

1 **Effects of the built environment on automobile-involved pedestrian crash**
2 **frequency and risk**

3
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10 **A B S T R A C T**

11 This area-based study explores the relationship between automobile-involved pedestrian crash
12 frequency versus risk and various built environment factors, such as road network and land use.
13 The methodology involves the use of Bayesian hierarchical intrinsic conditional autoregressive
14 model, which accounts for unobserved heterogeneities and spatial autocorrelations. The city of
15 Seattle is selected for this empirical study, and the geospatial unit of analysis is traffic analysis
16 zone. The primary data were obtained from Seattle Department of Transportation collision
17 profiles. The major findings of this research include: (1) the densities of 4-way intersections and
18 more than 5-way intersections, and land use mixture are positively correlated with the pedestrian
19 crash frequency and the risk; (2) sidewalk density and the proportion of steep areas are
20 negatively associated with the pedestrian crash frequency and the risk; (3) areas with a higher
21 bus stop density are likely to have more pedestrian crashes; (4) in areas with a greater proportion
22 of industrial land use, the pedestrian crash frequency is lower; (5) in areas with an averagely
23 higher posted speed limit, the pedestrian crash risk is higher; (6) in areas with a greater
24 employment density, the pedestrian crash risk is lower; (7) the mode share of walking and the
25 total number of trips are positively correlated with the pedestrian crash frequency, and the total
26 number of trips is negatively correlated with the pedestrian crash risk. These findings provide
27 supports for planning policy making and road safety programs. Local authorities should improve
28 walkability through providing more sidewalks and separate motorized traffic and pedestrian
29 travels in areas with different land use purposes. Compact development should be encouraged to
30 support building a safe walking environment.

31
32 *Keywords:*

33 Pedestrian crash frequency, pedestrian crash risk, built environment, spatial autocorrelation, roadway
34 design

35 1. Introduction

36 Walking is an environmentally friendly and healthy transportation mode. Its intrinsic
37 value can never be over-exaggerated. That is also why walking has been a lasting mode of travel
38 and should be so in the future. However, in the process of urbanization and motorization,
39 walking tends to be devalued to such a degree that it has become more vulnerable than ever, even
40 in developed countries like the US (The National Highway Traffic Safety Administration, 2012).
41 As car dependence increased, pedestrian travel has gradually stepped down as an unpopular
42 mode choice. From 1980 to 2010, the percentage of walking commuters in the US, for instance,
43 steadily decreased from 5.60% to 2.77% (American Association of State Highway and
44 Transportation Officials and US Department of Transportation, 2013). For work-related trips,
45 walking is mostly unattractive. However, as obesity rate grows, as a mode encouraging physical
46 activity, the importance of walking is gradually realized across nations and much has been done
47 to promote walking (Frank and Engelke, 2001; Pucher and Buehler, 2010). Walking is largely
48 advocated by the public, because it has great potential to mitigate environment and health
49 challenges that our society is facing (Newman and Kenworthy, 2006; Saelens et al., 2003).

50 Policy makers and urban planners advocate developing new urbanist communities that
51 promote sustainable cities through encouraging smaller lot size, more mixed land use, denser
52 blocks, and greater street connectivity (Ellis, 2002; Lee and Moudon, 2006; Lund, 2003). The
53 livable neighborhoods have better proximity to amenities, such as open spaces, parks, grocery
54 stores, and jobs, which contribute to a greater mode share of walking (Ellis, 2002; Lund, 2003).
55 Ideally, the popularity of walking could be greatly enhanced by improved pedestrian safety and
56 well-planned walking environments. Therefore, the attractiveness of walking has been
57 highlighted in the ideas of new urbanism and smart growth (Ellis, 2002; Lund, 2003). However,
58 the role of pedestrian safety is still paid little attention.

59 Pedestrians are actually vulnerable road users. For instance, in the US, 4,743 pedestrians
60 were killed and 76,000 pedestrians were injured in 2012, and pedestrian deaths accounted for 14%
61 of all traffic fatalities (The National Highway Traffic Safety Administration, 2012). Policy
62 makers have been undertaking efforts to promote safe walking environments. Taking Seattle as
63 an example, the Seattle Department of Transportation issued a pedestrian master plan to develop
64 strategies to decrease the number of pedestrian collisions and severe injuries. The proposed
65 countermeasures included maintaining pedestrian visibility at intersections, improving crossing
66 conditions, and regulating driving speed limits (Seattle Department of Transportation, 2009).

67 The role of the built environment in explaining the causes of pedestrian crashes has been
68 continually investigated (The National Highway Traffic Safety Administration, 2012). Existing
69 studies have linked aspects of the road network and pedestrian safety across different spatial
70 scales. For micro-level studies, an overall finding is that intersections have more pedestrian
71 crashes because there are more conflict points among travelers and vehicles (Ukkusuri et al.,
72 2012). The importance of conducting micro-level research is that its results can efficiently
73 inspire countermeasures for safety improvements. However, micro-level studies only catch the
74 intersection or midblock characteristics as pieces of road elements, while macro-level studies
75 understand a city as a complex system. In addition, specific crash site's location is often "scaled

76 up” to an intersection or midblock in practice. Therefore, corresponding built environment
77 features often lack accuracy, and fixed covariates could be biasedly measured when road features
78 along a road segment are not constant. Area-based studies examine the relationship between the
79 built environment and pedestrian crashes at a larger geospatial scale where data are richer and
80 more accurate, which help produce more stable estimates, and capture aggregated effects of more
81 covariates on pedestrian crashes and related risks.

82 This study contributes to the existing studies on the following three aspects. First, this
83 study innovatively includes travel demand forecasted number of pedestrian trips as a
84 denominator to measure pedestrian crash risk. Also, this study compares the variation between a
85 frequency model versus a risk model, targeting to provide a more objective understanding on
86 pedestrian safety. Second, by examining the effects of several commonly used density measures,
87 this study testifies the generalizability of the theory of safety in numbers in a US urban setting.
88 Third, this study considers the spatial spillover effects across the urban space at an area level
89 regarding pedestrian crash frequency versus risk. Building on existing studies, this study is
90 designed to identify the effects of land use and road network features on pedestrian safety.

91 To this end, the purpose of this study is to investigate what built environment factors are
92 associated with pedestrian crash frequency versus pedestrian crash risk at a macro-level. This
93 study considers quite a few area-based covariates that have not been considered before in
94 existing studies, such as travel demand forecast. Two Bayesian hierarchical intrinsic conditional
95 autoregressive (ICAR) models accounting for unobserved heterogeneities and spatial
96 autocorrelations are conducted to evaluate the pedestrian crash frequency and the risk across
97 traffic analytical zones (TAZs) in Seattle, Washington. The hypothesis of this study is that
98 compact developed urban environment is safer. Though a higher pedestrian crash frequency
99 could be observed in dense urban settings, the pedestrian crash risk could be actually lower. The
100 independent variables include various factors of the road network, land use, socio-demographics,
101 and travel demand. This paper begins with a literature review and research design, follows by
102 methodological details, and then presents the results of the ICAR models, and ends with
103 conclusions, a discussion, and future research.

104 **2. Literature Review**

105 Conventionally, traffic engineers and health professionals use the 5E’s and the Haddon’s
106 Matrix to analyze crash and injury outcomes, and to propose safety improvement strategies. The
107 5E’s analytical tool refers to Environment, Engineering, Enforcement, Education, and
108 Emergence Aid (Bergman et al., 2002; Morrison et al., 2003). The Haddon’s Matrix, as a
109 standardized framework, is made of Host, Agent, Event, and Environment (Runyan, 2015). Both
110 of these conceptual models highlight the importance of the built environment in explaining
111 pedestrian crashes occurred in urban settings.

112 *Key Definitions*

113 In most cases, a “pedestrian crash” refers to an automobile intersecting with a pedestrian.
114 “Crash frequency” is the number of collisions at a certain location per unit time. “Crash risk” is
115 often calculated by the number of collisions reported per 1,000 trips, 1,000 hours, or 1 kilometer
116 of exposure (de Geus et al., 2012).

117 *Effects of Built Environment Factors*

118 As aforementioned, the built environment plays an important role in explaining crash and
119 injury outcomes. A number of studies have examined the relationship between built environment
120 factors and pedestrian crash frequency versus risk at multiple geospatial scales. The scales
121 include signalized intersections (Miranda-Moreno et al., 2011; Pulugurtha and Sambhara, 2011),
122 state or city routes (Moudon et al., 2008; Moudon et al., 2011), census tracts (Narayanamoorthy
123 et al., 2013; Ukkusuri et al., 2011; Ukkusuri et al., 2012; Wang and Kockelman, 2013; Wier et
124 al., 2009), zip code boundaries (Ukkusuri et al., 2011; Ukkusuri et al., 2012), and TAZs
125 (Siddiqui et al., 2012). For studies done at the point or the polyline level, such as intersections
126 and state routes, a commonly observed bias is that those studies cannot cover all geographical
127 areas. For example, intersection-based studies cannot identify risk factors of pedestrian collisions
128 that occurred at mid-blocks. The unit of analysis varies greatly across the prior studies.

129 Though area-based research produces more stable estimates, it also has the threat of
130 “regression towards the mean” due to aggregation. Variables quantified at a larger scale are
131 relatively constant, and are easy to match other census information, such as household density,
132 employment density, and travel demand. However, the preciseness of built environment
133 measurements can be diluted due to aggregation. Some localized built environment features can
134 only be identified at a smaller scale. In other words, a smaller geo-spatial unit is preferred in the
135 analysis to avoid the threat of “regression towards the mean”.

136 Regarding road network features, the densities of local streets and sidewalks are
137 negatively associated with the number of pedestrian crashes (Miranda-Moreno et al., 2011;
138 Siddiqui et al., 2012; Wang and Kockelman, 2013), indicating that facilitating pedestrians
139 through sidewalk provisions and local street densifications decrease the number of crashes. On
140 the contrary, arterial density is positively correlated with pedestrian crash frequency (Miranda-
141 Moreno et al., 2011; Siddiqui et al., 2012; Wang and Kockelman, 2013; Wier et al., 2009). The
142 existing findings on the effects of freeway or highway density on pedestrian crash frequency
143 were mixed, both positive (Wang and Kockelman, 2013) and negative (Miranda-Moreno et al.,
144 2011; Moudon et al., 2011; Narayanamoorthy et al., 2013) associations were identified. Because
145 pedestrians are not allowed to walk on freeways and highways, those relationships could be case-
146 specific correlations rather than casual relations. A greater transit route density and a better
147 transit service were reported to correlate with more pedestrian crashes (Miranda-Moreno et al.,
148 2011; Ukkusuri et al., 2012; Wang and Kockelman, 2013).

149 In particular, the effects of intersection characteristics on pedestrian crashes were also
150 examined in the existing studies. The densities of signals, crosswalks (Moudon et al., 2011), 4-
151 way and 5-way intersections (Pulugurtha and Sambhara, 2011; Siddiqui et al., 2012; Ukkusuri et
152 al., 2012) were positively correlated with pedestrian crash frequency. Interestingly, a study found
153 that a greater number of 3-way intersections was associated with fewer pedestrian crashes
154 (Ukkusuri et al., 2012).

155 In terms of land use features, studies suggested that higher proportions of commercial
156 land use (Miranda-Moreno et al., 2011; Moudon et al., 2008; Narayanamoorthy et al., 2013;
157 Ukkusuri et al., 2011; Wang and Kockelman, 2013; Wier et al., 2009) and offices

158 (Narayanamoorthy et al., 2013) are correlated with more pedestrian crashes. But the findings on
159 residential land use were not in an agreement within the prior studies. Ukkusuri et al.'s studies
160 indicated that residential land use was negatively associated with pedestrian crash frequency
161 (2011, 2012), whereas a positive association was identified between the number of dwelling
162 units and pedestrian crashes in Siddiqui et al.'s study (2012). Miranda-Moreno et al.'s study
163 suggested that the effects of residential land use on pedestrian crashes were not constant as the
164 radius of signalized intersection buffers changed (2011). The findings on industrial land use and
165 open space were varied. Both positive (Ukkusuri et al., 2012) and negative (Miranda-Moreno et
166 al., 2011) associations had been identified in the prior research. More mixed land use was
167 associated with fewer pedestrian crashes (Wang and Kockelman, 2013). A short summary for the
168 effects of land use factors on pedestrian crash frequency is that many relationships were not
169 consistent across previous empirical studies.

170 The issue of students' walking safety had been emphasized in the prior studies. Since
171 students have a higher propensity of involvement in pedestrian crashes, a few studies included
172 the number of, the proximity to, and the density of schools for modeling. School density
173 suggested a positive relationship with the number of pedestrian crashes (Narayanamoorthy et al.,
174 2013; Ukkusuri et al., 2011; Ukkusuri et al., 2012), but parcels with higher proximities to schools
175 showed a negative association with pedestrian crashes (Wang and Kockelman, 2013). These
176 conclusions indicate that pedestrian crashes are apt to occur around school areas. However, the
177 likelihood of involving a pedestrian crash is decreasing when homes to schools are
178 approximating. Interestingly, the coefficients estimated for school density changed with the size
179 of signalized intersection buffers in Miranda-Moreno et al.'s study (2011).

180 With regards to socio-demographic factors, areas with higher employment density
181 (Pulugurtha and Sambhara, 2011) and population density (Moudon et al., 2011; Pulugurtha and
182 Sambhara, 2011; Ukkusuri et al., 2012; Wang and Kockelman, 2013; Wier et al., 2009) were
183 positively correlated with the number of pedestrian crashes.

184 In relation to travel demand, traffic volume was a key exposure variable in understanding
185 the pedestrian crashes (Roberts et al., 1992; Stevenson et al., 1995). A few studies confirmed that
186 either traffic volume or vehicle miles traveled was positively correlated with pedestrian crashes
187 (Miranda-Moreno et al., 2011; Wang and Kockelman, 2013; Wier et al., 2009). The other
188 commonly used exposure measurements for pedestrian crashes included walking mode share
189 (Narayanamoorthy et al., 2013), pedestrian volume (Miranda-Moreno et al., 2011; Pulugurtha
190 and Sambhara, 2011), and the total number of crashes (Moudon et al., 2008; Moudon et al.,
191 2011). Prior research showed a consistent result that pedestrian volume had a positive association
192 with crash frequency (Miranda-Moreno et al., 2011; Pulugurtha and Sambhara, 2011).

193 It is worth noting that pedestrian crash risk was less often investigated relative to
194 pedestrian crash frequency, because the measurements representing pedestrian volume data, such
195 as the number of pedestrian trips, pedestrian miles traveled, and pedestrian hours traveled, are
196 mostly unavailable.

197 **3. Research Design**

198 *3.1 Data Source*

199 This study examines how built environment factors are correlated with pedestrian crashes
200 and risks at an area-based macro level. Built environment features are quantified by factors of
201 road network and land use. Some previously under-investigated factors, such as density of stop
202 signs, the proportion of steep areas, and zonal average posted speed limit are included in this
203 study.

204 This research uses data from two major components, pedestrian crash records and built
205 environment features. The pedestrian crash records are obtained from Seattle Department of
206 Transportation (SDOT) during the period from January 2008 to December 2012. There are in
207 total 2,186 geocoded pedestrian crashes. The crash risk is measured by the number of pedestrian
208 crashes divided by the origin and destination-based forecast of the number of walking trips in
209 each TAZ accordingly. The number of walking trips and the total number of trips are the major
210 output of a regional activity-based travel demand model, called SoundCast (Puget Sound
211 Regional Council, 2014). The other data were obtained from three agencies, including SDOT,
212 King County, and the Puget Sound Regional Council. TAZ is selected as the unit of analysis
213 because it matches the existing travel demand output and quantifies the built environment factors
214 at a relative small geospatial scale. The built environment feature quantification is done using
215 ArcGIS overlay functions. *Table 1* defines the selected variables and includes a data summary.

216 *3.2 Variable Selection*

217 This study initially has considered a large set of variables for modeling. However, many
218 variables are dropped for highly correlating with other fixed covariates. Variables excluded for
219 collinearity are signal density, street parking sign density, crosswalk density, transit route density,
220 and street lane density. Additionally, some variables are not considered due to incomplete spatial
221 coverage. For example, traffic volume, the number of lanes, and street width are only available
222 to be measured at arterials for Seattle's data.

223 *3.3 Methodology*

224 The Bayesian hierarchical intrinsic conditional autoregressive model has been frequently
 225 employed in recent area-based crash studies. The flexibility in structuring complicated models
 226 and the ability to account for unobserved heterogeneities and spatial autocorrelations contribute
 227 to its popularity. A 3-stage hierarchical Bayesian inference is done in the process of estimation.
 228 In the first stage, a Poisson process is employed to model the observed area-based pedestrian
 229 crash frequency versus the risk that is measured by the TAZ-based number of pedestrian trips. In
 230 the second stage, both of the pedestrian crash frequency and the risk are specified as functions of
 231 explanatory variables and random effects. In the third stage, the unknown parameters are
 232 assigned according to their prior distribution. The Poisson process for the pedestrian crash
 233 frequency and the risk are specified as *Eqs. (1) and (2)*:

234
$$Y_i|\theta_i \sim \text{Poisson}(\theta_i) \tag{1}$$

235
$$Y_i|\theta_i \sim \text{Poisson}(E_i\theta_i) \tag{2}$$

236 Where Y_i is the number of pedestrian crashes in TAZ_i , θ_i is the joint distribution of
 237 explanatory factors and random effects in TAZ_i , and E_i is the forecasted number of walking trips
 238 in TAZ_i . The logs of the risk factors and random effects are modeled in the second stage, as
 239 shown in *Eq. (3)*:

240
$$\log(\theta_i) = \alpha + \beta_i X_i + V_i + U_i \tag{3}$$

241 Where X_i represents a vector of explanatory variables, β_i is a vector of estimated
 242 parameters, α is the intercept, V_i is the unobserved heterogeneity and U_i is the spatial
 243 dependence. The prior distribution for the unobserved heterogeneity V_i is given as *Eqs. (4) and*
 244 *(5)*.

245
$$V_i \sim N(0, \sigma_v^2) \tag{4}$$

246
$$\sigma_v^{-2} \sim \text{Ga}(0.5, 0.0005) \tag{5}$$

247 The spatial autocorrelation, U_i , is specified as if the values of the spatial random effects
 248 U_j in neighboring areas are known. Under the ICAR's specification, the spatial random effects
 249 are drawn from a normal distribution whose mean is based on their neighbors, with variances
 250 proportional to the number of neighbors. Therefore, TAZs with more neighbors have less
 251 variability. *Eqs. (6) and (7)* show the distribution of the random effect for capturing spatial
 252 autocorrelations.

253
$$U_i|U_j, j \in \text{ne}(i) \sim N(\bar{U}_j, \frac{\sigma_u^2}{m_i}) \tag{6}$$

254
$$\bar{U}_j = \frac{1}{m_i} \sum_{j \in \text{ne}(i)} U_j \tag{7}$$

255 Where $\text{ne}(i)$ is the set of neighbors of TAZ_i , and m_i is the number of neighbors, \bar{U}_j is the
 256 mean spatial random effects of its neighbors, σ_u^2 is a conditional variance, and its magnitude
 257 determines the amount of spatial variation. σ_u and σ_v control the amount of extra variability of
 258 the Poisson process, which is allocated to the unobserved heterogeneity and the spatial spillover

259 effect among adjacent TAZs. The proportion of the variance explained for spatial
260 autocorrelations by the two random effects is calculated by *Eq. (8)*.

$$261 \quad \theta = \frac{\text{Var}(U)}{\text{Var}(U)+\text{Var}(V)} \quad (8)$$

262 **4. Results**

263 *4.1 Descriptive analysis*

264 *Table 1* presents the data summary of selected variables for modeling. The dependent
265 variable of the frequency model is the number of pedestrian crashes that occurred in the 5-year
266 period, ranging from 0 to 27 observations with a mean of 2.50 in 863 TAZs, as shown in *Figure*
267 *1*. The exposure variable in the crash risk model is the TAZ-forecasted number of walking trips,
268 ranging from 1 to 7,212 with a mean of 553.95 trips, as shown in *Figure 2*. As noted from the two
269 figures, after adjusting the forecasted walking trips, the spatial patterns of the pedestrian crash
270 frequency and the risk are varied greatly in the two figures.

271 *4.2 Inferential analysis*

272 This section summarizes the results for the Poisson log-normal ICAR models applied to
273 the 5-year pedestrian crash data. *Table 2* presents the modeling estimates for the relationships
274 between built environment factors and the pedestrian crash frequency versus the risk. The
275 estimates of the marginal variance for the unobserved heterogeneity (V_i) and clustering effects
276 among adjacent zones (U_i) are used to calculate the proportion of variance in the random effects
277 to quantify the spatial dependence. The proportions of the spatial spillover effect are 31.07% in
278 the pedestrian crash frequency model and 17.05% in the risk model. These indicate that the
279 variability in the random effects cannot be explained by spatial autocorrelations in these two
280 models. Spatial autocorrelation is not a major concern when modeling the relationships between
281 the built environment and pedestrian crash versus risk at an area level regarding Seattle's data.

282 To further interpret the results estimated by the two ICAR models, coefficients with no
283 possible zero estimates within the credible intervals (2.50% CI to 97.5% CI) are counted as
284 significant effects, marked "*Italic*" in *Table 2*.

285 Regarding the estimates, in relation to road network factors, the densities of 4-way
286 intersections and more than 5-way intersections are positively associated with the pedestrian
287 crash frequency and the risk. Bus stop density is only positively associated with the pedestrian
288 crash frequency. In contrast, the sidewalk density and the proportion of steep areas suggest
289 negative associations with the pedestrian crash frequency and the risk. When it comes to the land
290 use variables, the pedestrian crash frequency is positively correlated with land use mixture, but
291 negatively correlated with the proportion of industrial land use. The pedestrian crash risk is also
292 positively correlated with land use mixture. For travel demand forecast, walking mode share is
293 positively correlated with the pedestrian crash frequency. The total number of trips is positively
294 correlated with the pedestrian crash frequency but negatively associated with the pedestrian crash
295 risk.

296

297 **Table 1**

298 Variable definitions and data summary of predictors for the pedestrian crash frequency and the risk in Seattle TAZs (n = 863) average.

	Mean	SD	Min	Max	Description	Source
<i>Dependent Variable:</i>						
Pedestrian Crash Frequency	2.50	3.46	0.00	27.00	Number of pedestrian crashes	SDOT
Pedestrian Crash Risk	0.01	0.07	0.00	2.00	Number of pedestrian crashes/Forecasted number of pedestrian trips	PSRC
<i>Fixed Effects:</i>						
3-way Intersection	0.32	0.28	0.00	2.92	Number of 3-way intersections/zonal area (1/ha)	SDOT
4-way Intersection	0.44	0.34	0.00	3.26	Number of 4-way intersections/zonal area (1/ha)	SDOT
5-way Intersection	0.04	0.13	0.00	1.33	Number of more than 5-way intersections/zonal area (1/ha)	SDOT
Sidewalk Density	17.51	5.98	0.76	46.48	Sum of sidewalk length/zonal area (1km/km ²)	SDOT
Steep Area Proportion	0.02	0.04	0.00	0.25	Proportion of steep areas (0~1)	PSRC
Bus Stop Density	0.24	0.43	0.00	2.97	Number of bus stops/zonal area (1/ha)	King County
Zonal Speed Limit	25.00	4.68	20.00	51.73	Zonal-mean posted driving speed limit [mph]	SDOT
Household Density	0.23	0.35	0.00	5.40	Number of households/zonal area (1k/ha)	PSRC
Employment Density	0.79	2.11	0.00	20.86	Number of employments/zonal area (1k/ha)	PSRC
Land Use Mix ¹	0.47	0.20	0.00	0.95	Entropy of five types of land use (0~1)	PSRC
Commercial Land	0.09	0.15	0.00	0.88	Proportion of commercial and mixed land use	PSRC
Government & Office	0.09	0.15	0.00	0.90	Proportion of office and government land use	PSRC
Parks	0.05	0.13	0.00	0.92	Proportion of public parks	SDOT
Industrial	0.07	0.14	0.00	0.95	Proportion of industrial land use	SDOT
School Density	0.01	0.04	0.00	0.50	Number of schools/zonal area (1/ha)	SDOT
Activity Center Density	0.07	0.15	0.00	1.18	Number of activity centers/zonal area (1/ha).	SDOT
Walking mode share	0.17	0.11	0.02	0.50	Proportion of pedestrian trips divided by total number of trips (0~1)	PSRC
Number of Trips	7.00	5.02	0.00	61.10	Total number of trips (1k)	PSRC

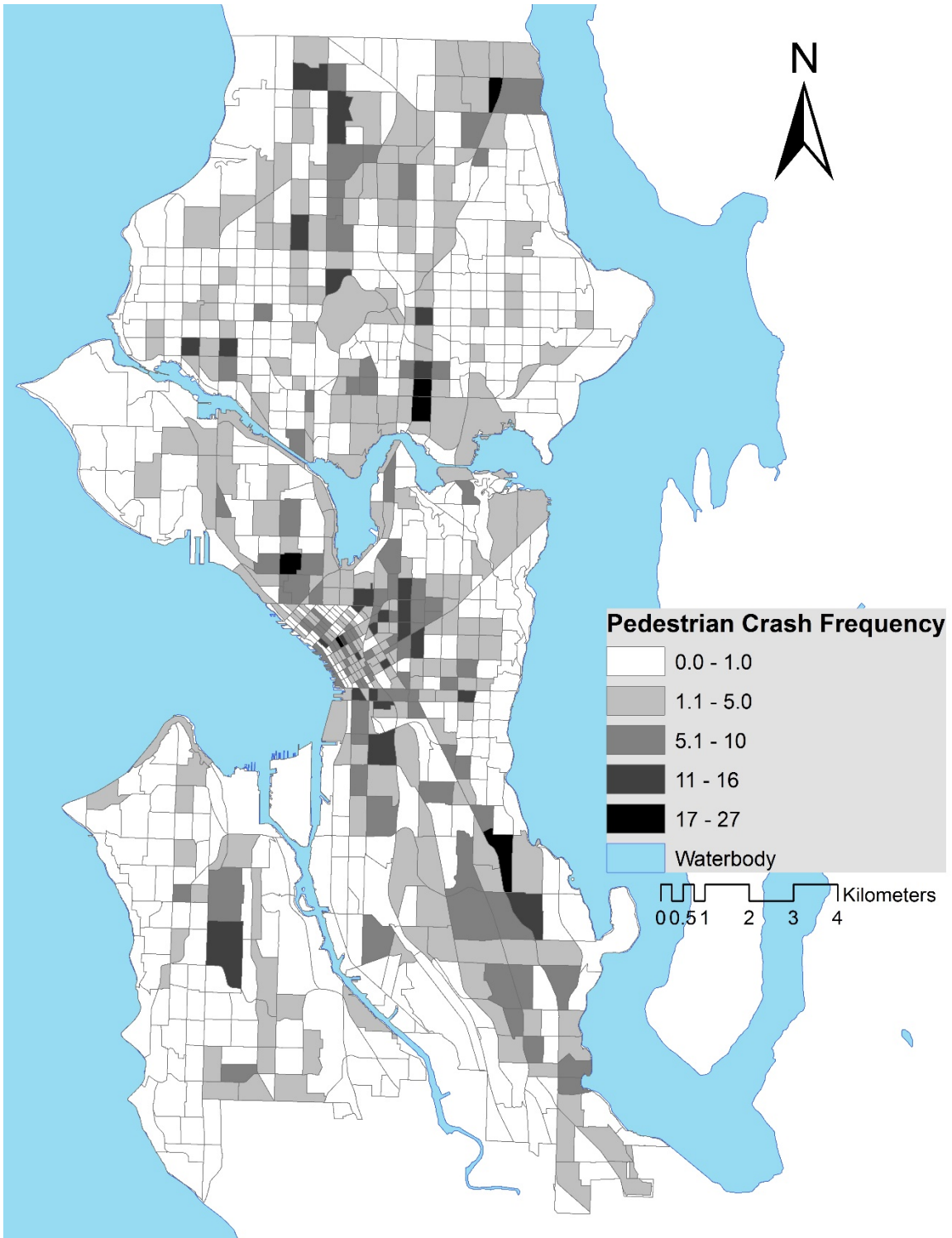
Considered but excluded variables						
<i>Transit Route Density</i>	<i>0.89</i>	<i>0.86</i>	<i>0.00</i>	<i>5.95</i>	<i>Sum of transit route length/zonal area (1km/km²)</i>	<i>King County</i>
<i>Street Lane Density</i>	<i>10.70</i>	<i>4.29</i>	<i>0.20</i>	<i>36.65</i>	<i>Sum of street length/zonal area (1km/km²)</i>	<i>SDOT</i>
<i>Crosswalk Density</i>	<i>0.68</i>	<i>1.18</i>	<i>0.00</i>	<i>11.70</i>	<i>Number of crosswalks/zonal area (1/ha)</i>	<i>SDOT</i>
<i>Average Slope</i>	<i>3.47</i>	<i>1.88</i>	<i>0.01</i>	<i>11.74</i>	<i>Zonal-mean gradient</i>	<i>SDOT</i>

299

300

301

302



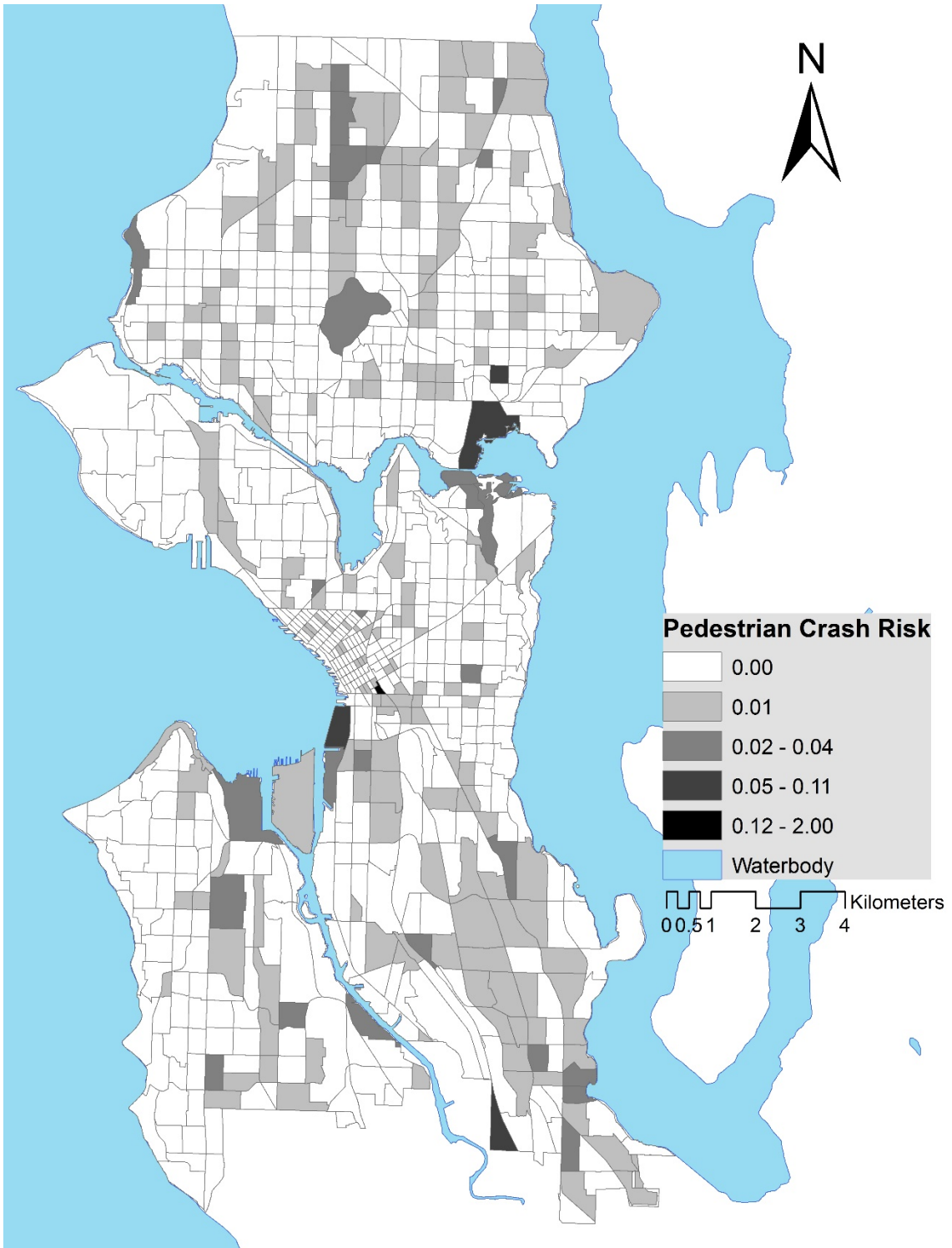
303

304

305

306

Fig. 1. The pedestrian crash frequency in Seattle TAZs, 2008~2012.



307

308

Fig. 2. The pedestrian crash risk in Seattle TAZs, 2008~2012.

309 **Table 2**

310 The estimates of Poisson-lognormal ICAR models (frequency versus risk) with 5-year pedestrian
 311 crash data.

	Pedestrian Crash Frequency Model			Pedestrian Crash Risk Model		
	Mean	2.5% CI	97.5% CI	Mean	2.5% CI	97.5% CI
Fixed effects:						
Intercept	-1.56	-2.38	-0.75	-6.88	-7.69	-6.09
3-way Intersection	0.03	-0.28	0.34	0.05	-0.27	0.37
4-way Intersection	<i>0.45</i>	<i>0.11</i>	<i>0.79</i>	<i>0.53</i>	<i>0.19</i>	<i>0.87</i>
5-way Intersection	<i>0.82</i>	<i>0.26</i>	<i>1.39</i>	<i>0.94</i>	<i>0.36</i>	<i>1.51</i>
Sidewalk Density	-0.03	-0.05	-0.01	-0.04	-0.07	-0.02
Steep Area Proportion	-5.72	-8.81	-2.73	-5.57	-8.65	-2.58
Bus Stop Density	<i>0.34</i>	<i>0.02</i>	<i>0.66</i>	0.28	-0.04	0.60
Stop Sign Density	-0.07	-0.30	0.16	-0.03	-0.26	0.19
Zonal Speed Limit	0.01	-0.01	0.03	<i>0.03</i>	<i>0.01</i>	<i>0.05</i>
Household Density	-0.08	-0.37	0.21	-0.22	-0.52	0.07
Employment Density	-0.04	-0.08	0.01	-0.05	-0.10	-0.01
Land Use Mix ¹	<i>2.05</i>	<i>1.48</i>	<i>2.62</i>	<i>1.41</i>	<i>0.85</i>	<i>1.98</i>
Commercial Land	0.29	-0.44	1.03	0.58	-0.12	1.28
Government & Office	-0.54	-1.23	0.15	-0.48	-1.15	0.20
Parks	0.32	-0.45	1.07	0.70	-0.09	1.47
Industrial	-1.25	-2.16	-0.34	-0.83	-1.68	0.02
School Density	-0.04	-1.79	1.69	0.06	-1.70	1.80
Activity Center Density	0.28	-0.19	0.75	-0.03	-0.50	0.44
Walking mode share	<i>3.43</i>	<i>1.30</i>	<i>5.62</i>	-0.66	-2.65	1.45
Number of Trips	<i>0.08</i>	<i>0.06</i>	<i>0.09</i>	-0.02	-0.03	0.00
Random effects:						
σ_v	3.08	1.88	4.67	2.45	1.72	3.34
σ_u	1.06	0.53	1.96	2.48	0.93	5.95
Marginal Likelihood	-2418.87			-2421.72		
Spatial Dependence $\frac{\sigma_u}{\sigma_u + \sigma_v}$	31.07%			17.05%		
Significant effects are marked in “ <i>Italic</i> ”.						

312

313 For road network features, the effects of intersection densities on the pedestrian crash
 314 frequency versus the risk vary depending on the types of intersections in this study. With regard
 315 to the densities of 4-way intersections and complicated intersections (more than 5-way), it shows
 316 positive associations with the pedestrian crash frequency and the risk. The effect of 3-way
 317 intersection density remains unclear. The findings of intersections’ effects on the pedestrian

318 crash frequency are generally consistent with a prior study was done for Montreal (Ukkusuri et
319 al., 2012). No previous study has examined the effects of different intersections on the pedestrian
320 crash risk. The positive associations between 4-way/5-way intersection and the pedestrian crash
321 risk may due to some unobserved factors, such as motorists' temporal behaviors or pedestrians'
322 traffic violation when crossing streets. In summary, pedestrians are more exposed to collisions
323 and risks at intersections.

324 Moreover, sidewalk density is negatively correlated with the pedestrian crash frequency
325 and the risk with Seattle's data, which is basically consistent with Wang and Kockelman's
326 finding (2013). This conclusion leads to a policy implication that densifying sidewalks can
327 improve walking environment safety for pedestrians.

328 The proportion of steep areas is selected to represent the zonal steepness of TAZs. This
329 variable suggests negative associations with the pedestrian crash frequency and the risk. This
330 may be due to that pedestrians are less likely to walk in steep areas by spending more physical
331 efforts and taking a higher risk of falling down.

332 The density of bus stops is a commonly used variable in modeling pedestrian crash
333 frequency. An agreed finding is that bus stop density is positively associated with pedestrian
334 crash frequency, with no exception of this study (Miranda-Moreno et al., 2011; Ukkusuri et al.,
335 2012; Wang and Kockelman, 2013). Stopped buses may block pedestrians' sights when crossing
336 the streets, and areas with better transit service are expected to have more human activities,
337 associated with more conflict between pedestrians and vehicles. These results indicate that
338 roadway design and bus stop location choice should be carefully considered. Separating barriers
339 should be placed between transit lanes and sidewalks. Bus drivers should slow down when they
340 are stopping, starting, and turning.

341 In relation to land use, a few studies suggest that pedestrian crash frequency is positively
342 correlated with commercial land use (Miranda-Moreno et al., 2011; Narayanamoorthy et al.,
343 2013; Wier et al., 2009), but this relationship is unclear with Seattle's data. This study shows a
344 negative association between industrial land use and pedestrian crash frequency, which is
345 consistent with Miranda-Moreno et al.'s finding for Montreal (2011), but inconsistent with
346 Ukkusuri et al.'s (2011, 2012) studies for New York. Industrial areas are mostly of the pedestrian
347 unfriendly environment. The likelihood of occurring a pedestrian crash in industrial areas is
348 expected to be rare event due to a low pedestrian volume. The effects of open lands on pedestrian
349 crashes were contradictory in two prior studies (Miranda-Moreno et al., 2011; Ukkusuri et al.,
350 2012), and such an effect is not able to be determined in this study. Land use mixture indicates
351 positive associations with the pedestrian crash frequency and the risk in this research, in contrast
352 with a negative association in Wang and Kockelman's study for Austin, Texas (2013). To
353 summarize, many land use effects appear to be inconsistently correlated with pedestrian crash
354 frequency in the prior research. Possibly the inconsistencies are due to the variations of different
355 urban forms between Montreal, New York, Austin, and Seattle, or due to the built environment
356 variables were quantified at different scales. More studies are expected to be conducted to raise
357 generalizable conclusions, or to confirm the effects of land use on pedestrian crash frequency
358 versus pedestrian crash risk are just case-specific.

359 Schools and activity centers are trip generators of pedestrian travels, especially for
360 teenagers, while the effects of school density are unclear in this research. The variable, density of
361 activity centers, including churches, public libraries, art centers, environment education centers,
362 playgrounds, neighborhood and community centers, also shows unclear effects with the
363 pedestrian crash frequency and the risk.

364 Prior research showed that traffic volume was positively associated with pedestrian crash
365 frequency (Miranda-Moreno et al., 2011). Since Seattle only has the traffic volume data on
366 arterials. This study chooses the TAZ-based forecasted number of trips as a substitute to traffic
367 volume. The effect shows a consistent positive relationship between the number of trips and the
368 pedestrian crash frequency with the data for Seattle. However, the number of trips shows a
369 negative association with the pedestrian crash risk in this study, indicating that pedestrians are
370 comparatively safe to walk in areas with a high level of traffic. To explain, pedestrians are more
371 exposed to crashes when there is more on-road traffic. As more cars and pedestrians on the
372 streets, driving speeds are declining, and thus the road environment is becoming safer. Similarly,
373 walking mode share indicates a similar contradictory relationship for the pedestrian crash
374 frequency and the risk. Walking mode share is positively associated with the crash frequency,
375 but negatively correlated with the crash risk. Again, as more pedestrians walking on the streets,
376 the likelihood of occurring a collision is increasing due to the increase of exposure.
377 Simultaneously, the crash risk is decreasing with pedestrians' increase because they are more
378 visible to motorists. Both of these results are reflections of the theory of *safety in numbers*.

379 Regarding socio-demographic factors, household density shows no significant effect
380 impacting the pedestrian crash frequency versus the risk; while employment density indicates a
381 negative correlation with the pedestrian crash risk. Again, it confirms the theory of *safety in*
382 *numbers* that walking is safer in dense employment centers.

383 **5. Conclusions and Limitations**

384 This study presents two TAZ-based ICAR models for pedestrian crash frequency versus
385 risk for Seattle, and various aggregated factors of road network, land use, socio-demographic,
386 and travel demand are investigated. The results show that spatial autocorrelations are
387 insignificant in the two models. The rest variability is mostly explained by unobserved
388 heterogeneities.

389 To conclude, intersection areas have more pedestrian crashes and higher risks because
390 both motorists and pedestrians are more exposed to collisions. However, it is not reasonable to
391 reduce the number of intersections, because intersection areas are the right places where
392 pedestrians and motorists interact with each other. Reducing intersections will result in more
393 speeding, less walking, and a greater probability of pedestrian's traffic violations at midblock.
394 Building footbridges or underpass at risk intersections are the other effective ways to reduce
395 pedestrian crashes. Additionally, the total number of trips show a contradictory relationship with
396 the pedestrian crash frequency and the risk. In particular, bus stop density and land use mixture
397 are positive predictors, while sidewalk density and zonal steepness are negative predictors of the
398 pedestrian crash frequency and the risk.

399 This rich data set allows us to draw important policy implications. Findings on the factors
400 of road network and land use are generally consistent between the two models, while
401 inconsistencies are shown in the estimates for travel demand characteristics and socio-
402 demographic factors. To make it brief, the policy recommendations drawn for local authorities
403 and transport engineers are: (1) densifying sidewalks can improve pedestrian safety; (2)
404 optimally isolating pedestrians and automobile traffic at intersection areas, especially those zones
405 with more bus stops; (3) assigning specific safety treatments to areas with multiple land use
406 purposes; and (4) advocating for walking conditional on the availability of well-planned facilities.
407 Pedestrian crashes are more likely to occur in activity centers, which are characterized as more
408 mixed land use and better street connectivity. It indicates that land use, roadway design, and road
409 safety management are jointly impacting the success of a walkable environment.

410 Urban design principles adopted from the new urbanism and smart growth encourage
411 applying the compact development to build sustainable cities, also called density, diversity, and
412 design (Cervero and Kockelman, 1997). These planning strategies contribute to the growth in the
413 number of pedestrians. However, this research suggests that greater street connectivity and more
414 mixed land use are associated with more pedestrian crashes and higher collision risks, which are
415 contradictory to these principles. The exposure to crashes is increasing along with the number of
416 on-road pedestrians. Yet, according to the aforementioned findings, planners and engineers
417 cannot blindly abandon those strategies for such induced pedestrian crashes and risks. Instead,
418 they should include pedestrian safety as a primary concern in practice as essential urban design
419 principles.

420 Regarding limitations of this research, a weakness is that the crash data covers a 5-year
421 period. The built environment features can be modified after crashes have occurred. In such a
422 long time, the temporal effect of built environment changes cannot be accurately tracked, and the
423 results can be possibly reported with biases. Secondly, underreporting of pedestrian crashes is
424 more likely to happen in suburban areas and local streets, especially for crashes of slight injuries.
425 In this context, the dependent variable can be biasedly reported. Thirdly, the geocoded crash sites
426 are snapped to the closest geometrical road centers or intersections in the ArcGIS, which are no
427 longer representing their original places. TAZs are mostly split by main arterials, and a crash
428 may just fall into the cross-boundary between two neighboring TAZs due to minor geocoding
429 errors. Accuracy improvements in geocoding and reporting are expected to improve the
430 preciseness of quantified built environment factors and the counted number of crashes. Fourthly,
431 a forecasted number of walking trips may not be the most appropriate exposure variable to
432 measure pedestrian crash risk. It cannot represent the real number of on road pedestrians because
433 its prediction is greatly based on origins and destinations. Better pedestrian counters should be
434 developed to record and forecast more accurate pedestrian volume data.

435 Future work could involve testing the inconsistencies shown in the effects of land use
436 factors, controlling the possible bias due to the temporal variations in the built environment and
437 different geospatial units, reporting crash geographical coordinates with improved accuracy, and
438 recording more precise pedestrian volume data for better safety research.

439

440 **Note**

441 1. LUM: land use mixture or the degrees of mixing land use, which is measured by

442
$$LUM = (-1/\ln n) * (\sum P_i * \ln P_i)$$

443 Where n is the number of different land use type classes in the TAZ and P_i is the proportion
444 of land in type i in the TAZ. This index is calculated separately for each TAZ. The resulting
445 variable LUM is the land use mix entropy index, which varies from 0 (homogeneous land use) to
446 1 (most mixed land use).

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