hybrid patterns. Subsequently, similar classifications have been widely
127 adopted in traffic safety studies through the visual inspection of street network structures.
128 Results reported in the literature suggest that the 'gridiron' pattern may be associated with a
129 greater frequency of total collisions than other patterns, particularly the 'loops and lollipops'
130 pattern (Gladhill and Monsere 2012, Rifaat and Tay 2009, Sun and Lovegrove 2013). However,
131 some studies indicate that gridiron patterns may mitigate the severity of collisions (Rifaat et al.
132 2012, 2011).

133 **2.2. Morphological Quantifications of Street Network Structures**

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

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

155 The concept of reachability is intricately linked with traffic safety. First, street links with
156 greater reachability at a large spatial scale (e.g., at a city scale) tend to attract more motorised
157 traffic volume, which increases the exposure to traffic risks in such links (Jayasinghe et al.
158 2015). In contrast, street links with greater reachability at a small spatial scale (e.g., at a
159 neighbourhood scale) may encourage the use of active transport to travel to and from those
160 links (Kang 2018), thereby reducing traffic exposure. Second, an increase in the reachability of
161 a street link increases the likelihood of conflicts amongst road users in their surrounding areas

162 due to the rise in the number of junctions. This, in turn, can result in a higher incidence of
163 collisions in these areas (Zhang et al. 2015). However, the need for frequent manoeuvres by
164 drivers in these areas may result in lower driving speeds (Aarts and van Schagen 2006), thereby
165 increasing reaction time in the event of a conflict, which helps reduce the occurrence and
166 severity of collisions.

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

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

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

198 **2.3. Street Network Morphologies and Traffic Safety**

199 Studies on the street network morphology-traffic safety relationships were predominately
200 conducted ecologically, with an exclusive focus on the direct impact of street network
201 morphologies within specific geographical areas. Zhang et al. (2015) investigated the
202 correlation between street network structures and the census-tract level frequency of total non-

203 motorist-involved collisions in California, US. They considered three morphological metrics:
204 farness (the reciprocal of closeness), betweenness, and the clustering coefficient. To model
205 census tract collisions, the authors used the average values of farness and the clustering
206 coefficient of street links in each census tract. The betweenness metric was aggregated at the
207 census tract level by calculating 'the average difference between the relative [betweenness]
208 centrality of the most central street and that of all other streets' (p. 38). The results suggested
209 that census tracts with street networks, which was associated with smaller farness (i.e., a higher
210 level of reachability), higher betweenness (i.e., a higher level of choice), and a larger clustering
211 coefficient (i.e., a higher level of reachability), tended to indicate fewer non-motorist-involved
212 collisions. Guo et al. (2017) examined the relationship between street network reachability and
213 the frequency of pedestrian-vehicle injury collisions at the TAZ level in Hong Kong, China.
214 The street network reachability of each TAZ was measured using the average integration metric
215 of the street links. The results indicated that TAZs with a higher level of street network
216 reachability were associated with an increased frequency of pedestrian-vehicle injury collisions.

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

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

243 3. Research Design

244 3.1. Data

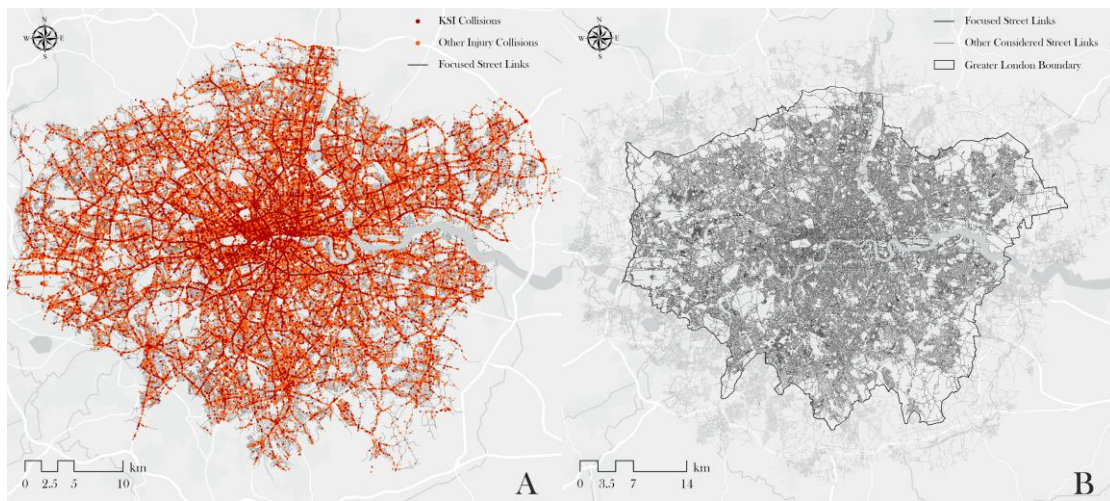
245 We focused on street-link level injury collisions in Greater London over the period 2015–2019.
246 We applied three types of data sets: (1) injury collision, (2) street network, and (3)
247 neighbourhood socioeconomic and land use data sets. We extracted 2015–2019 injury collision
248 data from STATS19,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

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

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

282 We obtained the neighbourhood socioeconomic characteristics, such as population

283 density, population age composition, and average household income, at the super output area
 284 level from the 2011 UK Census. Neighbourhood land use data from 2017 were obtained from
 285 Geomni UKLand. This data set comprises nine categories of land use, including both man-
 286 made and natural landscapes. We used the middle super output area (MSOA; n = 964)-level
 287 data for our main analysis and conducted sensitivity analyses using the lower super output area
 288 (LSOA; n = 2,252)-level data. The neighbourhood-level variables were used as covariates in
 289 estimating the safety impacts of street-link morphologies. The estimation, however, may be
 290 susceptible to the modifiable area unit problem (MAUP), which occurs when the aggregation
 291 of the covariates at different geographic scales affects the results. Using both MSOA- and
 292 LOSA-level data thus allowed us to examine the robustness of our results against the MAUP.
 293



294
 295 **Figure 1** The distributions of (A) injury collisions and (B) considered street links in Greater
 296 London.

297 3.2. Street Network Morphologies

298 We performed an sDNA to characterise street network morphologies at the street-link level
 299 (Cooper and Chiaradia 2020). In sDNA, street links are the unit of analysis for the theoretical
 300 planar graph model of a city. Unlike conventional space syntax and network analyses, sDNA
 301 enables the joint characterisation of topological and geometrical features of a network at various
 302 spatial scales, rendering it more relevant for planning practices. Owing to these features, sDNA
 303 has been applied in various fields, such as public health, transport, and housing studies, to better
 304 understand the role of street networks in shaping society (Donald et al. 2014, Grimaldi et al.
 305 2019). In light of the multiplicity of street network morphologies, we considered three concepts
 306 in sDNA, namely, unreachability, choice, and severance, to determine the applied
 307 morphological metrics, following our literature review.

308 First, we measured the opposite of the concept of reachability, i.e., unreachability, using
 309 the farness metric. This metric is defined as the average shortest distance between a street link
 310 and other links within a defined network radius. We did not use a measure of the reachability
 311 concept, namely the closeness metric. The reason is that the closeness metric is calculated using

312 the reciprocal of the farness metric, and thus it has an exponential distribution, which is difficult
313 to handle statistically (Cooper et al. 2021). A higher farness value indicates that the street link
314 investigated contains farther and fewer connections with other links (Zhang et al. 2015). Second,
315 we quantified the concept of choice using the betweenness metric, which is determined by the
316 weighted number of times a street link lies on the shortest path between other pairs of links
317 within a defined network radius. A higher betweenness value suggests a more centralised role
318 for a street link in connecting other links. Third, to measure the concept of severance, we used
319 the diversion ratio, which is defined as the mean ratio of the shortest length to the crow flight
320 distance between a street link and other links within the radius. A larger diversion ratio suggests
321 that a street link contains more twisted connections with other links. We refer our readers to
322 **Appendix A** for detailed mathematical calculations of the morphological metrics.

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

331 We considered street links located within 8 km of Greater London when computing the
332 morphological metrics to avoid spillover bias. In our main analyses, the shortest path for
333 measuring the morphological metrics was determined based on the Euclidean distance (also
334 known as the metric distance) along the network. The measured farness, betweenness and
335 diversion ratio of street links are displayed in **Figure 2**, **Figure 3**, and **Figure 4**, respectively.
336 We also used morphological metrics calculated based on angular distance for the sensitivity
337 analysis, since some studies have suggested that these metrics may explain traffic volume better
338 than metrics calculated based on Euclidean distance (Serra and Hillier 2019, Ciscal-Terry et al.
339 2016, Jayasinghe 2017).

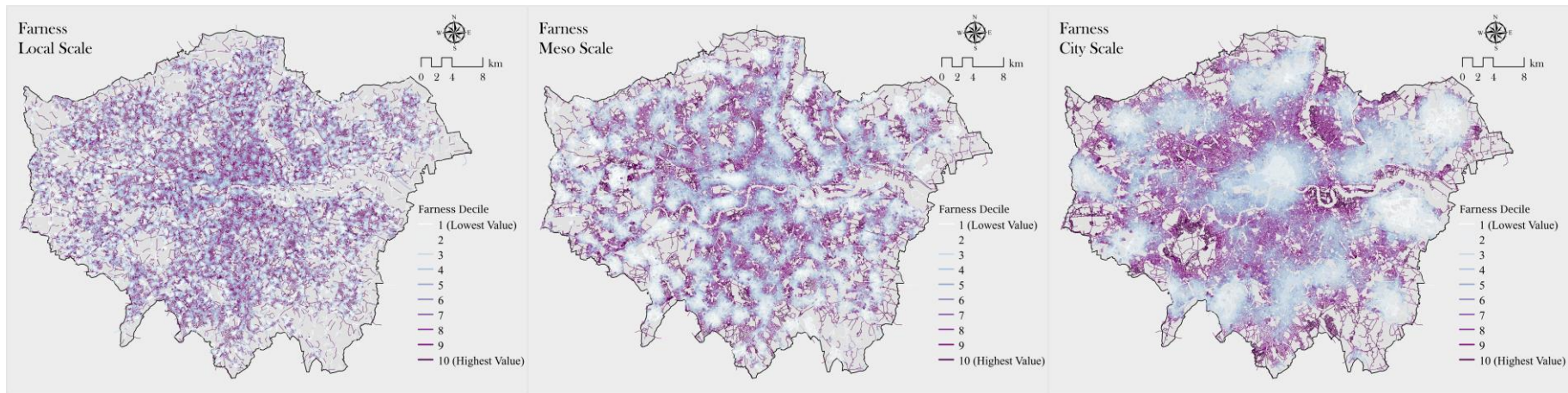


Figure 2 Farness of street networks at the link level.

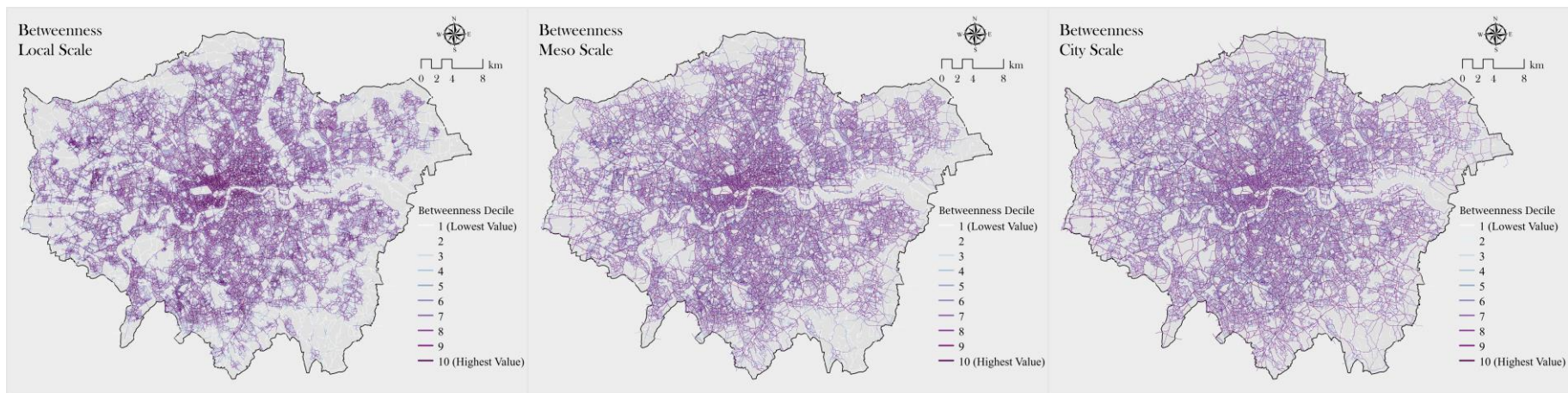
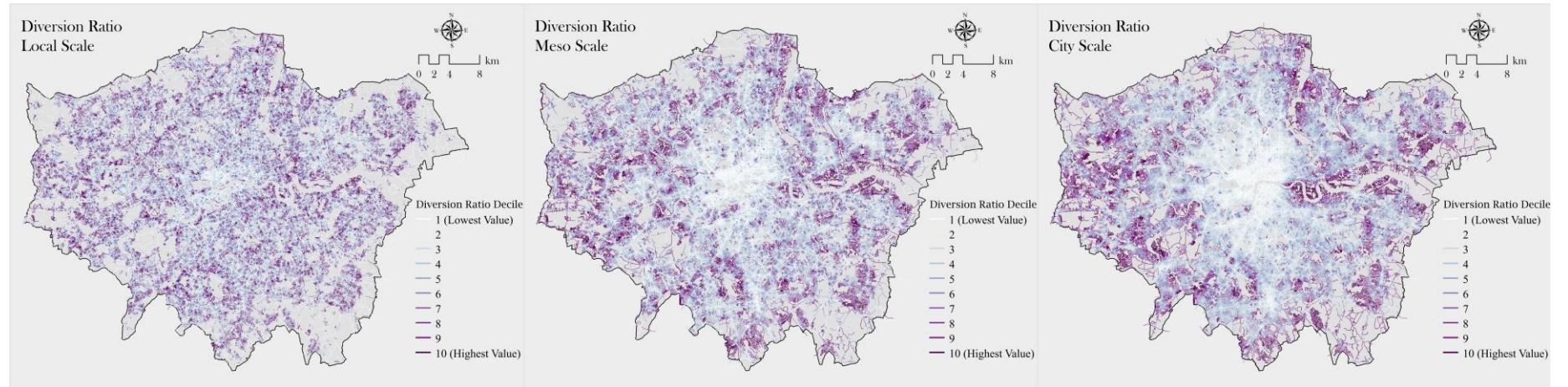


Figure 3 Betweenness of street networks at the link level.

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

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349 3.3. Covariates

350 We used two street-link-level covariates, namely, the length and function of street links. The
351 function of street links was categorised into four types: (1) motorway/A road¹; (2) B road²; (3)
352 minor road; and (4) local roads (OS 2017), which respectively constituted 12%, 3%, 10%, and
353 75% of street links in Greater London.

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

- 357 • Socioeconomics: Population density, average household income, and percentage of
358 households with children, work-age population, and white population (e.g., Kocatepe
359 et al. (2017); Lee et al. (2014); Lee and Abdel-Aty (2018); Lee et al. (2018); Quddus
360 (2008); Wang et al. (2016); Albalate and Fageda (2021)).
- 361 • Land use: The total land area and the proportion of business/commercial, industrial,
362 and recreational land uses (e.g., Pulugurtha et al. (2013); Xie et al. (2019a); Chen and
363 Lym (2021)).

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

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

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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).

384 **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 |

385

386 **3.4. Model**

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

391 **3.4.1. ANB Model**

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

$$393 \quad y_{Si} = \text{Negbin}(u_{Si}, r) \quad (1)$$

$$394 \quad \log(\mathbf{u}_S) = \rho \mathbf{W} \mathbf{y}_A + \mathbf{X}_S \boldsymbol{\beta} + \mathbf{C} \boldsymbol{\kappa} + \boldsymbol{\varepsilon};$$

$$\mathbf{y}_A = [\mathbf{y}_S^T, \mathbf{y}_O^T]^T \quad (2)$$

$$395 \quad \mathbf{W} = [w_{ij}];$$

$$w_{ij} = 1/d_{ij}, \text{ if } i \neq j \text{ and } d_{ij} \leq d_0;$$

$$w_{ij} = 0, \text{ otherwise} \quad (3)$$

396 Here, \mathbf{y}_S is a 198,880×1 vector of the collision frequency of street links in our study area.
397 y_{Si} is assumed to exhibit a negative binomial distribution with an expected value u_{Si} and a
398 dispersion parameter r . \mathbf{X}_S denotes a 198,880×3 matrix of morphological metrics at a given
399 scale of each street link in our study area; $\boldsymbol{\beta}$ is a vector of corresponding coefficients. \mathbf{C} is a
400 198,880×14 matrix of one and covariates, and $\boldsymbol{\kappa}$ is a vector of the coefficients. $\boldsymbol{\varepsilon}$ is a vector of
401 the residuals.

402 The ANB model allows accounting for the potential global network autocorrelation via
403 the introduction of a spatially lagged term $\rho \mathbf{W} \mathbf{y}_A$. Here, ρ is the global autocorrelation

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

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

$$421 \quad \mathbf{W}\mathbf{y}_A = \mathbf{X}_S\boldsymbol{\lambda} + \mathbf{C}\boldsymbol{\zeta} + \mathbf{v} \quad (4)$$

$$422 \quad \log(\mathbf{u}_S) = \rho^* \mathbf{v} + \mathbf{X}_S\boldsymbol{\beta}^* + \mathbf{C}\boldsymbol{\kappa}^* + \boldsymbol{\varepsilon}^* \quad (5)$$

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

440 3.4.2. EANB Model

441 Despite its computational flexibility, the ANB model centres on only the direct impact of each

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

$$449 \quad \log(u_s) = \alpha\sigma_k + \varphi_k \mathbf{x}_{Sk} + \delta_k \mathbf{W}\mathbf{x}_{Ak} + \mathbf{X}_{S(-k)}\xi_k + \mathbf{C}\omega_k + \tau_k; \quad (6)$$

$$\mathbf{x}_{Ak} = \left[\mathbf{x}_{Sk}^T, \mathbf{x}_{Ok}^T \right]^T$$

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

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

$$464 \quad \frac{1}{n} \sum_{i=1}^n \frac{\partial(E(y_{Si}))}{\partial(x_{Sik})} = \frac{1}{n} \sum_{i=1}^n \varphi_k \exp\left(\alpha\sigma_{ki} + \varphi_k x_{Ski} + \delta_k (\mathbf{W})_{i*} \mathbf{x}_{Ak} + (\mathbf{X}_{S(-k)})_{i*} \xi_k + (\mathbf{C})_{i*} \omega_k\right) \quad (7)$$

$$465 \quad \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n \frac{\partial(E(y_{Sj}))}{\partial(x_{Sik})} = \frac{1}{n} \sum_{i=1}^n \sum_{j=1}^n \delta_k w_{ji} \exp\left(\alpha\sigma_{kj} + \varphi_k x_{Ski} + \delta_k (\mathbf{W})_{j*} \mathbf{x}_{Ak} + (\mathbf{X}_{S(-k)})_{j*} \xi_k + (\mathbf{C})_{j*} \omega_k\right) \quad (8)$$

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

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

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

481 **4. Results**

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

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

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

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

518 overall decrease. Independent of the spatial scale, a larger diversion ratio of a street link was
519 linked to an overall decrease in the frequency of total injury collisions.

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

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

536

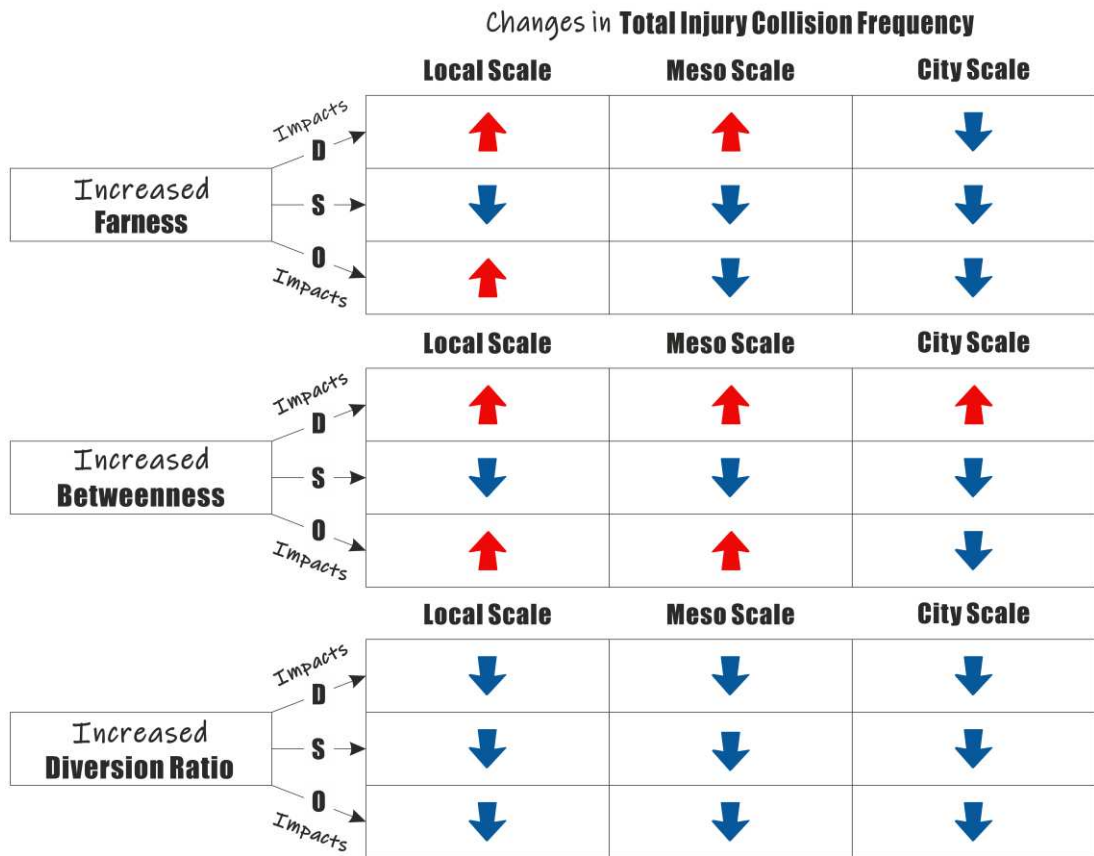
Table 2 Results of the EANB models on total injury collision frequency.

| 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) |



Legend

An **Increase** in Total Injury Collision Frequency
 A **Decrease** in Total Injury Collision Frequency
D (Direct Impact) **S** (Spillover Impact) **O** (Overall Impact)

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) |

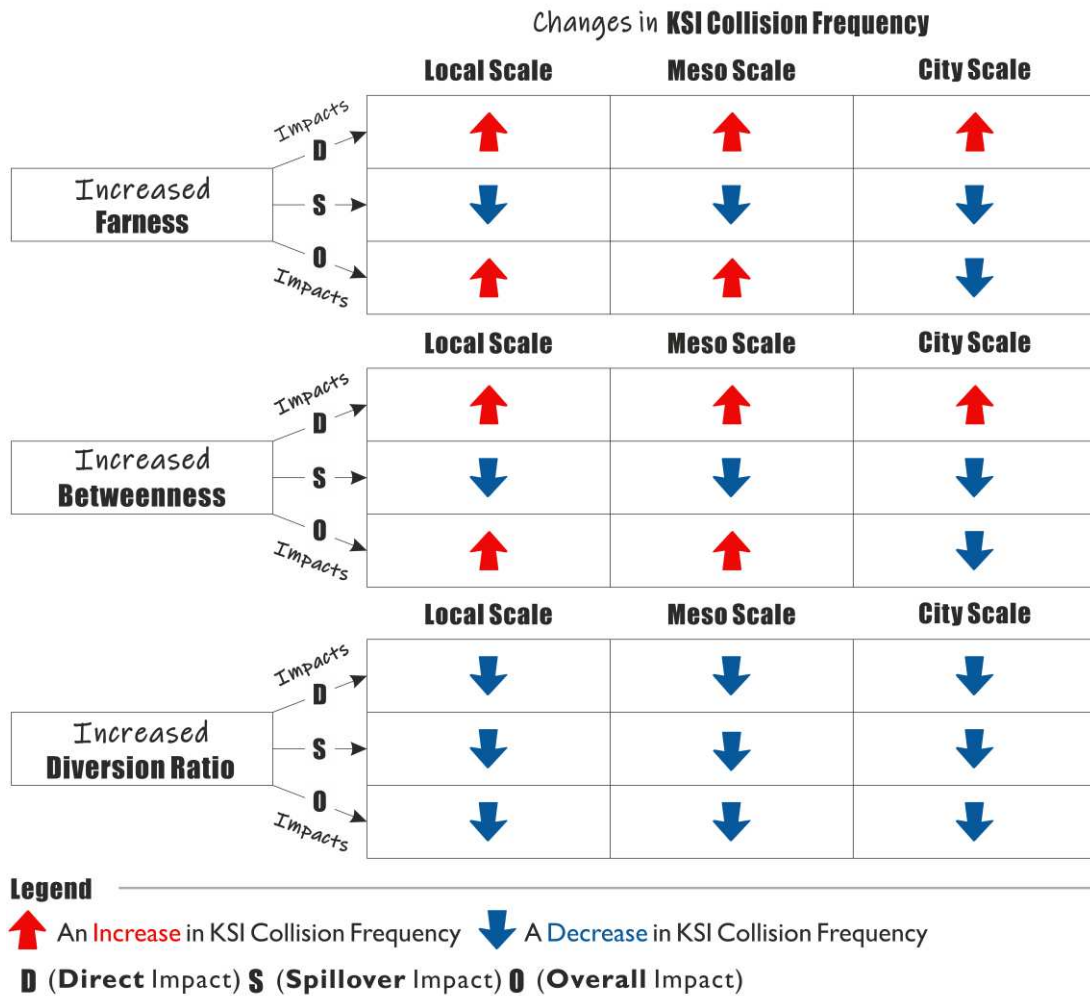


Figure 6 Summary of street-link morphologies' impacts on KSI collision frequency.

429 **5. Discussions**

430 **5.1. Discussions on Principal Findings**

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

436 First, for total injury and KSI collisions, higher farness of a street link at the local scale
437 corresponded to an overall increase in collision frequency at the same scale. However, higher
438 farness at the city scale had the opposite impact, resulting in an overall decrease in collisions at
439 that scale. At the meso scale, the overall safety impact of street-link farness depended on the
440 severity of collisions. Higher farness of a street link at the meso scale was associated with an

441 overall decrease in the frequency of total injury collisions at that scale, but an overall increase
442 in the frequency of KSI collisions. Existing studies conducted at the area level and an exclusive
443 spatial scale presented mixed findings regarding the relationship between street network
444 farness/closeness and traffic safety (Zhang et al. 2015, Guo et al. 2017). Our findings provide
445 a broader picture of this issue by uncovering the spatial heterogeneity of such a relationship.
446 Our findings show that this identified spatial heterogeneity can be largely ascribed to the
447 disparity in the direct impact of street-link farness across spatial scales. The reason is that,
448 independent of spatial scale, an increase in the street-link farness had a spillover impact that
449 contributed to fewer collisions in the street links surrounding the investigated link. By contrast,
450 increased street-link farness at the local and meso scales might have a direct impact leading to
451 more collisions of the link investigated, whereas there was no significant relation between city-
452 scale street-link farness and the collision frequency of the link investigated.

453 The positive spillover impact of higher street-link farness on traffic safety may be because
454 there tend to be fewer junctions in areas surrounding street links with higher farness, which
455 reduces the potential for conflicts between road users in these areas (Zhang et al. 2015). The
456 negative direct impact of higher street-link farness on traffic safety may be attributable to the
457 fact that the intensity to which street-link farness moderates motorised and non-motorised
458 traffic volumes varies by the spatial scale. The farness metric reflects the difficulty with which
459 a street can be reached via a network. The local and meso scales (0 – 3 km) correspond to the
460 median distance of trips made on foot and by cycling. Therefore, higher farness of a given street
461 at these two scales may increase physical barriers to walking and cycling to this street (Kang
462 2017, Kang 2018, Helbich 2017). As a consequence, there may be more motorised traffic
463 conditions in street links with higher farness, thereby resulting in the less satisfactory traffic
464 safety performance of such links. Compared with these two scales, motorised modes may
465 account for larger shares of trips at the city scale (i.e., 0 – 8 km). While as destinations, street
466 links with higher city-scale farness obstruct the use of non-motorised modes in short-distance
467 trips, such links may also be less attractive to motorised long-distance trips due to the increased
468 travelling time and costs (Jayasinghe et al. (2015), which contributes to less hazardous traffic
469 conditions in these street links.

470 Our results suggest that, overall, smaller farness of a street link indicates a safer traffic
471 environment at the local scale, but a riskier traffic environment at the city scale. Therefore,
472 changing farness of a given street link or the average farness of links in a network, which can
473 be achieved by modifying street network compactness, may be useful for improving traffic
474 safety. For example, planners can decrease street-link farness by de-densifying street networks
475 near a target street link, which would increase the distance between the link and the other links
476 to which it connects. In recent decades, promoting street network compactness, which aligns
477 well with the New Urbanism and the Compact City policy, has been seen as a proactive solution
478 to improving traffic safety. However, we argue that such a street network structure may *not*
479 necessarily be effective for an overall reduction in injury collisions across an entire city. While,
480 according to our findings, a more compact street network structure may indeed help mitigate
481 traffic risk at a small local spatial scale, it contributes to increased traffic risks overall when

482 considering large spatial scales. Our argument is partially aligned with that of Ewing and
483 Hamidi (2015), which suggests that increasing urban compactness may lead to more total injury
484 collisions at the county level. Nevertheless, considering the benefits of compact street networks
485 for public health and the quality of life (Xie et al. 2019b, Remali et al. 2015), it may be too
486 hasty to conclude that street networks need to be largely de-densified. Instead, we highlight that
487 a comprehensive assessment should be conducted ex-ante for planning projects involving the
488 change in street farness.

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

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

517 Our findings suggest that *ceteris paribus*, an increase in the average betweenness of street
518 links may benefit overall traffic safety at the city scale. To achieve this, it is important to focus
519 on the entire (sub)network, as an increase in the betweenness of one street link may come at the
520 expense of a decrease for others in the (sub)network. Within this context, a city-scale street
521 network structure with more links parallel to arterials with high-level betweenness helps
522 achieve an increase in the average betweenness of street links in the network, and may thus be

523 desirable for its traffic safety performance. This can be achieved through reconfiguring existing
524 street links or building new ones. For new construction projects, questions for the planners are
525 how to ensure the safety benefits derived from increased betweenness are not cancelled out by
526 the decrease in average city-scale fairness of street links, which had a negative overall safety
527 impact at the city scale.

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

542 Fourth, Euclidean distance-based and angular distance-based morphological metrics
543 exhibited similar results and performance in explaining the frequency of total injury and KSI
544 collisions. While some studies indicate that angular distance-based metrics outperform
545 Euclidean distance-based ones in explaining traffic volume (Serra and Hillier 2019, Jayasinghe
546 2017), our findings suggest that this may not apply to their traffic safety implications. A
547 plausible reason, as we previously outlined, is that traffic exposure is not the only influential
548 factor linking street network morphologies and traffic safety; traffic speed and traffic conflicts
549 also play crucial mediating roles in this relationship. Given the dominance of physical distance-
550 based approaches in current planning practices, it is notable that Euclidean distance-based
551 morphological metrics, with their robust explanatory power on injury collision frequency, could
552 continue to play a pivotal role in street network planning for traffic safety improvement.

553 **5.2. Discussions on Methodologies**

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

562 features in an acceptable time frame, whilst simultaneously yielding a desirable model fitness.

563 We also notice that the integrated nested Laplace approximation approach (Illian et al.
564 2012) allows the researchers to use the popular Bayesian analysis framework in the estimation
565 of network autocorrelations and spillover impacts for a relatively large network (see, Gómez-
566 Rubio et al. (2021)). While this approach has garnered increasing attention in recent years for
567 big-data modelling, it focuses on models that can be expressed as latent Gaussian Markov
568 random fields. It is thus limited by the use of a dense network weight matrix (Gómez-Rubio
569 2020). By contrast, EANB models provide a more flexible manner for constructing network
570 weights, for example, using inverse distance squared decay functions. Against this backdrop,
571 the EANB model allows location-specific distance decay functions identified using real-world
572 travel data (Chen and Fractals, 2015) to be applied in future studies to establish network weights.

573 **5.3. Strength and Limitations**

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

584 Nevertheless, our research presents several limitations. First, similar to most existing
585 studies, we did not consider graph-based morphological metrics, such as the robustness of street
586 networks, which may affect traffic safety-related elements (e.g., traffic volume, see Scott et al.
587 (2006)). Future studies could benefit from applying multilevel analyses to combine both node-
588 and graph-based metrics in their models. Nevertheless, the modifiable area unit problem must
589 be prioritised owing to the involvement of graph-based metrics. Second, we partially explained
590 our findings based on the moderating role of street network morphologies in shaping traffic
591 volumes. In the absence of high-resolution traffic volume data at the street-link level, we cannot
592 confirm the hypothesised mechanisms. As such, a multistage estimation strategy (see, e.g., An
593 et al. (2021)) could be applied in future studies to compare the change in the effect of street
594 network characteristics on traffic safety in models with and without traffic volume variables;
595 the results could help understand the interrelationship between street network morphologies,
596 traffic volume, and traffic safety. Thirdly, our EANB models lacked control for temporal
597 covariates, such as weather conditions, potentially introducing endogeneity concerns,
598 notwithstanding the satisfactory goodness of fit in our estimations. To tackle this concern,
599 future studies should highlight the development of statistical models capable of managing both
600 network and temporal autocorrelation within a big data context.

601 6. Concluding Remarks

602 We conducted a comprehensive, disaggregate-level, multi-scale examination on the impacts of
603 street network morphologies on traffic safety. We focused on five-year traffic injury collision
604 frequencies of more than 190,000 street links in Greater London. We characterised street-link
605 morphologies at local (0 – 1 km), meso (0 – 3 km), and city (0 – 8 km) scales using a spatial
606 design network analysis. For each spatial scale, we applied extended auto-negative binomial
607 models to examine the overall impact of street-link morphological characteristics on the injury
608 collision frequency, taking into account both the link being investigated and other surrounding
609 links determined by the spatial scale. We found significant spatial heterogeneity in the overall
610 safety impacts of street-link morphologies. At the local scale, higher farness of a street link
611 corresponded to an overall increase in total injury collisions, whereas at the meso and city scales,
612 it indicated an overall decrease. At the local and meso scales, higher betweenness of a street
613 link was associated with an overall increase in total injury collisions, but at the city scale, it
614 correlated with an overall decrease. Independent of the spatial scale, a larger diversion ratio of
615 a street link was linked to an overall decrease in total injury collisions. These findings were
616 similar to those on KSI-only collisions. We suggest that encouraging compact street network
617 structures, which aligns well with New Urbanism and the Compact City policy, may *not*
618 necessarily be effective for an overall reduction in injury collisions across an entire city.
619

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:

$$\text{Farness}(x) = \left(\sum_{y \in R_x} d(x, y) \right) / n \quad (1)$$

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:

$$\text{Betweenness}(x) = \sum_{y \in N} \sum_{z \in R_y} OD(y, z, x) \quad (2)$$

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:

$$\text{Div}(x) = \left(\sum_{y \in R_x} d(x, y) / CFD(x, y) \right) / n \quad (3)$$

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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