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Investigating proximity of crash locations to aging pedestrian residences

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A R T I C L E   I N F O

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A B S T R A C T

Many campaigns promote walking for recreation, work, and general-purpose trips for health and environmental benefits. This study investigated factors that influence the occurrence of crashes involving elderly pedestrians in relation to where they reside. Using actual pedestrian residential addresses, a Google integrated GIS-based method was developed for estimating distances from crash locations to pedestrian residences. A generalized linear mixed model (GLMM) was used to evaluate the effect of factors associated with residences, such as age group, roadway features, and demographic characteristics on the proximity of crash locations. Results indicated that the proximity of crash locations to pedestrian residences is influenced by the pedestrian age, gender, roadway traffic volume, seasons of the year, and pedestrian residence demographic characteristics. The findings of this study can be used by transportation agencies to develop plans that enhance aging pedestrian safety and improve livability.

1. Introduction

Transportation agencies across the United States (U.S.) are working with other organizations to promote walking due to its proven safety, health, and environmental benefits. Strategies such as complete streets policies, livable communities, and transit-oriented developments have been initiated to promote walking as a viable transportation mode. These efforts may not be successful if pedestrians perceive walking facilities as unsafe. Lower traffic fatality rates have been observed in walkable communities in comparison to automobile-oriented areas for both pedestrians and motorists (America Walks, 2017). Through walking, more than 50% of the U.S. population can meet the minimum requirements for moderate physical activity (America Walks, 2017). Moreover, walking contributes to environmental conservation by decreasing a portion of the greenhouse gas.

In 2014, on average, a pedestrian was killed every two hours and injured every eight minutes from traffic crashes on the U.S. roadways (NHTSA, 2014). There is a discernible increasing trend of pedestrian deaths caused by pedestrian-vehicle crashes (Fig. 1). As shown in Fig. 1, pedestrian fatalities increased by 4% from 2009 to 2015 (NHTSA, 2016, 2015, 2014). Even more alarming is the proportion of pedestrian crashes led to fatalities (pedestrian fatalities divided by total roadway fatalities), which increased from 10.5% in 2009 to 16% in 2015.

In Florida, walking is a common activity due to the year-round sunny and warm climate. Disturbingly, in 2000, Florida was ranked the highest in the nation for pedestrian fatalities at a rate of 3.13 per 100,000 residents, and 82% higher than the national average in 2003 (Dewey et al., 2003). Sixteen years later, Florida is still ranked top in the pedestrian fatalities at 2.66 annual pedestrian fatalities per 100,000 residents. Although the pedestrian crash rate has declined over the years, pedestrian safety continues to be a focus area in Florida. When considering the Pedestrian Danger Index (PDI), used to measure the condition of pedestrian facilities in an area, Jacksonville, Florida has the highest increase in the nation. Similarly, the Orlando-Kissimmee metro area is ranked in the top twenty areas with the highest increased PDI from 2011 to 2016 (Smart Growth America, 2017). The PDI is the rate of pedestrian fatalities relative to the number of people who walk to work in an area e.g. a city (Smart Growth America, 2017). These statistics are upsetting, especially for the aging population, which is expected to increase each year.

In 2014, the aging population (65 years and older, referred to as 65+) in the U.S. consisted of approximately 15% of the population; however, this proportion is expected to rise to 22% by 2040. In Florida, the 65+ age group represented 18% of the total population, according to the 2000 census, and is projected to be 27% by 2030 (U.S. Department of Health and Human Services, 2017). Due to the reduced visual, hearing ability and compromised agility, elderly pedestrians have a higher likelihood of being involved in a crash while walking (Dewey et al., 2003). The decline in cognitive ability coupled with dementing diseases such as Alzheimer's disease increase the possibility of involving elderly pedestrians in crashes (Gorrie et al., 2008). The U.S. crash data for 2014 indicated that elderly pedestrians (65+) accounted for 20% of all pedestrian fatalities despite being only 15% of the population (NHTSA, 2014; United States Census

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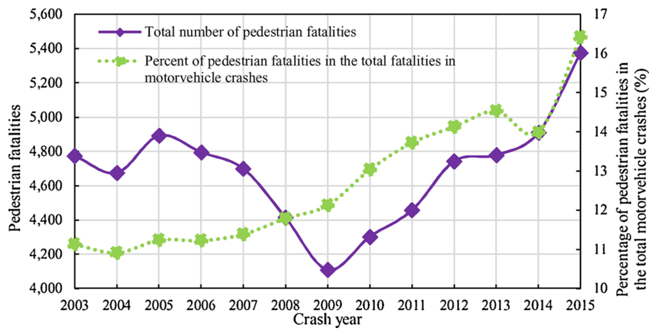


Fig. 1. Pedestrian fatalities in the U.S. traffic crashes from 2003 to 2015 source: (NHTSA, 2016, 2015, 2014).

Bureau, 2017. A recent report (Smart Growth America, 2017) provides further evidence that the 65+ age group has a higher than average risk of fatalities by suggesting that elderly pedestrians are 50% more likely to be involved in a fatality crash than younger pedestrians. In 2015 alone, 6,165 out of 35,092 (18%) pedestrian crashes nationwide involved elderly pedestrians (NHTSA, 2017). These statistics indicate the present and future challenges in ensuring the safety of aging pedestrians.

Aging road users (65+) travel less (24 person miles per person) and take longer to walk short distances than their younger counterparts (Santos et al., 2011; Yang and Diez-Roux, 2012). The number of fatalities per miles walked is greater for the elderly pedestrians than younger pedestrians (Dewey et al., 2003) due to a higher mortality rate of the elderly than the young for a comparative injury severity (Gorrie et al., 2008). In addition to the increase in aging population, this observation of the 65+ walking shorter distances than younger pedestrians, yet being overrepresented in fatalities, requires special attention, and raises concern about the proximity of crash locations to elderly pedestrian residences. Understanding the relationship between the proximity of crash locations to pedestrian homes may help transportation engineers and planners improve pedestrian safety. For example, walking facilities that accommodate common issues of elderly pedestrians, such as diminished hearing, poor vision, and the use of assistive devices, in areas with a high population of 65+, may reduce incidences. The literature on the influence of the distance between crash occurrence locations and pedestrian residences is scarce. Therefore, there is a need to investigate the proximity of crash locations to pedestrian residences and its relationship with demographic attributes to assist transportation officials in developing strategies that improve safety for aging pedestrians.

2. Literature review

In a recent study, the relationship of driver's residential proximity to crash location was conducted in South Carolina (Brown et al., 2016). The study observed that almost 35% of crashes in the state, overall, occurred within 5 miles of the involved driver's residence. However, these findings may not apply to pedestrian crashes since walking distances are shorter than distances covered by other modes of transportation. An older study (Abdalla et al., 1997) found that the frequency of pedestrian casualties diminished with decreasing distances from the residence location. Interestingly, the distance from residential zones to the crash locations increased with respect to the increase in age. However, this trend changed at the age 59 where crash location proximity decreased with the increase in age. The study also found that pedestrians who were involved in collisions that occurred at distances greater than 1.6 miles from their residences used other modes of transportation to reach the crash location site. This observation is supported by the fact that only 18% of walking trips in the U.S. are longer than 1 mile (Yang and Diez-Roux, 2012).

By associating crash occurrences with land-use attributes, Graham and Glaister (2003) suggested that the likelihood of pedestrian casualties is higher in residential areas than in commercial areas. Medium land use intensity is associated with more pedestrian crashes than both low and high land use intensity (Wang et al., 2016). Moreover, many corridors that pose a high injury risk to pedestrians carry heavy and high-speed traffic in the suburbs. These corridors also intersect with local streets comprised of businesses (e.g., restaurants or gas stations) that are mixed with residential properties (Dai, 2012). The pedestrian casualty rate is four times higher for residents in depressed areas than those in affluent areas (Abdalla et al., 1997). A similar remark by Graham and Glaister (2003) suggests that the probability of a pedestrian crash occurring in a considerably depressed area is 2.7 higher than in better areas. Higher pedestrian crash frequency in low-income households than in high-income households is influenced by higher unemployment rates, lower education attainment and low vehicle ownership (Chimba et al., 2018). Despite having distinct casualty rates, Abdalla et al. (1997) observed no difference in the number of elderly casualties between depressed and affluent areas which may be due to aging road users making fewer trips than younger groups and being more risk-averse.

Previous efforts to evaluate the relationship between crash locations and proximity to the residences had limitations, especially in determining the proximity distances. For example, Brown et al. (2016) used ArcGIS to establish centroids of 9-digit zip code zones which represented the driver's residence and established the distance to the corresponding crash location. This assumption is prone to underestimation or overestimation of the calculated distances, especially for residences located near the border of a zip code region. Similarly, Abdalla et al. (1997) used grid references to establish distances between crash location and the corresponding casualty's residence zone. This methodology is based on calculating the Euclidian distance between points, which does not reflect the actual distance between locations defined by the roadway network.

In order to fill the knowledge gap in understanding the proximity of residences to locations of aging pedestrian crashes, this study had two objectives. First, to demonstrate a GIS-based method of automating the computations of distances from pedestrians and the involved driver's residences to the crash locations. This study used actual physical addresses of pedestrians and drivers involved in crashes to address limitations of previous proximity studies. Second, the study evaluated the association of the proximity to both macro and micro-level characteristics to determine factors that influence the proximity of the pedestrian crash locations to residences. To achieve this objective, a generalized linear mixed model associated proximity of crash locations with variables that can impact the likelihood of an elderly pedestrian to be involved in a traffic accident close to or far from home.

3. Data description

This study used two main data sources – the Florida Department of Transportation (FDOT) Unified Basemap Repository (UBR) for crash data and the Florida Geographic Data Library (FGDL) for demographic and land-use data. A total of 1,068 crashes involving pedestrians aged 65 years and older that occurred on FDOT maintained roadways were retrieved from the FDOT UBR database for the study period of 2008–2013. These crashes involved pedestrians aged 65 years and older that occurred in the state of Florida from 2008 to 2013. Fig. 2 shows the spatial distribution of the analyzed crashes and residences of pedestrians involved in the crashes. The dataset contained crash attributes that include specific crash characteristics, driver/pedestrian information, and roadway attributes. Even with the abundance of crash attributes, UBR data did not include the residential addresses of individuals involved in crashes. Therefore, police crash reports were reviewed to obtain the corresponding residential addresses. The process involved reviewing each crash report and linking the pedestrians' and drivers' address to the corresponding crash data retrieved from the UBR. About 8% of crashes were not included in the analysis because the crash reports did not contain residential addresses of the involved drivers. Also not included in the analysis were records with addresses outside of U.S., indicating that the driver or pedestrian was not a U.S. resident.

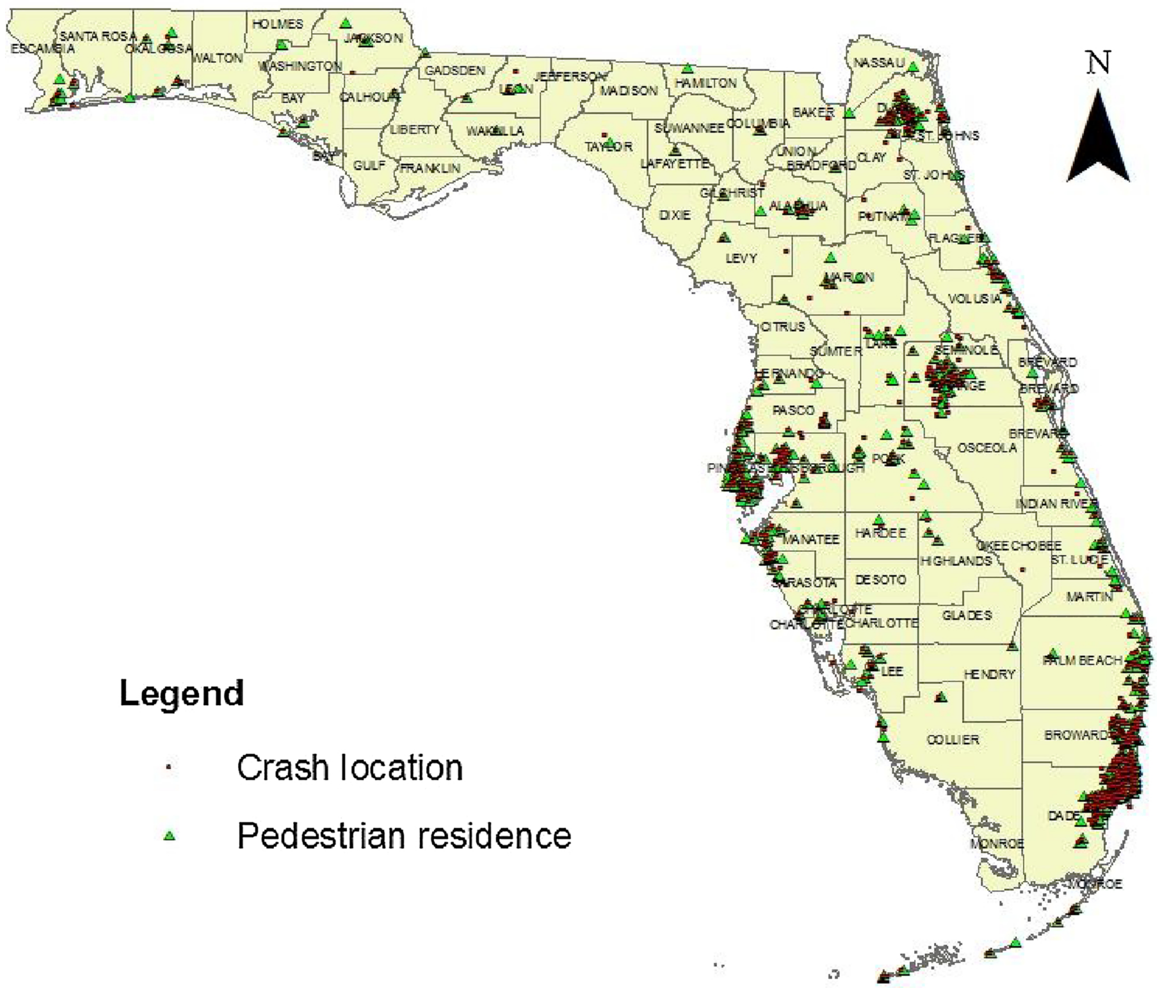


Fig. 2. A map of crash locations and pedestrian residences in Florida counties.

Florida demographic and land-use data used in were obtained from the FGDL. Two GIS geodatabases were used for the study: the 2010 census block groups in Florida prepared by the University of Florida GeoPlan Center, and the 2012 Florida parcel data prepared by the Florida Department of Revenue. Census block groups contained demographic data used by the FDOT for their Community Characteristic Inventory Report (CCI). Florida parcel data contained parcel boundaries with each parcel being associated with tax information from the Florida Department of Revenue tax database. Not all attributes in these geodatabases were used in the study. Selection of relevant attributes was consistent with previous literature related to the influence of demographic and land-use characteristics on crashes, such as Abdalla et al. (1997) and Graham and Glaister (2003).

4. Methodology

Two main techniques were used to analyze data for this study. The first technique employed the Geographic information system (GIS) for spatial analyses to determine the proximity of crash locations to pedestrian and driver residences and then to spatially associate demographic data with crashes. The second technique involved generalized linear mixed model in examining the significance of the considered factors on the proximity of crashes to pedestrian residences. The following sections provide a detailed discussion of the methods used.

4.1. GIS model

Fig. 3 shows a graphical presentation of the developed GIS model. The model is comprised of processes that include: geocoding residence addresses, estimating the shortest path distance from crash locations to residences, and associating crash locations and pedestrian residences to their surrounding demographic and land-use characteristics.

4.1.1. Geocoding residences

Geocoding addresses contained in the GIS input data involved the integration of GIS application to Google API (application programming interfaces) services. This process converts addresses into geographic coordinates that can be used as place markers or positions on the map. A python script provided in Appendix A was applied in the GIS model so that a request for coordinates of all addresses in the input crash data was sent to the Google Maps geocoding API. The returned coordinates were added to the attribute table of the input data as specified in the GIS model.

4.1.2. Computing distances from crash location to residences

The process of determining distances from crash locations to pedestrian residences for the entire dataset was automated by creating a tool using a python script provided in Appendix A. Embedded in GIS, the script requests the Google map distance matrix API to calculate the distance between crash location coordinates and their corresponding pedestrian and driver residence coordinates obtained from geocoding process. The Google map distance matrix API is a service that provides distance and duration of travel for a matrix of origins and destinations. Distances are calculated based on a network of travel facilities (roads, sidewalks) instead of the Euclidean distance, which measures the shortest distance between two points regardless of the existing spatial limitations. Considering that the actual route used by pedestrians who

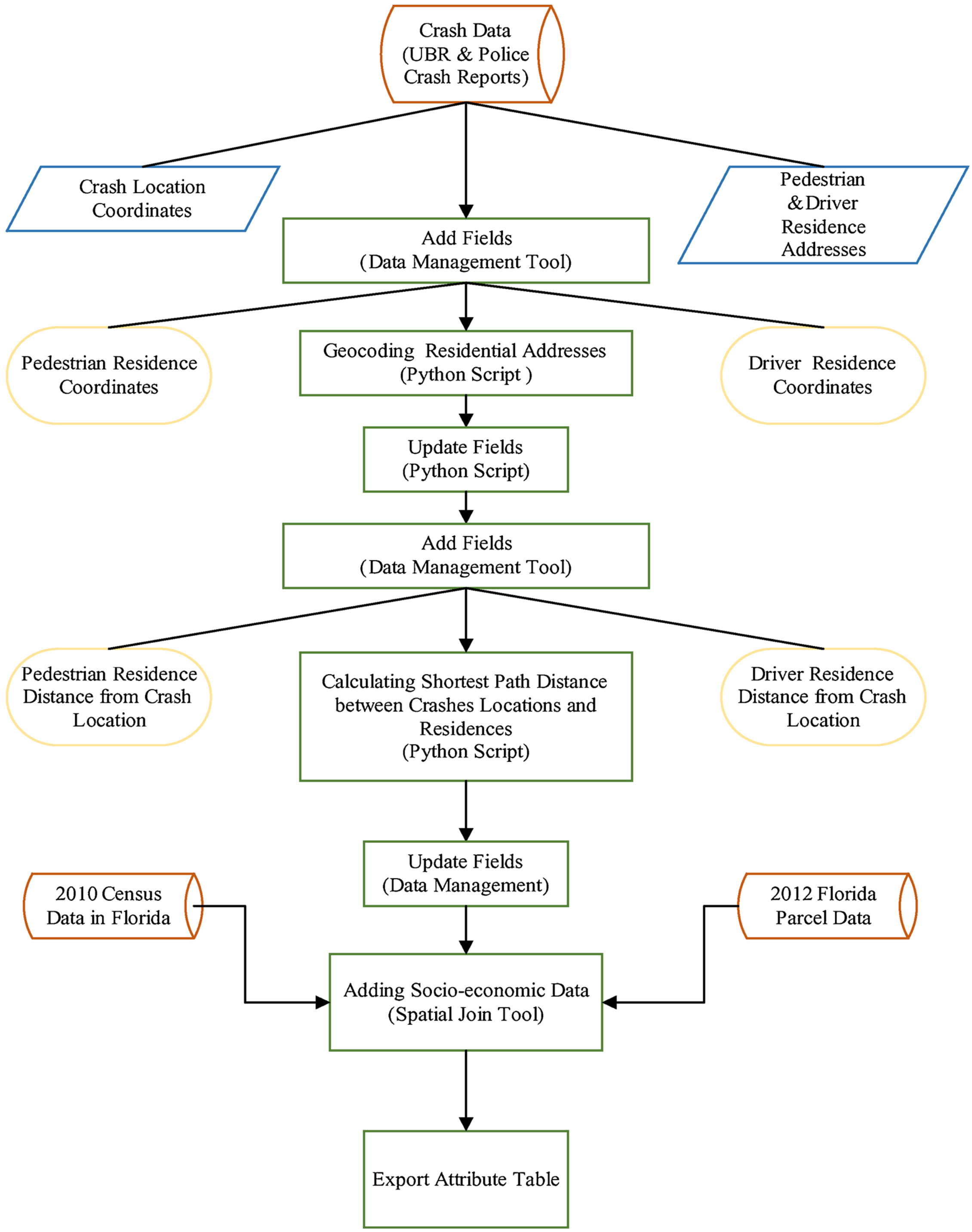


Fig. 3. GIS model processes.

were involved in crashes cannot be defined with certainty, the shortest path distance which is usually the first option provided to the users of navigation apps (e.g., Google maps) was used as the estimated distance between crash locations and residences. Google maps distance matrix API also offers options such as mode of travel. In this study, walking and driving were specified as modes of travel. For walking, distances were calculated based on a network of pedestrian paths and sidewalks. In the absence of pedestrian facilities, the API estimated distances along the driving roadway network.

A challenge in the estimation of distances between pedestrian residences and crash locations was to identify the mode of travel used by pedestrians before their involvement in a crash. Although there is no doubt that the pedestrians were involved in a crash while walking, it could not be confirmed whether pedestrians walked from their residences or used different mode(s) of transportation before walking. A statistical Welch *t*-test was performed to examine whether using a walking versus driving distance would yield different results. Data assumptions required for a Welch *t*-test, i.e., continuous data, related groups/matched pairs, the absence of outliers and normality, were checked before the test. Results from this preliminary process (Table 1) suggested the absence of sufficient evidence to signify that distances estimated considering the two modes of transportation are different at the 95% level of confidence. In other words, the estimated walking and driving distances between crash locations and pedestrian residences are

Table 1
Welch *t*-test results for the difference between walking and driving distance.

Difference = mu (Walking) − mu (Driving)			
Estimate for difference	−0.697		
95% CI for difference	(−4.306, 2.913)		
t-test of difference = 0 (vs not equal to 0)	*t*-value = −0.38	*p*-value = 0.705	df = 1551

not different. Walking and driving distances are statistically similar although estimation was based on different facilities i.e. sidewalks versus roadways. Therefore, the walking distance was used to measure the proximity of the crash locations to pedestrian residences.

4.1.3. Spatial join

A GIS spatial join tool was used to associate crash locations and respective pedestrian residences with demographic and land-use characteristics. The tool joined attributes of one feature class to another based on their spatial relationship and produced an output feature class. The output feature class contained all attributes of each crash that are important for statistical modeling.

4.2. Statistical modeling – generalized linear mixed model

4.2.1. Model formulation

A dichotomous response variable for describing proximity (close to or far from home) of crash locations to pedestrian residences was linked to explanatory variables using a generalized linear mixed model. This model extends the generalized linear model by adding normally distributed random effects on the linear predictor scale (Fong et al., 2010). The proximity of an elderly pedestrian's home to a crash location was modeled as a response variable using the generalized linear mixed model as shown in Eq. (1).

$$S_{ij} = \beta_o + \beta X_{ij} + \varepsilon_{ij} + \eta_j \tag{1}$$

Where S_{ij} is the value of the function (logit link) determining the involved pedestrian *i's* proximity from pedestrian *i's* residence within each group level *j* (in this case population density at the crash location), β_o is constant term, β is a vector of coefficient estimates, X_{ij} is a vector of covariates which affect the occurrence of accidents in the proximity of pedestrian residences, η_j is the group (crash locations) specific effect with zero mean and assumed to be normally distributed, and ε_{ij} is the error term at an observational level that is assumed to be normally distributed (Chen and Tarko, 2014; Heydari et al., 2014).

From the generalized linear mixed model with logit link function (Eq. (1)), the probability of pedestrian being involved in an accident close to pedestrian's home within a specific group level was estimated using Eq. (2).

$$P_{ij} = \frac{exp(\beta_o + \beta X_{ij} + \varepsilon_{ij} + \eta_j)}{1 + [\exp(\beta_o + \beta X_{ij} + \varepsilon_{ij} + \eta_j)]} \tag{2}$$

Where by P_{ij} is the probability of pedestrian *i* being involved in an accident at a distance close to pedestrian's home within location group *j* (defined by the population density). Other notations have similar description provided for the generalized linear mixed model function (Eq. (1)).

4.2.2. Model goodness-of-fit

The goodness-of-fit for each developed model was assessed using the marginal R-squared ($R^2_{GLMM(m)}$) and the conditional R-squared ($R^2_{GLMM(c)}$). $R^2_{GLMM(m)}$ and $R^2_{GLMM(c)}$, represent the variance explained by fixed factors, and the variance explained by both fixed and random factors, respectively (Nakagawa and Schielzeth, 2013). Eqs. (3) and (4) show mathematical formulae of the two goodness-of-fit tests.

$$R^2_{GLMM(m)} = \frac{\sigma_f^2}{\sigma_f^2 + \sum_{i=1}^{u}\sigma_i^2 + \sigma_e^2 + \sigma_d^2} \tag{3}$$

$$R^2_{GLMM(c)} = \frac{\sigma_f^2 + \sum_{i=1}^{u}\sigma_i^2}{\sigma_f^2 + \sum_{i=1}^{u}\sigma_i^2 + \sigma_e^2 + \sigma_d^2} \tag{4}$$

Whereby σ_f^2 is variance calculated from fixed components, σ_e^2 is the additive dispersion component of residual variance, σ_d^2 is the distribution-specific variance, σ_i^2 is the variance component of the i^{th} random factor and u is the number of random factors in the mixed model (Nakagawa and Schielzeth, 2013).

4.2.3. Response variable categorization

A response variable, proximity (close or far from home), was categorized by using four different distance thresholds (D = 0.5 miles, 1 mile, 1.5 miles and 2 miles). Four models were developed, one for each response variable category. It was important to use different thresholds to examine the effect of different variables as the distance increased. Yang and Diez-Roux (2012) observed that most walking trips (97%) are less than 2 miles. Therefore, the study used a distance of 2 miles as the upper limit for defining distances close to home. The selection of other thresholds apart from 2 miles, in the increment of 0.5 miles was arbitrary.

4.2.4. Selection of independent model variables

Table 2 lists all the independent variables used in the model development. All the variables except traffic volume and population were categorical. Driving distance of 5 miles was considered as a threshold for driver's proximity to crash location based on literature (Brown et al., 2016). A residential property value of $220,000, which represents the median property value in the state of Florida (Wilson, 2009), was used as a threshold for categorizing low and high property values. A $50,000 cut-off was used to define low and high income based on data from the U.S. household income survey (Posey, 2016). Furthermore, using the correlation matrix provided in Appendix B, it was observed that there is no strong correlation among independent variables.

Crashes were divided into the following three groups based on the population density of the crash location: population density $\leq$2000 persons per square mile, between 2000 and 3500 persons per square mile, and $\geq$3500 persons per square mile. Table 2 provides the distribution of crashes according to the population density of crash locations. About 24%, 18%, and 58% crashes occurred in areas with the population density $\leq$2000, between 2000 and 3500, and $\geq$3500 persons per square mile, respectively. The average and standard deviation of the distance between crash locations and pedestrian residences in areas with the population density $\leq$2000 persons per square mile were 4 miles and 5.7 miles, respectively. Similarly, the average and standard deviation of the distance between crash locations and pedestrian residences in areas with the population density between 2000 and 3500 persons per square mile were 3 miles and 4.5 miles, respectively. Finally, the average and standard deviation of the distance between crash locations and pedestrian residences in areas with the population density $\geq$ 3500 persons per square mile were 2 miles and 4 miles, respectively.

5. Results and analysis

5.1. Descriptive statistics

Over the study period, 89% of pedestrian crashes involved the 65+ pedestrians who primarily reside in Florida. Of the 1068 crashes, 87% involved drivers who reside in Florida. For the remaining 13% of drivers, 5% were drivers who reside out-of-state while 8% were unknown drivers. After removing crashes involving pedestrians or drivers who were out-of-state residents or were unknown, a total of 784 crashes contained complete data for further analysis. Fig. 4 shows the percentage of the 784 crashes with their respective distance thresholds used

Table 2
Description of Independent Variables for Crash Proximity Model.

Variable	Category	Count	Share
Pedestrian and driver attributes			
Pedestrian age (years)	65–75	471	60%
	76+	313	40%
Pedestrian gender	Male	469	60%
	Female	315	40%
Pedestrian injury severity	Non-Fatal	600	77%
	Fatal	184	23%
Driver proximity (miles)	≤5	360	46%
	> 5	424	54%
Demographic attributes			
PR[a] median household income (USD)	≤50,000	572	63%
	> 50,000	212	27%
PR[a] property value (USD)	≤220,000	485	62%
	> 220,000	299	38%
PR[a] population	Continuous data		
PR[a] population density (persons/square mile)	≤2000	161	5%
	2000–3500	126	21%
	≥3500	497	16%
PR[a] elderly population (%)	0–20%	491	63%
	> 20%	293	37%
CA[b,c] population density (persons/square mile)	≤2000	191	24%
	2000–3500	141	18%
	≥3500	452	58%
Land-use attribute			
CA[b] land-use	Commercial	478	61%
	Other (Residential, school zones, etc.)	306	39%
Roadway attributes			
Crash location	Intersection	479	61%
	Not Intersection	305	39%
Traffic volume (vehicles/day)	Continuous data		
Environmental attributes			
Season	Spring (January – April)	283	36%
	Summer/Fall (May – December)	501	64%
Weather condition	Clear	619	79%
	Other (Cloudy, Fog, Rain)	165	21%
Crash day	Weekday	612	78%
	Weekend	172	22%
Traffic condition	Off-peak hour (19:00–6:00, 10:00–15:00)	337	43%
	Peak hour (6:00–10:00, 15:00–19:00)	446	57%

Notes:
[a] Pedestrian Residence.
[b] Crash Area.
[c] Random effects variable.

for proximity categories. Fig. 4 indicates that 36% of the elderly pedestrian crashes occurred within 0.5 miles of the pedestrian residences. A one-mile threshold suggests an approximately equal split of the pedestrian crashes occurring within and outside of a mile from home. More than 60% of crashes happen within 2 miles of a pedestrian home.

It is worth mentioning that the Florida metropolitan areas of Miami, Tampa, Orlando, and Jacksonville were associated with the highest number of residents involved in pedestrian crashes compared to other cities, which is attributed to the high population in these metropolises. An estimated 52% of 65+ pedestrians involved in crashes occurred in these cities compared to the remaining 48% occurring throughout the state. Fig. 5(a) provides further details on the proximity of 65+ pedestrian crashes to their residences for metropolitan areas in Florida. It can be observed that the Miami-Ft. Lauderdale area contains the most crashes involving 65+ pedestrian regardless of their residence proximity. Fig. 5(b) shows a similar trend in the distance of occurrence of pedestrian crashes for all major cities except the Orlando-Kissimmee area. Approximately 50% of crashes in Orlando-Kissimmee occur at a distance of more than 2 miles from home. This trend is associated with the presence of many travelers in the region, which means most of the elderly involved in these crashes do not live near the city (Fig. 5).

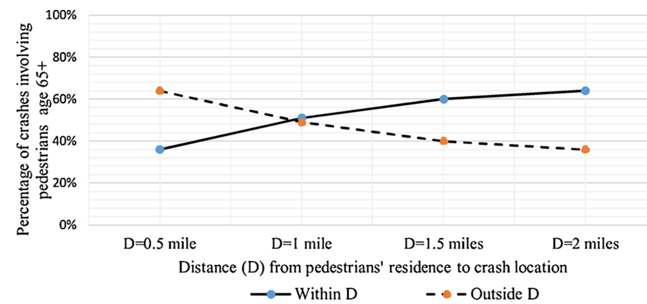


Fig. 4. Crashes occurrence distance from pedestrian residences in Florida.

5.2. Model results

The crash proximity mixed-effect models for different distance thresholds (D) show factors that affect the occurrence of pedestrian crashes close to or far from pedestrian residences. The values given in Table 3 describe factors that influence the proximity of crash locations to residences of 65+ pedestrians. The goodness-of-fit results $R^2_{GLMM(m)}$ and $R^2_{GLMM(c)}$ in Table 3 shows the percentage of explained variance in all models. The values are greater than 0.1 which can indicate a quality model (Islam and Jones, 2014; Ulfarsson et al., 2010) considering that the predictor variables such as personal attributes and environmental characteristics are highly susceptible to randomness and unpredictability. In other words, the model is able to explain a little of a lot of variance as opposed to a lot of a little variance as suggested by Washington et al. (2003). The following sections discuss the significant variables that influence the proximity of the crash location to elderly pedestrians.

5.2.1. Pedestrian age

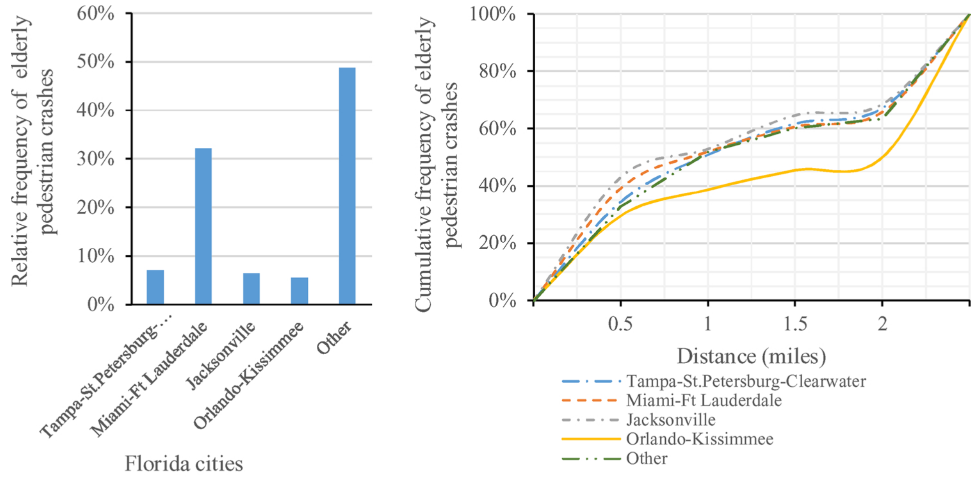
Table 3 shows that pedestrian age is a significant variable regardless of the distance threshold. Negative coefficients (−0.338, −0.592, −0.587, −0.623) for pedestrian age indicate a reduction in the likelihood of pedestrians aged 76 years and above being in a crash closer to home as compared to those aged 65 to 75 years. This observation is associated with the walking behavior of cohorts within the elderly pedestrian age group. Individuals aged less than 75 years are more inclined to walk, which increases their exposure to crashes close to home. In contrast, people aged 75+ years, who are less physically active, perform fewer walking activities, yet tend to be involved in crashes at distances far from home. This observation is associated with the use of other modes of transportation to reach areas near the crash location before walking.

5.2.2. Gender

Results from the study suggest that elderly male pedestrians (0.264, 0.276, 0.217, 0.233) have a higher likelihood of being involved in pedestrian crashes closer to their residences, compared to female pedestrians. This may be attributed to higher physical activity levels amongst older men than older women (Lim and Taylor, 2005; Sun et al., 2013) and the general population characteristic of men walking longer distances and durations than women (Yang and Diez-Roux, 2012). Moreover, women have a higher risk perception of being involved in a crash when walking at neighborhood locations than men (Rankavat and Tiwari, 2016). For these reasons, senior men are more involved in crashes close to their residences while senior women are associated with crashes that are far from home, most of which include the use of another mode of transportation presumably driving before getting into a crash as pedestrians.

5.2.3. Drivers' residence proximity

The positive coefficients (0.287, 0.398, 0.643, and 0.714) suggest a higher likelihood for drivers who live far from the crash location to be involved in a crash with pedestrians walking close to their homes. Drivers are usually familiar with the traffic pattern, challenges, or



(a) (b)

Fig. 5. Distribution of crash events involving 65 + pedestrians: (a) in Florida (b) according to the proximity of crash locations to pedestrians' residence.

conflicts related to roadways near their residences; this helps them avoid conflicts with other road users such as pedestrians. Drivers who are using roadway facilities that a far from their residences are more susceptible to conflicts with pedestrians who are walking close to their residences than drivers who live near pedestrians' homes. This observation is consistent with results from Brown et al. (2016) which suggested that 65% of crashes (pedestrian or not) occurred outside 5 miles of the driver residences.

5.2.4. *Traffic volume*

Results from Table 3 (0.195, 0.123, 0.089, 0.088) show that roadways with high traffic volume are associated with crashes that involve elderly pedestrians who are residents of the areas close to the crash locations. This finding can be related to the impact of a mixed environment on non-motorized road users. Pedestrians are likely to be subjects of a crash when walking close or along high volume facilities near their residences due to the increased risk for pedestrian crashes with the increase in traffic flow (Leden, 2002). Typically, these facilities have vehicles moving at high speeds which make it difficult for pedestrian activities and older pedestrians are vulnerable at crossing locations where vehicles usually proceed unimpeded (Koepsell et al., 2002).

Table 3
Model Estimation Results for Different Proximity Thresholds.

		D = 0.5 mile		D = 1 mile		D = 1.5 mile		D = 2 miles	
Variable	Category	Coef.	Pval.	Coef.	Pval.	Coef.	Pval.	Coef.	Pval.
Constant		−0.478	0.224	−0.064	0.085	−0.751	0.046	−0.977	0.012
Pedestrian and driver attributes									
Pedestrian age(years)	75 +	−0.338	0.040	−0.592	0.000	−0.587	0.000	−0.623	0.000
Pedestrian gender	Male	0.264	0.108	0.276	0.078	0.217	0.178	0.233	0.161
Pedestrian injury severity	Fatal	−0.252	0.202	−0.125	0.503	−0.168	0.383	−0.200	0.319
Driver proximity(miles)	Above 5	0.287	0.076	0.398	0.009	0.643	0.000	0.714	0.000
Demographic attributes									
PR[a] median household income(USD)	Above 50,000	0.519	0.006	0.376	0.029	0.424	0.014	0.375	0.036
PR[a] property value(USD)	Above 220,000	−0.573	0.000	−0.657	0.000	−0.552	0.000	−0.543	0.001
PR[a] population	Continuous	0.093	0.208	0.163	0.020	0.151	0.021	0.178	0.012
PR[a] population density(persons/square mile)	2000–3500	0.102	0.713	0.011	0.966	0.063	0.807	−0.013	0.961
	Above 3500	−0.258	0.243	−0.233	0.264	−0.326	0.211	−0.407	0.063
PR[a] elderly population(%)	Above 20%	0.257	0.138	0.019	0.908	−0.025	0.877	−0.117	0.501
Land-use attribute									
CA[b] land-use	Other	0.222	0.182	0.060	0.701	−0.036	0.819	−0.146	0.376
Roadway attributes									
Crash location	Not Intersection	0.150	0.372	−0.039	0.802	−0.057	0.163	0.061	0.716
Traffic volume	Continuous	0.195	0.000	0.123	0.000	0.089	0.039	0.088	0.050
Environmental attributes									
Season	Summer/Fall	0.306	0.067	0.209	0.188	0.179	0.273	0.139	0.411
Weather condition	Other	0.110	0.224	0.049	0.791	0.123	0.519	0.173	0.310
Crash day	Weekend	−0.191	0.322	−0.203	0.274	−0.244	0.203	−0.106	0.592
Traffic condition	Peak	−0.068	0.667	−0.084	0.587	−0.232	0.144	−0.234	0.155
σ_ε		0.300		0.207		0.462		0.447	
σ_u		0.457		0.475		0.251		0.341	
$R^2_{GLMM(m)}$		0.12		0.12		0.13		0.15	
$R^2_{GLMM(c)}$		0.14		0.12		0.13		0.16	

Coef. = Coefficient, Pval. = P-value, Underlined P-values show significant variables at 90% level of confidence.
Notes:
[a] Pedestrian Residence.
[b] Crash Area.

5.2.5. Census tract population

An increase in the population of a census tract increases the probability of elderly pedestrians being hit closer to home (0.093, 0.163, 0.151, 0.178). It is hypothesized that high-populated areas result in the origin and destination of many pedestrian trips; hence, pedestrian-vehicle conflicts are more likely to occur close to these locations. This finding agrees with Graham and Glaister (2003) which indicated that more pedestrian casualties occur in populated areas than in other locations due to the increase in potential pedestrians and higher traffic generation. Similarly, LaScala et al. (2000) and Ukkusuri et al. (2011) observed that larger populations resulted in more pedestrian crashes and suggested that countermeasures to minimize pedestrian vehicle-conflicts in highly populated areas will reduce pedestrian crashes.

5.2.6. Residence value

Coefficients from Table 3 (−0.573, −0.657, −0.552, −0.543) suggests that higher residential property values decrease the probability of elderly pedestrian crashes to occur close to home. This residence characteristic has a significant impact when crashes occurring close to home are within one mile of pedestrian residences. Elderly pedestrians may feel less comfortable walking in areas where higher property values are associated with heavy commercialized properties, such as downtown highrise condominiums or apartments. These areas commonly possess higher traffic volumes, congested intersections and crosswalks, impatient drivers with little respect for the rules of the road, and poor visibility (Chaudhury et al., 2012). In suburban areas, where higher property values are associated with more gated communities, there may be fewer destination sites in the vicinity, in turn limiting elderly pedestrian activities close the residences.

5.2.7. Pedestrian income

High pedestrian income (more than $50,000) has a positive impact (0.519, 0.376, 0.424, 0.375) on the likelihood of pedestrian crash that occurred near a pedestrian's residence. This suggests that residents of areas with higher household incomes tend to experience crashes close to their homes. On the contrary, residents of areas with lower household incomes are more likely to be involved in crashes far from their residences. For incidents that a pedestrian did not use another mode of transportation before being involved in a crash, previous literature such as that by Yang and Diez-Roux (2012) supports the obtained results by suggesting that individuals from lower-income households walk longer distances for work, shopping, and social events than individuals from higher-income households.

5.2.8. Seasons of the year

Summer and fall seasons were observed to increase the likelihood of pedestrian crashes occurring closer to pedestrian residences (0.306, 0.209, 0.179, 0.139). The influence of seasons is significant for pedestrian crashes that occur only within 0.5 miles of their residences. These seasons (summer/fall) are characterized by more pedestrian walking trips due to favorable weather conditions, in which most trips are close to the residential areas. As suggested by Islam and Jones (2014) and Dewey et al.(2003), these seasons are associated with the clear weather which increases the likelihood of pedestrian activities.

6. Conclusions and recommendations

Knowledge of the proximity of pedestrian crash locations to their residences is vital in serving the vulnerable road users. It is useful in identifying better ways for improving pedestrian safety while sharing roadways with other road users. More specifically, this knowledge with the focus on the aged population is essential due to the predicted increase in this age group and the shortage of studies dedicated to them. In order to fill this existing literature gap, this study evaluated the proximity of elderly pedestrian crash locations to their residence.

Results show that various factors ranging from pedestrian attributes to demographic characteristics affect the proximity of crash locations to residences of aged pedestrians. As many as 64% of these crashes occurred within 2 miles of pedestrian residences. The results revealed that proximity varies with elderly age groups. The elderly group aged 65 to 75 years have a higher probability of crash involvement close to home compared to the group of pedestrians aged 76 years and above. Regarding gender, elderly male pedestrians are more susceptible to crashes near their homes than elderly female pedestrians.

Moreover, elderly pedestrian crashes that occur close to the pedestrian homes are more likely to involve drivers who live relatively far from the area. Roadway and environmental attributes that have a significant impact on the proximity of crash locations to pedestrian residences are traffic volume and seasons of the year. Summer or fall season and roadways that have high traffic volume are associated with crash occurrence near residential areas. Results related to demographic factors suggests that aging pedestrian crashes are more likely to occur near their residences when they live in high-populated areas. According to the results, high property values increase the probability of elderly pedestrian crashes occurring far from their homes.

In addition to providing insight on factors associated to the proximity of elderly pedestrian crashes to their residences, this study demonstrated a new approach of using actual addresses to precisely compute distances in lieu of zip codes or census tracts that have been used in previous studies. This approach that integrates GIS and Google API services has the potential to improve the accuracy of distance computations not only for safety analyses but also for other transportation research areas including travel demand modeling, which still uses zip codes and census tracts for computing distances.

This study has some limitations that are worth mentioning. This study assumed that the pedestrians involved in the crashes walked from home, which may not necessarily be true. The distances estimated in the study considered the shortest path because it was not possible to identify the actual route taken by a pedestrian before being involved in a crash. Since the study was limited to analyzing data that had complete pedestrian and driver physical addresses, it was not possible to analyze hit-and-run crashes. This study has developed the mixed effects model using only three subjects (i.e., three groups of population density), and assumes a normal density (i.e., a random effect) over these three subjects. A model developed using more subjects may result in a better estimation of the random effects variance.

Finally, while the study attempts to fill the gap in the literature, some areas require further research. For instance, future research could investigate whether a pedestrian used another transportation mode before walking. It would be interesting to associate the location of aging pedestrian crashes with the type of residence such as own versus rent, private property versus senior living facility, and self-sustaining or living with family. Apart from aged pedestrians, future research work can focus on children who are other road users suffering from higher crash injury susceptibility as compared to adults. Addressing these questions requires additional information about the pedestrians involved in crashes, which is a challenging task for future research.

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Appendix A. Python code for estimating distance

```
#Import arcpy module
import arcpy
import urllib, json

# Function to get driving distance and time using Google Distance Matrix API
# orig - Origin point (longitude,latitude)
# dest - Destination point (longitude,latitude)

def getLatLong(address):
   url = "https://maps.googleapis.com/maps/api/geocode/json?address=" + address + "&key= "
    #url = "https://maps.googleapis.com/maps/api/geocode/json?address= "
    #url = "https://maps.googleapis.com/maps/api/geocode/json?address= &key= "
    result = json.load(urllib.urlopen(url))
    if result['status'] == "OK":
        lat = result['results'][0]['geometry']['location']['lat']
        lng = result['results'][0]['geometry']['location']['lng']
        pnt = (lng,lat)
    else:
        pnt = (-999,-999)
    #arcpy.AddMessage("aaaa: " + str(result))
    return pnt
# Function to get driving distance and time using Google Distance Matrix API
# orig - Origin point (longitude,latitude)
# dest - Destination point (longitude,latitude)
def getDriveDistance(orig, dest):
    if dest[0] == "-999" or dest[0] == "-999":
        d["seconds"] = -999
        d["minutes"] = -999
        d["meters"] = -999
        d["miles"] = -999
        return d
    d = {}
    p1 = str(orig[1]) + "," + str(orig[0])
    p2 = str(dest[1]) + "," + str(dest[0])
    #arcpy.AddMessage("aaaa: " + str(dest))
    #url = "https://maps.googleapis.com/maps/api/distancematrix/json?origins=&destinations=&mode=driving&key= "
    url = "https://maps.googleapis.com/maps/api/distancematrix/json?origins=" + p1 + "&destinations=" + p2 + "&mode=driving&key= "
    result = json.load(urllib.urlopen(url))
    if result['rows'][0]['elements'][0]['status'] == 'ZERO_RESULTS':
        d["seconds"] = -999
        d["minutes"] = -999
        d["meters"] = -999
        d["miles"] = -999
    else:
        d["seconds"] = result['rows'][0]['elements'][0]['duration']['value']
        d["minutes"] = float(d["seconds"] / 60.00)
        d["meters"] = result['rows'][0]['elements'][0]['distance']['value']
        d["miles"] = d["meters"] * 0.00062137
    return d
if __name__ == '__main__'
    # Get parameter for crash table
    inputTable = arcpy.GetParameterAsText(0)
    valid_inputTable = arcpy.Exists(inputTable)
    arcpy.AddMessage("Input feature class: " + inputTable)
    # Add Latitude and Longitude fields for both Pedestrian and Vehicle
    arcpy.AddField_management(inputTable,"P_Lat","Float")
    arcpy.AddField_management(inputTable,"P_Lng","Float")
    arcpy.AddField_management(inputTable,"P_DriveMiles","Float")
    arcpy.AddField_management(inputTable,"P_DriveTime","Float")
    arcpy.AddField_management(inputTable,"V_Lat","Float")
    arcpy.AddField_management(inputTable,"V_Lng","Float")


    arcpy.AddField_management(inputTable,"V_DriveMiles","Float")
    arcpy.AddField_management(inputTable,"V_DriveTime","Float")
    try:
        fields =
["OBJECTID","Crash_Repo","PStreet","PCity","PState","PZip","VStreet","VCity","VState","VZip","C_UTM_X","C_UTM_Y","C_Lat","C_Ln
g","P_Lat","P_Lng","V_Lat","V_Lng","P_DriveMiles","P_DriveTime","V_DriveMiles","V_DriveTime"]
        with arcpy.da.UpdateCursor(inputTable, fields) as cursor:
            for row in cursor:
                # Get Latitude and Longitude for Pedestrian, using street address
                p_address = str(row[2]) + ", " + str(row[3]) + ", " + str(row[4]) + ", " + str(row[5])
                p_address = p_address.replace(" ", "+")
                p_coord = getLatLong(p_address)
                # Get Latitude and Longitude for Vehicle, using street address
                v_address = str(row[6]) + ", " + str(row[7]) + ", " + str(row[8]) + ", " + str(row[9])
                v_address = v_address.replace(" ", "+")
                v_coord = getLatLong(v_address)
                orig = (row[13],row[12])
                p_drive_dist = getDriveDistance(orig, p_coord)
                v_drive_dist = getDriveDistance(orig, v_coord)
                # Update Latitude and Longitude fields for both Pedestrian and Vehicle
                row[14] = p_coord[1]
                row[15] = p_coord[0]
                row[16] = v_coord[1]
                row[17] = v_coord[0]
                # Update distance and time fields for both Pedestrian and Vehicle
                row[18] =  p_drive_dist["miles"]
                row[19] =  p_drive_dist["minutes"]
                row[20] =  v_drive_dist["miles"]
                row[21] =  v_drive_dist["minutes"]
                cursor.updateRow(row)
                arcpy.AddMessage("Processing point " + str(row[0]) )
    except arcpy.ExecuteError:
        arcpy.AddMessage("Error: Processing points..."
    arcpy.AddMessage("Complete....")
```

Appendix B. Correlation Matrix

	Property value	PR population density	PR median income	Driver proximity	Season	Traffic condition	CA population density	CA land use	Crash day	Weather condition	Crash location	Pedestrian age	Pedestrian gender	PR population	PR elderly population	Injury severity	Traffic volume
Property value	1.000	0.019	−0.106	0.009	0.038	−0.011	0.061	0.122	−0.010	0.013	−0.067	−0.029	−0.075	−0.074	0.099	−0.069	−0.110
PR population density	0.019	1.000	−0.177	−0.067	−0.045	0.031	0.638	0.017	0.013	−0.049	−0.083	0.012	−0.066	−0.037	−0.103	−0.130	0.264
PR median income	−0.106	−0.177	1.000	−0.014	−0.033	−0.073	−0.125	−0.031	−0.024	0.003	0.015	−0.021	0.012	0.076	0.011	0.042	−0.022
Driver proximity	0.009	−0.067	−0.014	1.000	−0.011	−0.076	−0.072	−0.029	−0.018	0.014	0.030	0.001	0.031	0.060	−0.035	0.057	0.054
Season	0.038	−0.045	−0.033	−0.011	1.000	−0.086	−0.034	0.057	0.052	0.101	0.029	−0.022	−0.059	0.051	−0.007	0.065	−0.052
Traffic condition	−0.011	0.031	−0.073	−0.076	−0.086	1.000	−0.023	−0.095	−0.124	−0.050	−0.072	0.010	−0.049	−0.058	0.002	−0.028	−0.036
CA population density	0.061	0.638	−0.125	−0.072	−0.034	−0.023	1.000	0.043	0.021	−0.015	−0.084	0.055	−0.068	−0.049	−0.046	−0.144	0.249
CA land use	0.122	0.017	−0.031	−0.029	0.057	−0.095	0.043	1.000	0.045	0.067	−0.085	0.017	0.006	0.003	−0.036	−0.038	−0.062
Crash day	−0.010	0.013	−0.024	−0.018	0.052	−0.124	0.021	0.045	1.000	−0.017	0.115	0.040	0.059	−0.016	0.017	0.026	0.021
Weather condition	0.013	−0.049	0.003	0.014	0.101	−0.050	−0.015	0.067	−0.017	1.000	−0.014	−0.044	−0.035	−0.003	0.009	0.002	−0.003
Crash location	−0.067	−0.083	0.015	0.030	0.029	−0.072	−0.084	−0.085	0.115	−0.014	1.000	−0.047	0.022	0.057	−0.010	0.255	0.102
Pedestrian age	−0.029	0.012	−0.021	0.001	−0.022	0.010	0.055	0.017	0.040	−0.044	−0.047	1.000	0.030	−0.027	0.119	0.083	0.022
Pedestrian gender	−0.075	−0.066	0.012	0.031	−0.059	−0.049	−0.068	0.006	0.059	−0.035	0.022	0.030	1.000	−0.014	−0.104	0.050	−0.030
PR population	−0.074	−0.037	0.076	0.060	0.051	−0.058	−0.049	0.003	−0.016	−0.003	0.057	−0.027	−0.014	1.000	−0.162	0.073	0.070
PR elderly population	0.099	−0.103	0.011	−0.035	−0.007	0.002	−0.046	−0.036	0.017	0.009	−0.010	0.119	−0.104	−0.162	1.000	0.107	0.015
Injury severity	−0.069	−0.130	0.042	0.057	0.065	−0.028	−0.144	−0.038	0.026	0.002	0.255	0.083	0.050	0.073	0.107	1.000	0.046
Traffic volume	−0.110	0.264	−0.022	0.054	−0.052	−0.036	0.249	−0.062	0.021	−0.003	0.102	0.022	−0.030	0.070	0.015	0.046	1.000

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