Pedestrian and Car Occupant Crash Casualties Over a 9-Year Span of Vision Zero in New York City

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Keywords: Road Safety, Safe System Approach, Vision Zero, Clustering, Negative Binomial Regression

Word Count: 9,995 words

Revised and Submitted [June 1, 2024]

ABSTRACT

Vision zero has been increasingly embraced by jurisdictions in the U.S. Existing research primarily focuses on the theoretical principles and the effectiveness of specific engineering measures. However, there is limited understanding of the holistic effects of Vision Zero treatments, in the context of street types and urban environment. In this study, we developed a street typology framework to categorize street segments using four street design and operational features: street width, traffic direction (one-way vs. two-way), number of travel lanes, and presence of on-street parking. We applied a sample-based Partitioning Around Medoids algorithm to classify 90,327 street segments in NYC. This process results in six distinctive types of street segments. To integrate the neighborhood level factors (e.g., land use variables and socio-demographics), we aggregated street segments of a given street type for each neighborhood. Negative binomial regression models were developed for pedestrian and car occupant crash injuries and fatalities separately for three periods - 2014-2016, 2017-2019, and 2020-2022. Our findings show that street segment groups with narrower, two-way sections, and higher tree canopy coverage are significantly associated with a lower risk of casualties for both pedestrians and motorized users. In addition, street segment groups located in neighborhoods with a larger percentage of African American and Hispanic American residents experienced significantly greater risk of casualties. Vision zero treatments had mixed effects on safety outcomes. Streets treated with leading pedestrian interval showed a lower risk of casualties. Neighborhood slow zones and arterial slow zones were associated with lower risk of car occupants' casualties.

Keywords: Road Safety, Safe System Approach, Vision Zero, Clustering, Negative Binomial Regression

One Sentence: This research proposes a framework for other Vision Zero cities to conduct a similar mesoscopic, multi-scalar study and demonstrates how data transparency can foster a data-driven approach that can improve road safety planning and ultimately save lives on the streets, using open data.

INTRODUCTION

Vision Zero is a systems-based approach to improve road safety. Pioneered in Sweden in the 1990s, Vision Zero has attracted a lot of attention from road safety professionals, policy makers, and safety advocates across the world. More than 45 cities have committed to Vision Zero in the U.S. (*1*). New York City (NYC) was an early adopter, launching its "Vision Zero" initiative in February 2014, implementing engineering treatments such as left turn traffic calming and leading pedestrian intervals, and providing open data sources to encourage data-driven assessment and research. Even though in the U.S. pedestrian fatalities have sky-rocketed since 2009 and increased 54% from 2010 to 2020 (*2*), NYC has made good progress in protecting people on the streets. In 2020, total fatalities fell by 10% and pedestrian fatalities fell by 37% compared to the five-year averages prior to the official adoption of Vision Zero (*3*). Several recent studies have focused on road traffic safety in NYC. Nevertheless, research on Vision Zero outcomes is still relatively limited, especially regarding the planning of safety projects and comprehensive quantitative analyses of Vision Zero treatments. Researchers have proved the rationality of zero road deaths goal (*4*, *5*), outlined safety philosophy and principles in Vision Zero (*6*, *7*), and highlighted investment strategies for implementing Vision Zero (*8*, *9*). Researchers have also argued that Vision Zero policy may aggravate inequity and social injustice in terms of investment allocation and enforcement (*4*).

To unravel the patterns and better understand the effects of Vision Zero, we undertook a finer-scaled study that considered both street design and contexts as well as equity issues. We chose NYC for our study area because it was an earlier adopter that consequently had a larger number of implemented projects. In addition, NYC had a large sample of road crashes and various built environments to conduct a rigorous statistical analysis. Finally, New York City has a relatively comprehensive database covering traffic safety outcomes and the data to characterize the street design and the built environment.

For this study, we developed a street typology using cluster analysis. The street typology was combined with neighborhood level factors to define different street-place types. We then explored the association between street-place type and road safety outcomes for pedestrian and car occupants using statistical modeling. This paper is based on the analysis of 90,327 street segments. We seek to answer the following questions:

1) What is the association between road safety outcomes and street design, streetscape design features and Vision Zero treatments throughout the Vision zero deploying process?
2) How are other area-level factors, such as income levels, land use, and race/ethnicity composition, associated with road safety?

LITERATURE REVIEW

This section reviews the related literature from three perspectives. The first section reviews studies regarding the Vision Zero approach in Sweden and other places in the world. The second section summarizes the units of analysis and explanatory variables used for non-motorized road safety research. The third section focuses on more general road traffic safety research in NYC and presents findings from the existing studies.

Vision Zero

Vision Zero is an innovative policy requiring a paradigm shift that puts safety and quality of life at the forefront of our thinking about transportation planning, design, and implementation (*6*). Before it was largely accepted by the safety professionals and the public across the world, researchers worked diligently to prove the rationality of the zero road deaths goal. Rosencrantz et al. (*5*) analyzed criticisms of the concept by evaluating the precision, evaluability, approachability, and motive of Vision Zero planning. They demonstrated that Vision Zero is a rational goal that has led to many interventions and a subsequent reduction in road deaths in Sweden. Vision Zero researchers have also focused on the theoretical framework and underlying principles. For example, Johansson (*7*) summarized the safety philosophy inherent in contemporary road and street design, and developed the framework for a new design of streets and roads based on principles in Vision Zero. In more recent years, researchers and practitioners explored investment and planning strategies in practice. Fleisher et al. (*8*) developed a framework of traffic safety practices to help cities identify effective strategies and benchmark their efforts relative to other jurisdictions. Kronenberg et al. (*9*) presented a data-driven investment strategy for pedestrian safety improvement projects in San Francisco, California.

A few efforts were made to evaluate the effectiveness of the overall Vision Zero policy or some specific engineering measure in improving road safety. For example, Auerbach et al. (*10*) investigated the overall effect of the Vision Zero initiative in NYC, using hierarchical Bayes adjustment approach that adjusts for selection bias in before-after study. They estimated that the number of fatalities reduction as a result of implementing a Vision Zero strategy was roughly 18 percent. On the other hand, Jiao et al. (*11*) focused on one particular Vision Zero treatment—neighborhood slow zones (NSZs)—and highlighted that road casualties in NYC fell by 8.74% in the NSZs through a time series analysis.

One of the core principles of Vision Zero is to keep track of the process by employing data-driven approaches. Yet to date, few studies have systematically attempted to explore the efforts of Vision Zero treatments at a finer scale through data-driven study. Therefore, research regarding street level analysis with context considerations could provide meaningful insights in guiding Vision Zero implementation and planning.

Units of Analysis and Explanatory Variables

Various geographic units of analysis have been explored in the transportation safety area. Some studies focused on geographic area-level analysis, ranging from block groups (*12*, *13*), census tracts (*14*), zip codes (*15*, *16*), and traffic analysis zones (*17*, *18*). Other studies have focused on micro-level analysis (e.g., intersection level and corridor comparison) (*19*, *20*) or on macro-level analysis (nation or citywide study) (*21*). In terms of selecting units of analysis, Abdel-Aty et al. (*22*) found that the significance of explanatory variables is not consistent among analyses at different geographic units of analysis although the signs of coefficients are consistent. Therefore, it is important to define the appropriate units of analysis for different studies.

Researchers have investigated different exploratory variables in road safety analyses, including sociodemographic, built environment, and street network characteristics. Studies have revealed a higher risk of being involved in crashes and suffering from injuries and fatalities for people in racial minorities and lower-income neighborhoods (*13*, *23*). Several studies have found a positive relationship between population density and crashes that resulted in pedestrian injuries (*19*), while other studies have found that higher population density tends to correspond with fewer pedestrian injuries and fatalities (*24*). Although research findings have been mixed, it is broadly accepted that higher density development results in lower average speeds, thus decreasing the crash severity, as Ewing and Dumbaugh argued (*25*). Existing studies have found that a higher proportion of commercial areas is positively associated with pedestrian and bicyclist involved injuries (*14*, *18*). More residential land use was negatively correlated with pedestrian crash frequency (*15*). The severity of pedestrian injury in commercial areas tended to be lower than that in residential areas (*26*). However, the effect of mixed land use was unclear. Chen and Zhou (*18*) found a positive relationship between land use mix and pedestrian crash frequency and risk for years 2009-2012 in Seattle. In contrast, Wang and Kockelman (*27*) found a negative relationship between land use entropy (e.g., land use balance, where a smaller value means less balanced land use patterns) and pedestrian crash for the years 2007-2009 in Austin. The effects of street network features on pedestrians' and bicyclists' safety outcomes are also mixed in the literature. For example, Yin and Zhang (*19*) examined the impact of intersection density on pedestrian-involved injuries in Buffalo, NY and found that both three-way and four-way intersection density were positively correlated with pedestrian injuries. However, Marshall and Garrick (*13*) found that higher intersection density was significantly associated with fewer crashes across all severity levels when conducting analysis on street level characteristics in 24 Californian cities.

Road Safety in NYC

Several studies have focused on road traffic safety in NYC, partially due to the readily available and diverse open data resource in the city. The research covered topics including effectiveness of countermeasures (*11*, *28*, *29*), equity and justice of safety programs (*23*, *30*), built environment impacts (*15*, *31*), road safety during COVID-19 (*16*, *32*), and travelers' behaviors (*33*, *34*). These studies have provided invaluable insights regarding the impacts of contributing factors on road safety outcomes at various units of analysis.

For example, Chen et al. (*28*) identified that signal related countermeasures and traffic calming measures were found to have significant safety benefits while high visibility crosswalks and posted speed limit reduction signs appeared to have a lesser effect. Kang (*29*) found that treatments with pedestrian refuge island or pedestrian plaza had reductions in pedestrian collision count and rate by reviewing 118 intersections.

Research about road safety equity showed that low-income and communities of color are overrepresented in severe injury and fatality rates among cyclists and pedestrians between 2009 and 2018 in NYC (*23*). Road safety inequality issues have become more severe during COVID-19. Researchers found that the proportion of crashes unexpectedly increased for Hispanic people, male cohorts and low-income areas during the pandemic (*32*). Furthermore, Li and Zhao (*16*) discovered that the declaration of the New York State stay-at-home order was significantly associated with a higher risk of casualties at the zip code level. In terms of built environment variables, Ukkusuri et al. (*15*) reported that census tracts with greater fraction of commercial land use types, and higher proportion of larger number of lanes and wider road had greater likelihood for pedestrian crashes.

Overall, there are few studies that focus on a finer-scale analysis that considers a comprehensive list of street design, streetscape design features and Vision Zero treatments in a megacity context. Our study contributes to filling this research gap.

DATA AND METHOD

Conceptual Framework

The research framework for the study is shown in **Figure 1**. We categorized citywide street segments using street design and operational features through a sample-based Partitioning Around Medoids algorithm. We aggregated street segments of a given street type for each of city's 195 neighborhoods as the unit of analysis named street segment group. We obtained street designs, streetscape design features, and Vision Zero treatments at the street segment level, and aggregated them at the street segment group level. Land use variables and socio-demographics were collected at area level. Negative binomial models were used to uncover the effects of different factors and Vision Zero safety treatments on crash injuries and fatalities for three periods. The following sections will explain how we compiled the dataset and explored the links between safety outcomes and these variables using an empirical modeling test

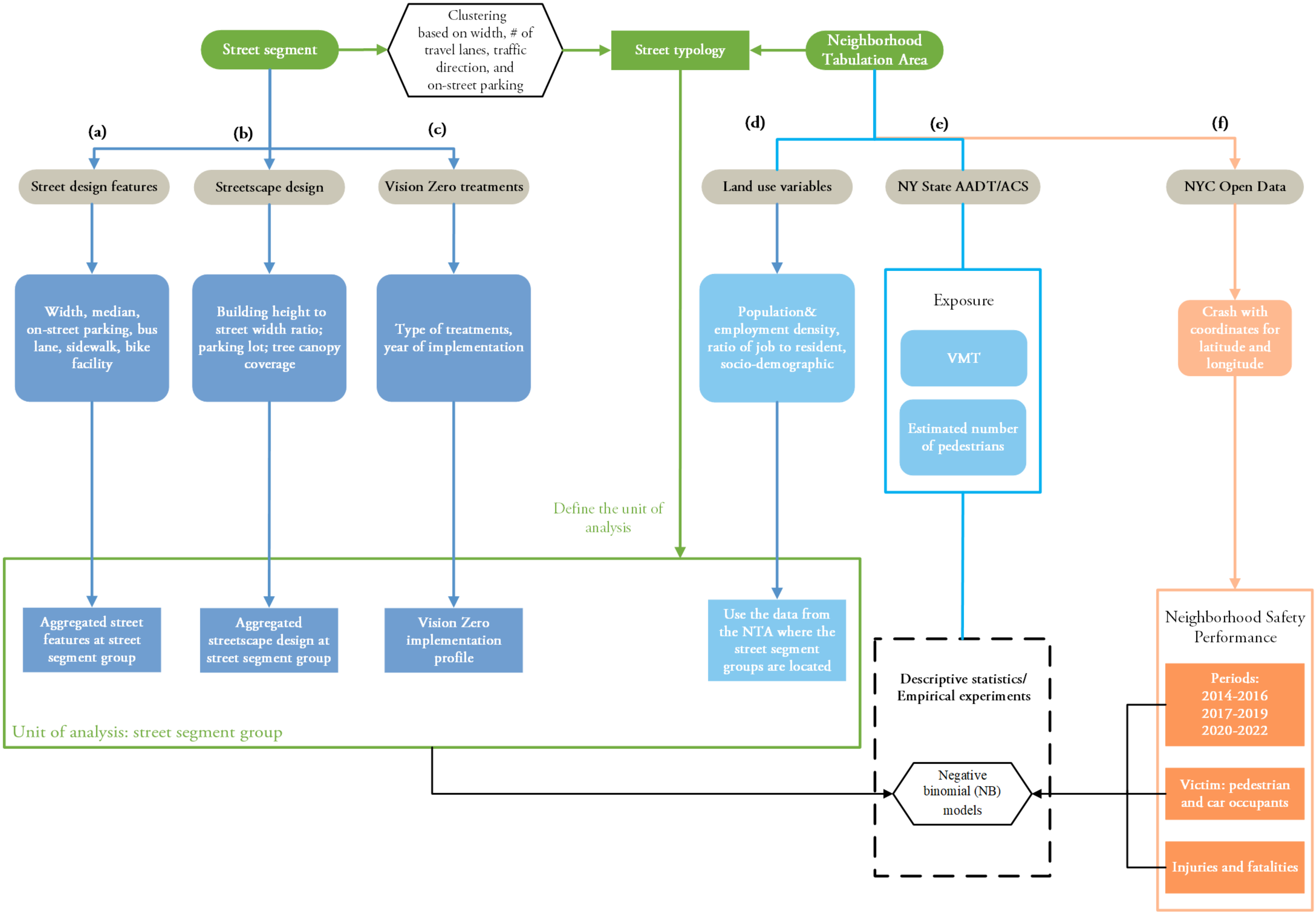


Figure 1 Research framework

Data

This study compiled a dataset containing 90,327 street segments in New York City, along with their street design features, streetscape design, Vision Zero treatments, and neighborhood land use by leveraging large-scale, multi-source data. Most data were obtained from NYC Open Data portal or derived from related sources, as shown in **Table 1**. We used spatial joining in QGIS to snap different GIS shapefiles together.

In terms of street-segment data, we used citywide street centerline as the master shapefile. It was first filtered from all road segments (120,512 segments citywide) to road segments with road type- "street" (99,324 segments citywide), and excluded the nonvehicular streets and street segments with length less than 20 meters (66 ft) long (90,327 segments citywide remains). All related variables were joined into the master shapefile to get the street design features (Figure 1, (a)). For streetscape design variables (Figure 1, (b)), we adopted the methods developed by Harvey and Aultman-Hall to calculate the metrics (*35*). Input data for the methods included street centerline, building footprint and height (*36*), and tree canopy layers (*37*, *38*) in NYC. The method searched for building façade within 40 m of each side of each centerline (80 m in total). The space between edges defined the horizontal extent of each streetscape. In terms of Vision Zero treatments (Figure 1, (c)), we developed different methods for different categories of treatments. For each street segment, we created a buffer of 15 meters along its boundary. For intersection-based treatments (such as Left Turn Traffic Calming), we counted the numbers by installation year. For corridor-based treatments (such as speed hump), we counted the segment length by installation year. For area-based treatments (such as Neighborhood Slow Zones), we calculated the overlapping areas of the treatment with each street 15-meter buffer.

Land use and socio-demographic variables (Figure 1, (d)) were obtained from the Smart Location Database versions 3.0 and American Community Survey and were aggregated at the Neighborhood Tabulation Area (NTA) level. For crash data, we used police-reported data from the NYC Motor Vehicle Collisions database (Figure 1, (f)). We verified the crashes by cross-referencing the Fatality Analysis Reporting System (FARS). Crash data entries, which do not have latitude and longitude coordinates but included accurate street or intersection names, were geocoded. In terms of exposure variables, traffic volume data were derived from the traffic data viewer maintained by the New York State Department of Transportation (*39*). The number of estimated pedestrians was calculated by multiplying the total population and jobs by the walking mode share at each census tract, and then was aggregated at the NTA level.

Table 1 Data source and definition of variables

Variable	Definition	Original scale	Data sources
Road Crash			
Road Fatality and Injury	Individual crash by mode with coordinates	Point with Lat/Lon	Motor Vehicle Collisions – NYC Open Data
Land Use			
Job-resident ratio	Ratio between jobs and population	Census block group	Smart Location Database (*40*)
Population & Employment density	(Population + number of jobs) / acre	Census block group	Smart Location Database
Socio-demographics			
Poverty	Percentage of workers that earns less than 1250 USD per month	Census block group	Smart Location Database

Race and ethnicity	Percentage of racial and ethnic group	Census tract	American Community Survey (ACS)
Exposure			
Annual Average Daily Traffic (AADT)	Sum of AADT for all the segments	Street segment	NYS DOT
Vehicle Miles Traveled (VMT)	Sum of AADT × length for segments	Street segment	NYS DOT
Road length	Sum of street length	Street segment	Citywide Street Centerline (CSCL)
# of estimated road users	Sum of estimated road users by mode	Census tract	ACS
Streetscape Design			
Height-to-width ratio	the ratio of building height divided by building-to-building width	Street segment	NYC Building Footprints Citywide Street Centerline (CSCL)
Tree canopy coverage	Proportion of street area (between building edges) covered by tree canopy	Street segment	Practical Canopy for New York City
Street Setbacks	The distance between curb and building	Street segment	CSCL NYC Building Footprints
Parking lot	Number of parking lot between buildings on two sides	Street segment	NYC Parking Lot
Street Design Features			
Average width of travel lane	Width in feet, of the paved area of the street	Street segment	CSCL
Presence of bike lane by length	Bike lane type: protected; conventional; signed/ marked route; link	Street segment	New York City Bike Routes
Presence of on-street parking	Whether the street has on-street parking lane	Street segment	Department of City Planning (DCP) LION
Average sidewalk width	Weighted average width of sidewalk on both sides	Street segment	Sidewalk Widths NYC
Number of lanes	The total number of travel lanes	Street segment	(DCP) LION CSCL
Presence of median by type	Median type hierarchy: barrier, rail, fence, curb, grass and painted	Street segment	NYC Planimetric Database Median
Intersection	Intersection location from topological simplification based on OSM	Point with Lat/Lon	OSMnx (*41*)
Vision Zero Treatments			
Enhanced crossings	Marked high-visibility crosswalks on calm streets with low vehicle volumes and high pedestrian traffic.	Intersection	NYC Vision Zero Open Data
Leading pedestrian interval (LPI) signals	Installed signals that show a pedestrian walk sign before showing a green light to vehicle traffic in the same direction	Intersection	NYC Vision Zero Open Data
Turn traffic calming	Traffic calming measures that guide drivers to turn left or right at a safer speed and angle, as well as increase visibility for pedestrians in the crosswalk.	Intersection	NYC Vision Zero Open Data
Raised crosswalk	Mid-block locations constructed at a higher	Intersection	NYC Vision Zero Open Data

	elevation than the adjacent roadway.		
Speed Hump	Raised area of a roadway designed to reduce vehicle speeds	Corridor-	NYC Vision Zero Open Data
25MPH signal retiming	Signal progression has been changed to match the 25 MPH speed limit.	Corridor	NYC Vision Zero Open Data
Arterial slow zone	Slow corridors implanted via a combination of speed limits, signal timing changes, distinctive signs, and increased enforcement	Corridor	NYC Vision Zero Open Data
Neighborhood slow zone	Neighborhood areas where the speed limit has been reduced to 20 mph	Area	NYC Vision Zero Open Data

Cluster Analysis

Neighborhoods and street segments vary tremendously in type across the five boroughs of NYC. We used cluster analysis algorithms to categorize street segments based on four separate variables: street width, traffic direction (one-way vs. two-way), number of travel lanes, and presence of on-street parking.

We used the Gower distance to represent the similarity/dissimilarity between the data points as the dataset contains both numerical and categorical variables. However, this process is computationally intensive. Therefore, we apply a sample-based clustering method (*42*). The cluster analysis process, along with the Gower distance and the Partitioning Around Medoids (PAM) algorithm are described as follows.

The procedure involves: a) taking a sample of 10,000 street segments from the dataset. b) running clustering analysis using the subsample, find the center point for each cluster group. c) cluster the remaining data points based on the shortest distance between center points. The cluster analysis is heuristic and 10,000 (about one-ninth of the whole dataset) is a reasonably sized subsample for finding any patterns of street type as well as bearing reasonable computational cost. For smaller cities, it may be easier to directly identify the center point for each cluster group as there are fewer types of streets, compared with NYC.

The universal similarity coefficient of Gower is defined as follows (*43*):

$$S_G = \frac{\sum_{i=1}^{n} w_{i,j,k}\, s_{i,j,k}}{\sum_{i=1}^{n} w_{i,j,k}} \tag{1}$$

Where weight $w_{i,j,k}$ is either 1 or 0, depending on whether the comparison is valid or not (missing data). The scores $s_{i,j,k}$ are assigned as follows: (a) For qualitative variables (i.e., traffic direction, number of travel lanes, existence of on-street parking), $s_{i,j,k} = 1$ if individuals i and j are equal in kth variable, $s_{i,j,k} = 0$ otherwise. (b) For quantitative variables (i.e., street width), use Equation (2)

$$s_{i,j,k} = 1 - \frac{\left|X_{i,k} - X_{j,k}\right|}{R_k} \tag{2}$$

Where R_k is the range of variable k in the sample. The distance between points can be represented by $\sqrt{1 - S_G}$.

To conduct this cluster analysis, PAM was applied to calculate the Gower distance matrix. The Silhouette method suggested that five to eight clusters would be optimal. We identified five cluster groups using the algorithm we discussed above. However, the cluster process failed to identify some types of two-way segments. This error resulted from the data source that boulevard-like roads and roads with middle viaduct were mislabeled as pairs of two parallel one-way sections in the “traffic direction” attribute.

To combat this issue, we developed a method to identify the mislabeled one-way segments that are part of two-way segments with separations such as medians. The algorithm is illustrated as follows.

a) If there is more than one centerline for the 30-meter buffered segment that has similar bearing (within a 5-angle-degree difference) with the original segment, then it indicates that there are one or more parallel sections. b) For segments that were originally coded as one-way streets, if there is more than one nearby parallel streets, then they are reclassified as the new group. This new group includes a mixture of two-way street segments with concrete medians, which will be discussed in more detail in the Results section.

Previous studies have identified a large and growing discrepancy in fatality rates across different land use features at the area level in NYC (*31*). To consider both street type and its surrounding environment, this study developed a unique approach that created the street segment group level within geographic neighborhood areas. More specifically, we aggregated the street segments of a given street type in each NTA. NTAs are 195 statistical areas of aggregated census tracts in NYC. In this study, we excluded the NTAs that are parks, cemeteries, airports, and other special-use areas. **Figure 2** shows a map of NTAs and an example of street segment group aggregation. At the NTA Gramercy in Manhattan, there are five different street types. Street segments with the same street type were aggregated as one of the five street segment groups at this NTA. There are 1,094 street segment groups citywide. Street design and streetscape design variables were calculated by taking the weighted average per length of streets segments in each group. Vision zero treatments are adjusted by dividing the numbers of intersections (for intersection-based treatments), accumulative length of streets (for corridor-based treatments), or areas of street buffer zone (for area-based treatments). We created the street segment group as the unit of analysis for several reasons: 1) it incorporates both street design features at street segment level and the contexts that are usually at area level; 2) it facilitates collection of more representative exposure data compared to the street-level analysis; and 3) it lessens the excessive zero observation problem by aggregation.

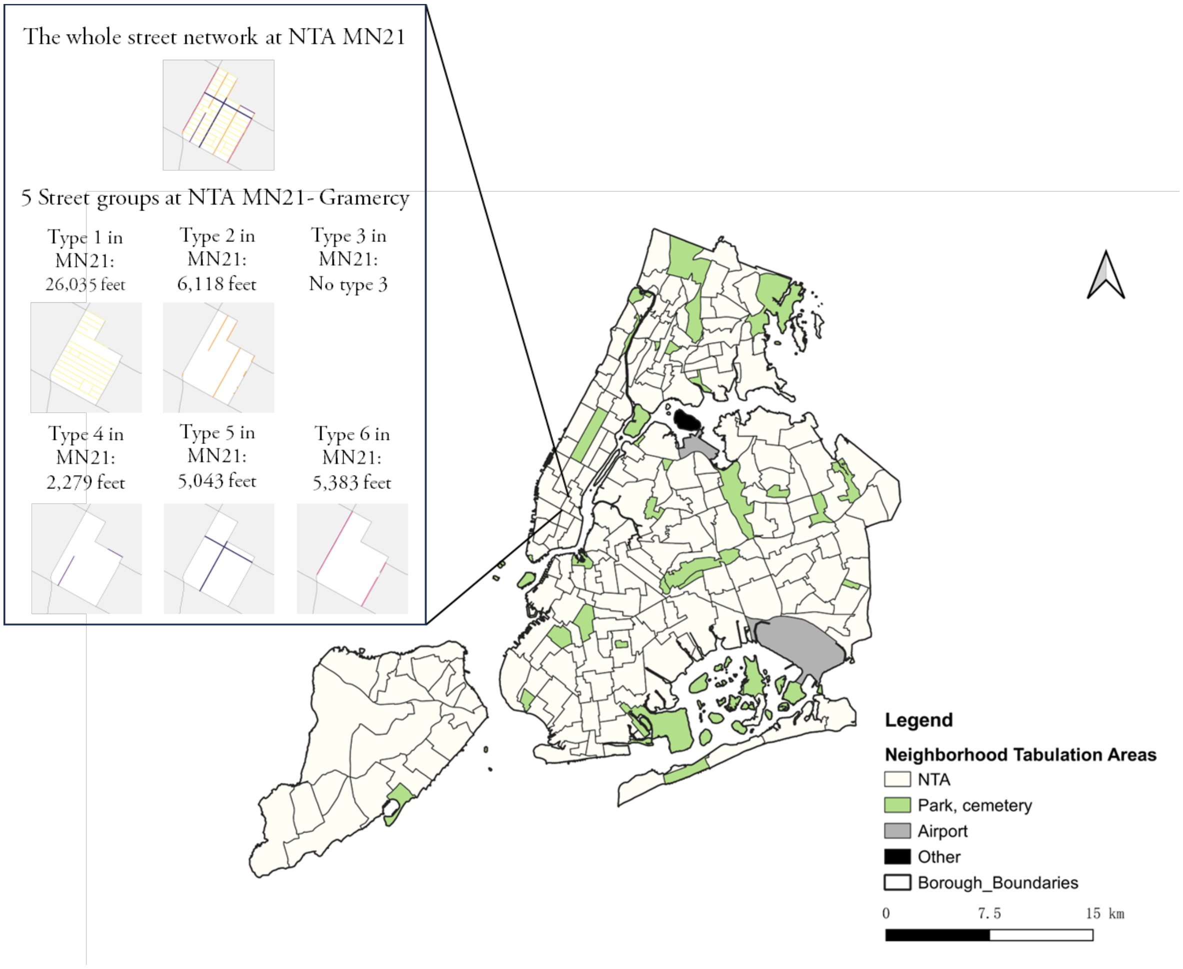


Figure 2 NYC Neighborhood Tabulation Areas and an example of street segment group in neighborhood

Regression

We used a standard negative binomial (NB) regression model to explore the relationship between road safety outcomes and contributing factors at the street-group level. Because we aggregate the street segments at the NTA, it attenuates the excessive zero problem. NB model also considers the over-dispersion and location heterogeneity of crash variation, so it is preferable for the scope of our analysis.

$$y_i|\theta \sim Possion\ (\theta_i)$$

$$\theta_i = f(D_i, \beta)exp(\varepsilon_i) \qquad (3)$$

Where the $exp(\varepsilon_i)$ is the multiplicative random effect of the model, following a Gamma distribution, $f(D_i, \beta)$ is a function of the variables, D_i is the continuous variables or categorical variables, and β is the coefficients.

RESULTS

Street Types

Figure 3 shows the overall distribution of street segments by cluster types. The six types of street segments show distinctive patterns and features. Type 1 streets are one-way streets with an average width of 28 feet. Most of them have one travel lane along with space for on-street parking. Type 1 streets comprise 29% of the entire street network in NYC and are the most common street type in the Bronx, Brooklyn, and Manhattan.

Type 2 streets are predominantly one-way multi-lane street segments with an average width of 40 feet. They are evenly distributed across Brooklyn, Manhattan and Queens and about one third of them have on-street parking.

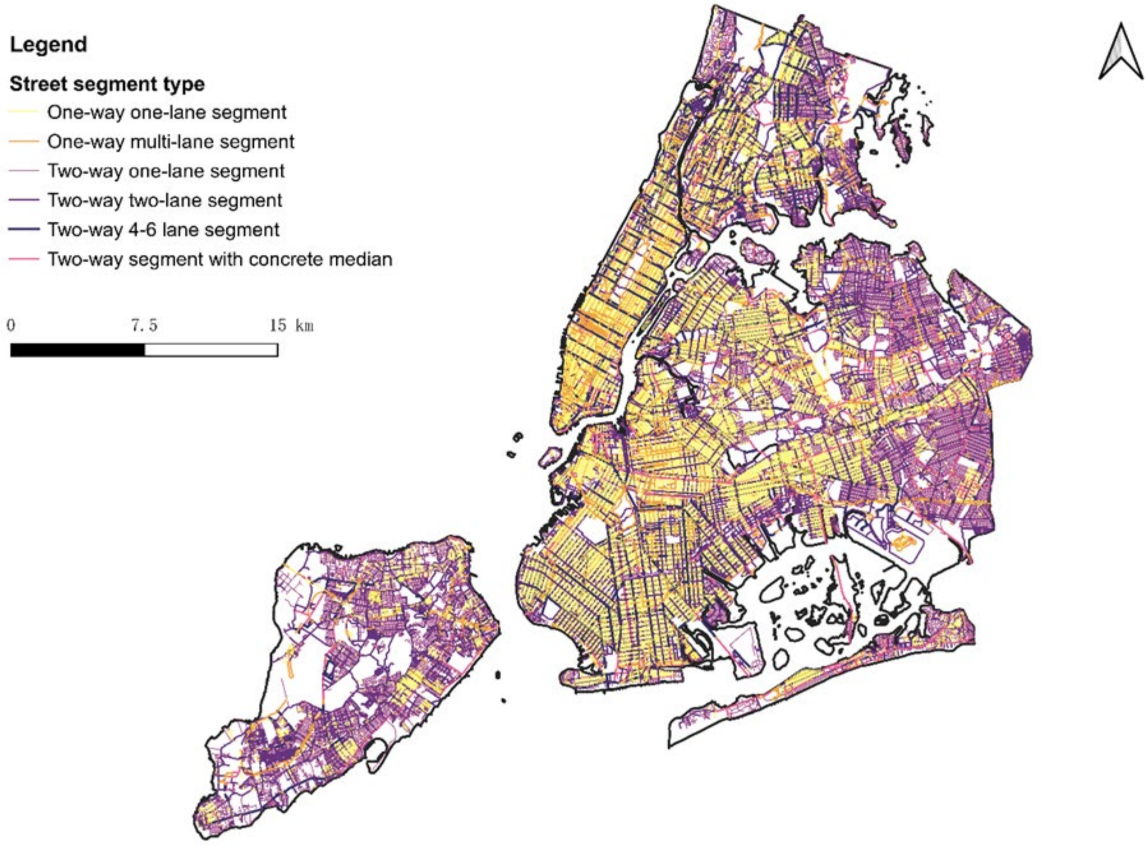
Type 3-6 streets are all two-way street segments but have a distinct functionality for road users. Among these types, type 3 streets are the narrowest, with a mean width of 30 feet. It features a bidirectional travel lane mostly with on-street parking. The majority of them are located in residential neighborhoods in Queens and Staten Island.

Type 4 streets are two-travel-lane streets with an average width of 42 feet. They are largely loaded in Brooklyn and Queens and 8% of type 4 streets have a conventional bike facility.

Type 5 streets are the thoroughfare corridor across the city, with 4-6 lanes and an average width of 60 feet.

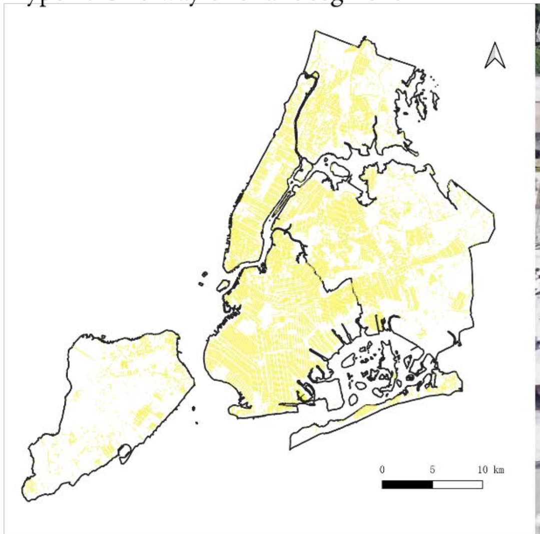
Type 6 streets are a unique collection that consists of two-way segments with concrete median, viaduct, or subway overpass in the middle of lanes. It may have the most diverse road environment within individual groups, ranging from boulevards to the wide roads with viaduct or subway overpass. This type of street is less rare in NYC, compared with other places but comprise 6% of the total network.

Figure 4 shows a detailed map of distribution and an example of street segment image from Google Earth 3D model and Google Street view for each type of street.

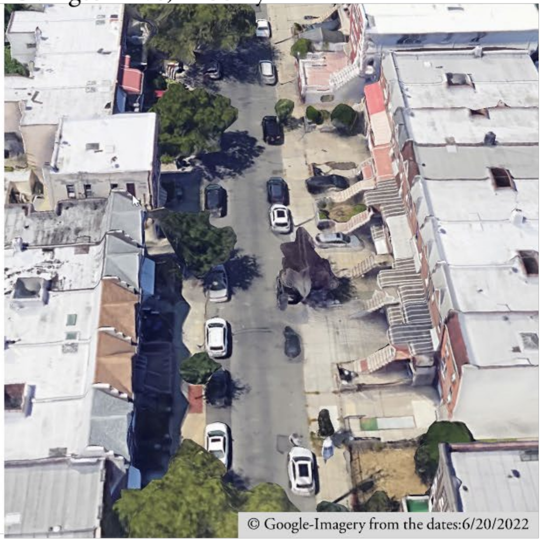


1
2 **Figure 3 Map of street network with cluster types in NYC**

Type 1: One-way one-lane segment



Ovington Ave, Brooklyn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Ovington Ave, Brooklyn

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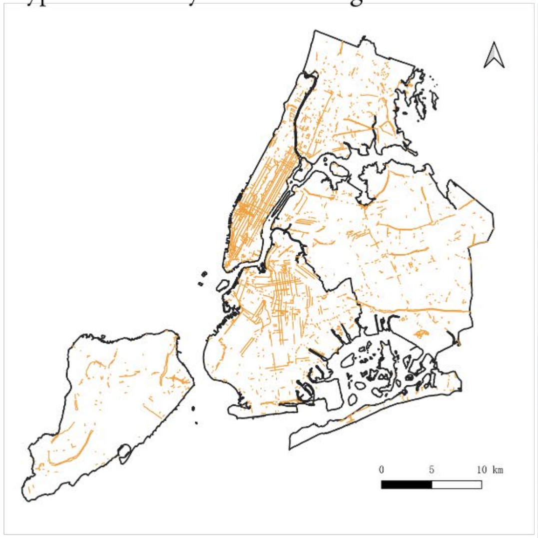
Type 2: One-way multi-lane segment



8th Ave, Manhattan

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8th Ave, Manhattan

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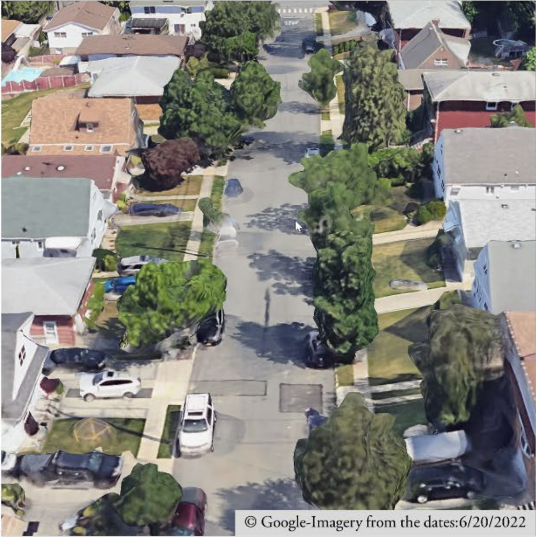
Type 3: Two-way one-lane segment

Gower St, Staten Island



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Gower St, Staten Island

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Type 4: Two-way two-lane segment

31st Ave, Queens

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31st Ave, Queens

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Type 5: Two-way 4-6 lane segment

East 149th St, Bronx

East 149th St, Bronx

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Type 6: Two-way segment with concrete median

Park Ave, Manhattan

Park Ave, Manhattan

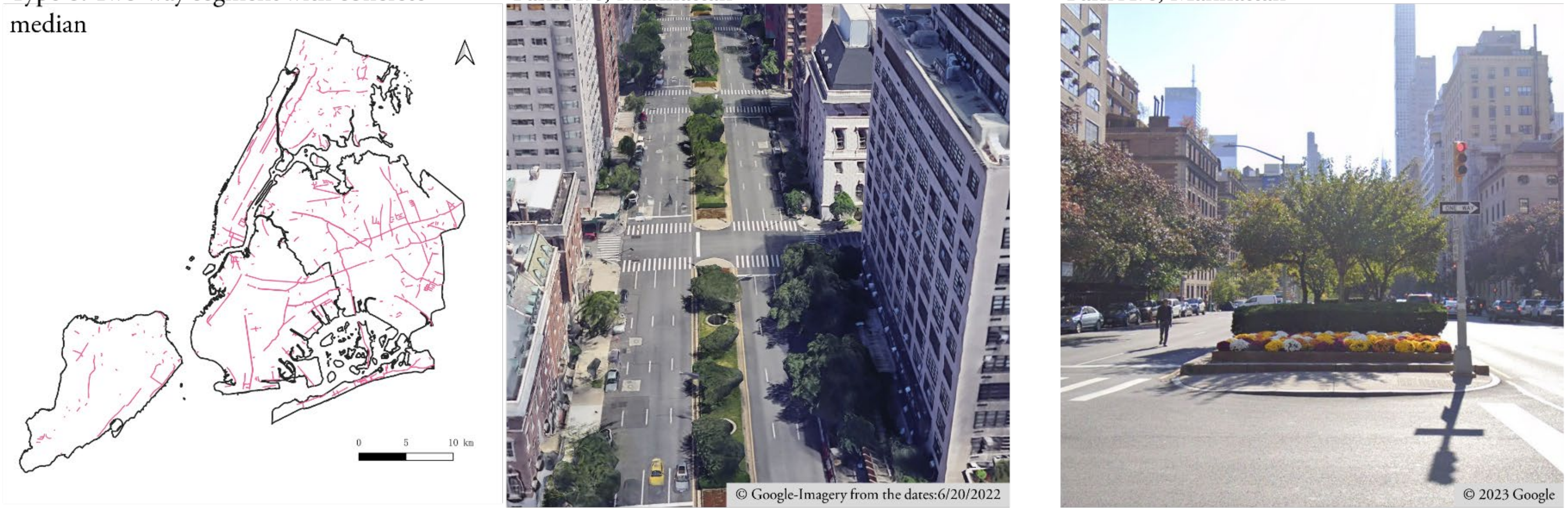

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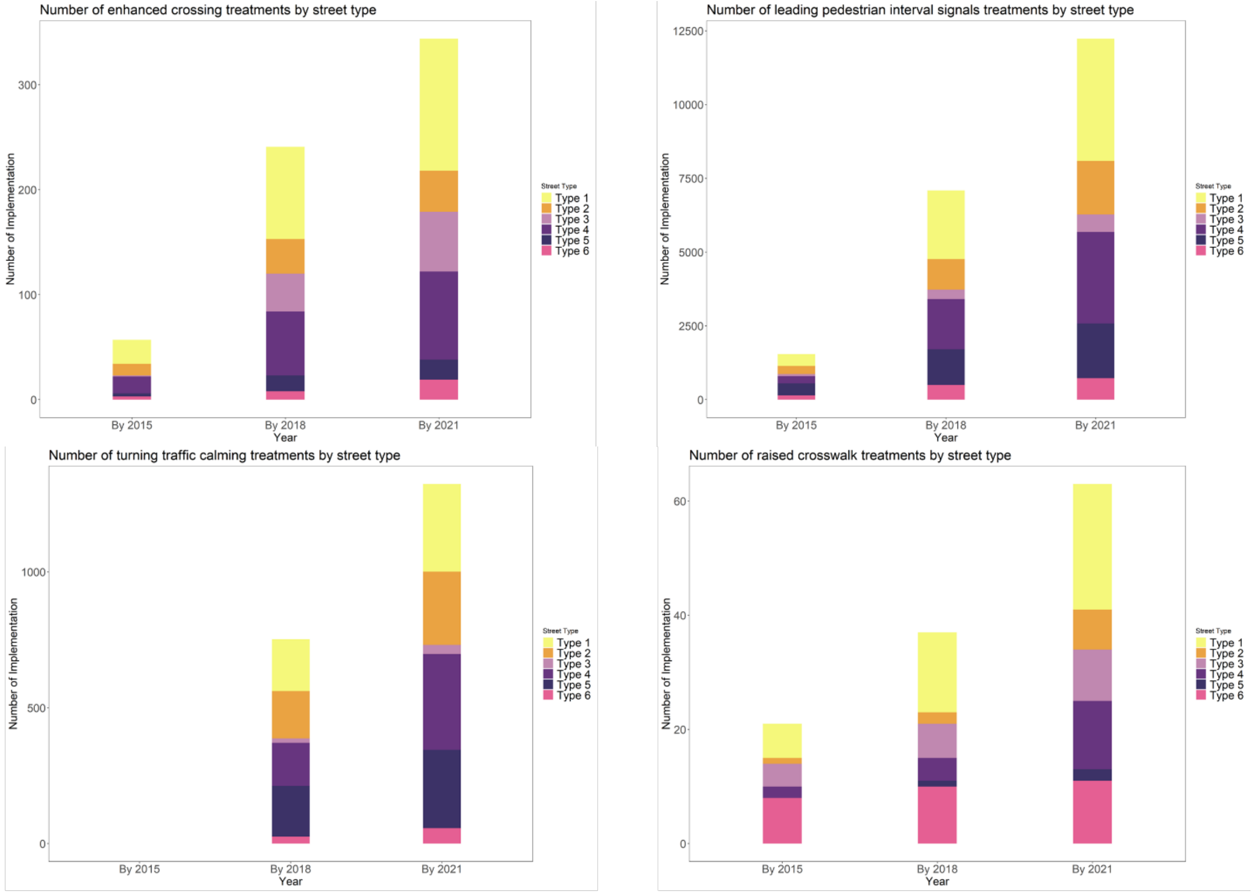
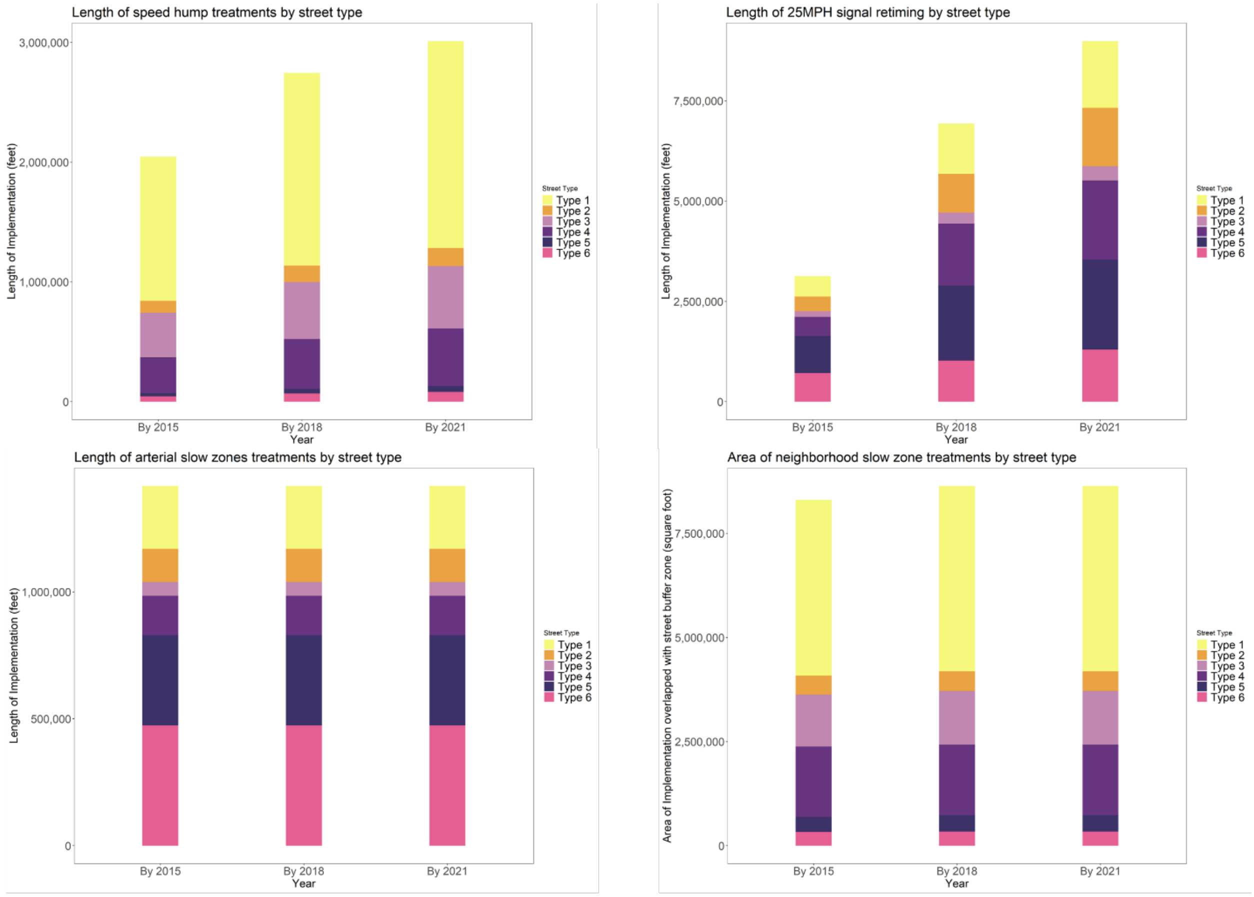
Figure 4 Example of street cluster type from Google Earth and Google Maps Street View

Vision Zero Implementation by Street Type

This section examines the spatial distribution of Vision Zero treatments in NYC. Specifically, we want to examine if there is any discrepancy in Vision Zero engineering investment in different street types by looking at number/length of each treatment at three stages- by the end of 2015, 2018, and 2021. **Figure 5** shows the differences in growth of the implementations. For enhanced crossing, Type 1 and Type 4 streets had the largest amounts of treatment. Type 5 and 6 streets showed an increase over time. For leading pedestrian interval signals, Type 1 and Type 4 streets had more implementations and show steady growth. In terms of traffic calming treatments, Type 1, 2, 4 and 5 streets maintained roughly equal numbers in 2018 and 2021. For raised crosswalks, more treatments were concentrated in Type 1, 4 and 6 streets. Type 1 streets were overwhelmingly treated with speed humps over the years. However, the signal retiming treatments, corresponding to the citywide speed limit reduction to 25 MPH, were more often implemented in type 4 and 5 streets. Not surprisingly, the implementation of arterial slow zones concentrated on the larger streets (Types 4, 5 and 6), while neighborhood slow zones focused more on the local streets (Type 1). This shows that the disparities of Vision Zero treatments did exist in different types of streets, and we will test the efforts of each treatment in the next section.



* The first implementation of turning traffic calming was started in 2016.



* * The latest implementation of arterial slow zone was done in 2014.

* The latest implementation of neighborhood slow zone was done in 2016.

Figure 5 Number/length of Vision Zero treatments by street type

Regression Models

Negative binomial regression models were developed for street-segment-group-level pedestrian and car occupant crash injuries and fatalities. The descriptive statistics of variables included in the models are shown in **Table 2**.

Table 2 Descriptive statistics of variables at street- segment group level

Variable	*count*	*Mean*	*SD*	*Min*	*Max*
Area level variables					
#of estimated pedestrians	188	10117	30638	147	392745
Population & employment Density (/acre)	188	109	122	8	1161
Job-residence ratio	188	0.53	2	0.049	28
Percentage of low income	188	0.21	0.042	0.099	0.38
Percentage of African American	188	0.23	0.26	0.0012	0.93
Percentage of Hispanic American	188	0.28	0.21	0.039	0.88
Street-group level variables					
Average lane width (feet)	1094	38	12	12	78
Average sidewalk width (feet)	1094	9.8	2.7	0	24
VMT	1094	68032262	92680628	13053	9.63E+08
Proportion of on-street parking	1094	0.81	0.25	0	1
Height-to-width ratio	1094	0.53	0.69	0	8.3
Tree canopy coverage (%)	1094	0.17	0.11	0	0.7
Time variant variables					
Pedestrian injuries in 2014-2016	1094	28	49	0	686
Pedestrian fatalities in 2014-2016	1094	0.33	0.82	0	8.5
Car occupant injuries in 2014-2016	1094	85	122	0	1021
Car occupant fatalities in 2014-2016	1094	0.16	0.5	0	5
Pedestrian injuries in 2017-2019	1094	29	46	0	524
Pedestrian fatalities in 2017-2019	1094	0.32	0.75	0	10
Car occupant injuries in 2017-2019	1094	99	136	0	1241
Car occupant fatalities in 2017-2019	1094	0.18	0.47	0	3

Table 2 Continued

Variable	*count*	*Mean*	*SD*	*Min*	*Max*
Pedestrian injuries in 2020-2022	1094	20	31	0	334
Pedestrian fatalities in 2020-2022	1094	0.28	0.69	0	5.5
Car occupant injuries in 2020-2022	1094	74	106	0	1100
Car occupant fatalities in 2020-2022	1094	0.25	0.6	0	4
Enhanced crossings by 2015	1094	0.00084	0.0065	0	0.14
Leading pedestrian interval by 2015	1094	0.033	0.072	0	0.67
Raised crosswalk by 2015	1094	0.00036	0.0044	0	0.11
Speed Hump by 2015	1094	0.055	0.11	0	2.2
25MPH signal retiming by 2015	1094	0.22	0.42	0	5.1
Arterial slow zones by 2015	1094	0.096	0.24	0	1.7
Neighborhood slow zones by 2015	1094	0.036	0.12	0	0.98
Enhanced crossings by 2018	1094	0.0039	0.018	0	0.33
Leading pedestrian interval by 2018	1094	0.12	0.17	0	1
Turn traffic calming by 2018	1094	0.015	0.044	0	0.64
Raised crosswalk by 2018	1094	0.00057	0.0064	0	0.17
Speed Hump by 2018	1094	0.074	0.12	0	2.4
25MPH signal retiming by 2018	1094	0.43	0.68	0	5.1
Arterial slow zones by 2018	1094	0.096	0.24	0	1.7
Neighborhood slow zones by 2018	1094	0.037	0.12	0	0.99
Enhanced crossings by 2021	1094	0.0058	0.025	0	0.33
Leading pedestrian interval by 2021	1094	0.19	0.24	0	1.5
Turn traffic calming by 2021	1094	0.025	0.057	0	0.64
Raised crosswalk by 2021	1094	0.00084	0.0068	0	0.17
Speed Hump by 2021	1094	0.08	0.12	0	2.4
25MPH signal retiming by 2021	1094	0.54	0.78	0	5.4
Arterial slow zones by 2021	1094	0.096	0.24	0	1.7
Neighborhood slow zones by 2021	1094	0.037	0.12	0	0.99

Model results for the three periods of 2014-2016, 2017-2019, and 2020-2022 are shown in Tables 3, 4, and 5 respectively. We separated the models for the three periods because we wanted to test how road safety evolved with different stages of Vision Zero initiatives. 2020-2022 was also different because this period coincided with the COVID-19 pandemic. For each period, pedestrian injuries, pedestrian fatalities, car occupant injuries, and car occupant fatalities are modeled separately. The same set of independent variables are used, except that the pedestrian models included an extra exposure variable, the estimated number of pedestrians that approximates the level of pedestrian mobility.

Table 3 presents models for the early stage of Vision Zero in NYC, showing associations between different street types and safety outcomes. Street Types 2, 3, 4, and 5 have higher pedestrian injuries compared to the base Street Type 1, while Street Type 6 with two-way segments and a median divider has lower pedestrian injuries. Street Types 2, 4, 5, and 6 exhibit higher pedestrian fatalities, while Street Type 3 is not significantly different from Type 1 in this regard. Car occupant injuries are higher in Types 2, 4, and 5, but lower in Types 3 and 6. All Street Types from 2 to 6 are linked to higher car occupant fatality numbers than Type 1.

The results also show significant associations between land use variables and safety outcomes. Increased population and employment density are correlated with more pedestrian injuries but fewer car occupant fatalities. A higher job-residence ratio is associated with lower pedestrian injuries but higher car occupant fatalities. Regarding socio-demographics, a higher percentage of Hispanic American residents and African American residents correlates with more pedestrian injuries, car occupant injuries, and fatalities. A higher percentage of low-income residents correlates with more pedestrian injuries. Street and streetscape design features also play a role, with wider sidewalks associated with fewer pedestrian fatalities, while more on-street parking is linked to more pedestrian injuries, fatalities, and car occupant injuries. Increased tree canopy coverage, however, is associated with lower numbers of pedestrian injuries, fatalities, and car occupant injuries.

Vision Zero safety treatments like LPI signals are associated with reduced pedestrian injuries, while speed humps show higher pedestrian injuries but lower car occupant injuries. 25-mph signal retiming treatments are associated with higher numbers of pedestrian and car occupant injuries, while raised crosswalk treatments are associated with lower numbers of pedestrian and car occupant injuries. On the other hand, neighborhood slow zone implementations are found to be negatively associated with car occupant injuries.

Table 3 Negative binomial (NB) models of crash injuries and fatalities in 2014-2016

Variable	Pedestrian injuries		Pedestrian fatalities		Car occupant injuries		Car occupant fatalities	
	Coefficient	*(S.E.)*	*Coefficient*	*(S.E.)*	*Coefficient*	*(S.E.)*	*Coefficient*	*(S.E.)*
Intercept	-13.210*	(0.473)	-17.170*	(1.496)	-7.972*	(0.396)	-14.461*	(1.903)
Traffic & mobility characteristics								
Log (VMT)	1.596*	(0.044)	1.765*	(0.157)	1.535*	(0.041)	1.637*	(0.202)
#of estimated pedestrians	0.471*	(0.085)	0.263	(0.235)	-	-	-	-
Street cluster type (type 1 as reference)								
Street type 2	0.382*	(0.093)	0.866*	(0.285)	0.290*	(0.098)	0.579	(0.443)
Street type 3	0.049	(0.092)	-0.104	(0.452)	-0.018	(0.094)	0.216	(0.460)
Street type 4	1.003*	(0.082)	1.281*	(0.255)	0.891*	(0.090)	1.142*	(0.364)
Street type 5	1.457*	(0.108)	1.885*	(0.312)	1.149*	(0.115)	1.800*	(0.443)
Street type 6	-0.256*	(0.100)	0.872*	(0.316)	-0.016	(0.103)	0.249	(0.458)
Lands use & sociodemographic								
Population & employment Density	0.002*	(0.0006)	-0.0007	(0.001)	-0.0006	(0.0006)	-0.006**	(0.003)
Job-residence ratio	-0.047**	(0.021)	-0.00003	(0.046)	0.021	(0.024)	0.300*	(0.093)
Percentage of low income	1.767**	(0.700)	2.388	(1.626)	-0.979	(0.736)	-3.738	(2.853)
Percentage of African American	0.565*	(0.097)	0.046	(0.247)	0.975*	(0.101)	0.528***	(0.281)
Percentage of Hispanic American	0.525*	(0.133)	-0.188	(0.343)	0.591*	(0.142)	0.439	(0.508)
Street and Streetscape Design Features								
Average sidewalk width	0.004	(0.014)	-0.081**	(0.038)	-0.019	(0.014)	0.003	(0.056)
Proportion of on-street parking	1.077*	(0.132)	1.176*	(0.409)	0.235***	(0.128)	0.246	(0.433)
Height-to-width ratio	-0.001	(0.072)	0.212	(0.216)	-0.020	(0.073)	-0.372	(0.553)
Tree canopy coverage	-1.164*	(0.379)	-2.677**	(1.193)	-1.299*	(0.350)	0.435	(1.281)
Vision Zero Treatments								
Enhanced crossings	-1.768	(4.306)	0.240	(10.910)	0.168	(4.207)	-9.492	(22.944)
Leading pedestrian interval signals	-1.018**	(0.461)	0.446	(0.946)	-0.137	(0.441)	-1.357	(1.878)
Turn traffic calming	-	-	-	-	-	-	-	-
Raised crosswalk	-9.835***	(5.418)	1.699	(14.540)	-9.806***	(5.815)	-3579	(1.01×10^{8})
Speed Hump	0.602***	(0.315)	0.662	(1.218)	-0.776**	(0.356)	-1.319	(2.022)
25MPH signal retiming	0.510*	(0.099)	0.281	(0.235)	0.513*	(0.102)	-0.018	(0.381)
Arterial slow zones	0.031	(0.164)	-0.324	(0.402)	-0.244	(0.172)	-0.261	(0.663)
Neighborhood slow zones	0.095	(0.214)	-0.595	(0.730)	-0.569**	(0.234)	-1.876	(1.481)

* Statistically significant at 1%. ** Statistically significant at 5%. *** Statistically significant at 10%.

As shown in **Table 4**, during the middle stage of Vision Zero deployment in NYC, Street Types 4 and 5 have higher numbers of pedestrian injuries, while Street Type 3 and 6 experiences fewer pedestrian injuries compared to the base Street Type 1. All Street Types from 2 to 6 have higher pedestrian fatalities than Type 1, while Types 2, 4, and 5 exhibit higher car occupant injuries and Types 1 and 6 show lower car occupant fatalities. Notably, Street Type 1 has the lowest car occupant fatalities, while Types 4 and 5 have significantly higher numbers.

In this stage, there is no significant relationship between density and safety outcomes. The job-residence ratio shows a slight negative correlation with pedestrian injuries, similar to the early-stage model, while the percentage of Hispanic American and African American residents demonstrates notable positive associations with pedestrian injuries, car occupant injuries, and fatalities. Street and streetscape design features keep playing a role, with on-street parking showing positive correlations with pedestrian injuries and fatalities, and car occupant fatalities, whereas tree canopy coverage is negatively associated with both pedestrian and car occupant injuries.

Regarding Vision Zero treatments, enhanced crossings are connected to lower car occupant injuries, while LPI signals continue to be associated with reduced pedestrian injuries and car occupant injuries and fatalities. Turn traffic calming treatments show an association with decreased car occupant fatalities, while speed humps are correlated with lower car occupant fatalities. However, 25-mph signal retiming projects show concerning trends, as they are associated with increased injuries and fatalities for both pedestrians and car occupants. On the positive side, zonal safety treatments, such as arterial slow zones and neighborhood slow zones, display some negative correlations with adverse safety outcomes, showing reductions in car occupant injuries and fatalities, and pedestrian fatalities.

Table 4 Negative binomial (NB) models of crash injuries and fatalities in 2017-2019

Variable	Pedestrian injuries		Pedestrian fatalities		Car occupant injuries		Car occupant fatalities	
	Coefficient	*(S.E.)*	*Coefficient*	*(S.E.)*	*Coefficient*	*(S.E.)*	*Coefficient*	*(S.E.)*
Intercept	-12.296*	(0.442)	-15.967*	(1.431)	-7.147*	(0.400)	-12.850*	(1.619)
Traffic & mobility characteristics								
Log (VMT)	1.535*	(0.042)	1.492*	(0.147)	1.447*	(0.041)	1.372*	(0.168)
#of estimated pedestrians	0.470*	(0.079)	0.748*	(0.236)	-	-	-	-
Street cluster type (type 1 as reference)								
Street type 2	0.081	(0.088)	0.772**	(0.292)	0.300**	(0.098)	0.342	(0.375)
Street type 3	-0.142***	(0.086)	0.082	(0.377)	-0.020	(0.094)	0.209	(0.402)
Street type 4	0.818*	(0.077)	1.096*	(0.261)	0.762*	(0.091)	0.936*	(0.313)
Street type 5	1.031*	(0.104)	1.432*	(0.325)	1.094*	(0.117)	1.242*	(0.389)
Street type 6	-0.439*	(0.094)	0.355	(0.328)	-0.159	(0.102)	0.269	(0.389)
Lands use & sociodemographic								
Population & employment Density	0.0007	(0.0006)	-0.001	(0.002)	0.0003	(0.0006)	0.002	(0.002)
Job-residence ratio	-0.030	(0.020)	0.022	(0.049)	0.013	(0.024)	-0.055	(0.068)
Percentage of low income	1.892*	(0.648)	-2.045	(1.650)	-1.274	(0.732)	-1.072	(2.299)
Percentage of African American	0.649*	(0.090)	-0.213	(0.255)	1.010*	(0.101)	0.779*	(0.254)
Percentage of Hispanic American	0.375*	(0.125)	0.516	(0.338)	0.834*	(0.142)	0.259	(0.432)
Street and Streetscape Design Features								
Average sidewalk width	0.002	(0.013)	-0.039	(0.037)	-0.006	(0.014)	-0.036	(0.048)
Proportion of on-street parking	1.006*	(0.122)	0.943**	(0.380)	0.218	(0.127)	0.770***	(0.440)
Height-to-width ratio	0.074	(0.065)	-0.299	(0.257)	-0.158**	(0.074)	-0.116	(0.308)
Tree canopy coverage	-1.167*	(0.352)	-0.975	(1.095)	-1.284*	(0.349)	-0.907	(1.152)
Vision Zero Treatments								
Enhanced crossings	0.164	(1.359)	4.308	(3.518)	-3.224**	(1.551)	-7.766	(8.659)
Leading pedestrian interval signals	-0.532*	(0.199)	-0.529	(0.522)	-0.868*	(0.227)	-1.285***	(0.754)
Turn traffic calming	-0.271	(0.543)	-0.102	(1.239)	-0.892	(0.664)	-4.591***	(2.600)
Raised crosswalk	0.600	(3.263)	-12.043	(20.431)	-4.082	(3.938)	-6869	(6.53×10^{7})
Speed Hump	0.355	(0.262)	-0.950	(1.136)	-0.084	(0.267)	-2.890***	(1.508)
25MPH signal retiming	0.375*	(0.056)	0.436*	(0.135)	0.370*	(0.063)	0.395**	(0.193)
Arterial slow zones	-0.051	(0.134)	-0.210	(0.341)	-0.320**	(0.152)	-1.086**	(0.523)
Neighborhood slow zones	-0.028	(0.193)	-1.704***	(0.871)	-0.696*	(0.221)	-0.788	(0.975)

* Statistically significant at 1%. ** Statistically significant at 5%. *** Statistically significant at 10%.

The most recent three-year period of Vision Zero deployment in NYC coincided with the COVID-19 pandemic. **Table 5** shows that, during this period, Street Types 4 and 5 had a higher number of pedestrian injuries compared to the base Street Type 1, while Street Type 6 exhibited lower pedestrian injuries. Pedestrian fatalities were more prevalent on streets of Types 2, 4, and 5, while car occupant injuries and fatalities were more common on Type 4 and 5 streets, with Type 6 streets recording fewer car occupant injuries than Type 1.

Land use and socio-demographics also played a role in safety outcomes. Density exhibited a slight negative correlation with car occupant fatality numbers. Streets in areas with higher proportions of low-income residents had significantly more pedestrian injuries compared to those in areas with lower proportions, and the percentage of Hispanic American and African American residents consistently showed positive correlations with pedestrian injuries, car occupant injuries, and fatalities. Several street and streetscape design features keep demonstrating significant correlations with safety outcomes. Average sidewalk width was negatively related to pedestrian fatalities, while the proportion of on-street parking showed positive correlations with pedestrian injuries, fatalities, and car occupant injuries. Streetscape height-to-width ratio was negatively related to car occupant injuries, and tree canopy coverage consistently exhibited negative correlations with pedestrian injuries and car occupant injuries and fatalities.

During the pandemic period, certain safety treatments continued to show effectiveness. Streets with implemented LPI signals were associated with reduced numbers of pedestrian injuries and car occupant injuries and fatalities. However, speed humps were correlated with a higher number of pedestrian injuries. The 25-mph signal retiming showed a concerning pattern, with increased injuries and fatalities for both pedestrians and car occupants, consistent with the middle-stage model. Additionally, arterial slow zones and neighborhood slow zones were related to reductions in car occupant injuries and fatalities.

Table 5 Negative binomial (NB) models of crash injuries and fatalities in 2020-2022

Variable	Pedestrian injuries		Pedestrian fatalities		Car occupant injuries		Car occupant fatalities	
	Coefficient	*(S.E.)*	*Coefficient*	*(S.E.)*	*Coefficient*	*(S.E.)*	*Coefficient*	*(S.E.)*
Intercept	-13.162*	(0.457)	-17.574*	(1.511)	-7.879*	(0.395)	-14.701*	(1.581)
Traffic & mobility characteristics								
Log (VMT)	1.551*	(0.043)	1.741*	(0.161)	1.518*	(0.041)	1.766*	(0.165)
#of estimated pedestrians	0.516*	(0.079)	0.479*	(0.238)	-	-	-	-
Street cluster type (type 1 as reference)								
Street type 2	0.088	(0.089)	1.088*	(0.290)	0.108	(0.096)	0.451	(0.311)
Street type 3	0.068	(0.086)	0.255	(0.394)	-0.047	(0.091)	-0.179	(0.406)
Street type 4	0.864*	(0.076)	1.167*	(0.266)	0.625*	(0.088)	0.925*	(0.258)
Street type 5	1.008*	(0.105)	1.439*	(0.331)	0.899*	(0.117)	1.293*	(0.334)
Street type 6	-0.437*	(0.096)	-0.217	(0.373)	-0.369*	(0.101)	0.123	(0.335)
Lands use & sociodemographic								
Population & employment Density	0.0002	(0.0006)	-0.002	(0.002)	-0.0002	(0.0006)	-0.004**	(0.002)
Job-residence ratio	-0.019	(0.020)	0.051	(0.047)	0.028	(0.023)	0.094	(0.070)
Percentage of low income	2.507*	(0.642)	0.314	(1.674)	-0.357	(0.710)	-4.061***	(2.296)
Percentage of African American	0.784*	(0.089)	0.366	(0.231)	1.246*	(0.097)	0.683*	(0.241)
Percentage of Hispanic American	0.534*	(0.125)	0.218	(0.354)	0.786*	(0.139)	1.132*	(0.401)
Street and Streetscape Design Features								
Average sidewalk width	0.013	(0.013)	-0.080***	(0.041)	-0.015	(0.014)	-0.003	(0.043)
Proportion of on-street parking	0.844*	(0.125)	0.717***	(0.388)	0.257**	(0.125)	0.008	(0.366)
Height-to-width ratio	0.017	(0.070)	0.099	(0.249)	-0.212*	(0.077)	0.438***	(0.262)
Tree canopy coverage	-1.100*	(0.357)	-0.269	(1.193)	-2.069*	(0.344)	-1.832***	(1.049)
Vision Zero Treatments								
Enhanced crossings	0.369	(0.999)	0.390	(4.178)	-1.236	(1.121)	-7.384	(6.490)
Leading pedestrian interval signals	-0.271**	(0.136)	0.177	(0.366)	-0.552*	(0.152)	-0.780***	(0.463)
Turn traffic calming	0.246	(0.443)	0.847	(1.052)	0.779	(0.512)	-1.746	(1.669)
Raised crosswalk	-0.631	(3.077)	-1.828	(13.590)	-2.107	(3.575)	-15.769	(21.535)
Speed Hump	0.651*	(0.247)	0.885	(1.052)	-0.229	(0.275)	0.760	(0.985)
25MPH signal retiming	0.290*	(0.047)	0.348*	(0.109)	0.270*	(0.051)	0.228	(0.153)
Arterial slow zones	-0.036	(0.128)	0.242	(0.341)	-0.238**	(0.140)	-0.921**	(0.461)
Neighborhood slow zones	0.175	(0.191)	-1.001	(0.792)	-0.616**	(0.219)	-0.748	(0.819)

* Statistically significant at 1%. ** Statistically significant at 5%. *** Statistically significant at 10%.

Findings from the regression models are summarized as follows:

The results show that different street types are associated with significant differences in safety outcomes. Type 6 street (two-way segments with concrete median) has a higher risk of fatalities, although it observes a significant decrease in pedestrian and car occupant injuries. Type 1 and 3 streets generally have a lower risk of injuries and fatalities across the three periods.

Vision Zero treatments have a mixed effect on safety outcomes. The leading pedestrian interval shows a significantly negative correlation with pedestrian injuries, car occupant injuries and car occupant fatalities. 25-mph signal retiming shows a constantly positive correlation with all four adverse safety outcomes, except for car occupant fatality in 2014-2016. Enhanced crossing and raised crosswalk show a negative relationship with casualties in 2014-2016 and 2017-2019. However, they see an opposite effect on safety during 2020-2022. Neighborhood Slow Zones and Arterial Slow Zones are associated with lower risk of car occupant injuries and fatalities while the association is not obvious for pedestrian safety outcomes.

Findings regarding sociodemographic and racial variables are alarming. Street segment groups at NTAs with a larger percentage of low-income workers, and Hispanic American and African American residents tend to suffer significantly greater risk of injuries and fatalities for both pedestrians and car occupants across the three periods.

Among street and streetscape design features, street trees provide a “good shade” for protecting road users. The percentage of tree canopy at the street segment group level was associated with a lower risk of crashes resulting in injuries and fatalities. The presence of on-street parking is associated with higher numbers of pedestrian and car occupant casualties. Other variables such as sidewalk, height-to-width ratio, job-residence ratio, and speed humps, do not show significant association with casualties.

DISCUSSION

In the road safety domain, researchers usually apply two distinctive approaches (*44*). Microscopic level studies focus on certain road design feature at specific road locations (e.g., intersections or corridors) and macroscopic level studies emphasize road safety indicators at larger geographic areas (e.g., census tract, traffic analysis zone, city, country). Our study defines a mesoscopic level approach that aggregates street segments at the scale of the neighborhood. This mesoscopic, multi-scalar approach allows us to consider factors in our analysis, including both the street design and the streetscape features based on the street segments level and land use contexts that must be characterized at the neighborhood level. It highlights the importance of the street/place nexus that is defined by both the street typology and neighborhood level factors. These latter factors have tended to be neglected in previous studies. By investigating safety outcomes at this mesoscopic level, this study would inform policy makers about how these different sets of factors and Vision Zero safety treatments affect crash injuries and fatalities and offer insights on how to allocate safety improvements resources for different place types.

The street network in NYC consists of a diverse set of street types and physical context, which we assume would differ in safety outcomes due to their difference in design characteristics. Our models verified this assumption, as the results show that different types of streets have significantly different crash injury and fatality outcomes. Specifically, considering pedestrian safety, streets of Types 2, 4, and 5 are more dangerous than the base Type 1. Type 3 streets are as safe as Type 1, and Type 6 streets became as safe as Type 1 over the process of Vision Zero. A similar pattern is also seen in car occupant safety. The increase in the number of lanes and width increases the complexity of traffic movements and potentially brings higher risks to all road users. The narrow two-way one-lane design of Type 3 streets and wide multi-lane but divided design of Type 6 streets potentially help reduce safety risks, but a more in-depth study is needed to understand their mechanisms.

Streetscape design features are usually overlooked when modeling safety outcomes. In our models, we observe significant effects on pedestrian and car occupant casualties of features such as tree canopy coverage and height-to-width ratio. These factors should be considered in addition to street geometric design features when considering safety treatments for Vision Zero, as appropriately adapting these design features would significantly help mitigate crash injuries and fatalities.

We observed consistencies regarding Vision Zero treatments. The effects of each treatment are consistent over the three time periods that we examined. The directions of treatments' correlations with different types of safety outcome are also consistent, but values vary, as one type of treatment may be more effective for pedestrian safety or car occupant safety, or more effective in addressing injury crashes versus fatal crashes.

This study has some limitations. First, the study only evaluates the association between safety outcomes and important explanatory variables within NYC. Although NYC includes a variety of street design and built environments, it is also one of the densest cities with large percentages of pedestrians in U.S. The results may not be directly transferred to other places. Nevertheless, this study proposed a framework for other Vision Zero cities to conduct a similar mesoscopic level study. Second, a cross-sectional analysis, as in this study, may not fully explain the users' behavior change in response to the treatments and the intertwining temporal and spatial effects in the complex reality of road safety. Some street design and built environment features will change over the years with the implementation of the Vision Zero initiatives in the city. Therefore, a temporal-spatial model should be considered to account for the resulting dynamic changes. Lastly, this study is based on all publicly available data, most from the NYC open database. Data quality may be a potential concern. For example, we ran into the problem of the divided roadways being mislabeled as separate streets. Nevertheless, the analyses would not have been possible without the depth and breadth of the open data. It shows how open data transparency can promote a data-driven approach so that it can better guide the direction of Vison Zero planning. Vision Zero communities will benefit from building and maintaining a more standard and robust system to collect, host, and share complete data for street features and Vision Zero treatments.

CONCLUSIONS

This study shows that different street types have distinct safety outcomes. More specifically, street segment groups with narrower, two-way sections, and higher tree canopy coverage tended to have a lower risk of casualties for both pedestrians and motorized users. Vision Zero treatments had mixed effects on safety outcomes. Risk of injuries and fatalities was higher for street segment groups located in neighborhoods with a larger percentage of African American and Hispanic American residents, further signaling as an equity issue for Vision Zero implementation. Current practice still relies on a hot-spot method for Vision Zero planning (*45*). This study suggests that a context-based approach to Vison Zero planning is needed for a more sustainable and equitable transportation system. In the U.S., there is still no comprehensive street typology that quantitatively characterizes street design features for the purpose of road safety planning. This research contributes to filling the gap by taking a first step to develop a street typology based on street design and further testing it using empirical studies.

This study also outlines some potential directions for future studies. For example, research can investigate where the treatments are most needed by looking at the differences between different types of street facilities. Exploring the underlying mechanism of safer street-place types, such as the effect of tree canopies, is also worthwhile. Studies should also focus on a before-after study to estimate what crash injuries and fatalities in NYC would be like without the various Vision Zero implementations and the most effective treatments within the Vision Zero framework.

ACKNOWLEDGMENT

The authors wish to acknowledge the fellowship support from the Connecticut Transportation Safety Research Center (CTSRC) and the Connecticut Transportation Institute (CTI) in conducting this research.

FUNDING

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was partially funded via the fellowship from the Connecticut Transportation Safety Research Center (CTSRC) and the Connecticut Transportation Institute (CTI).

AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows: study conception and design: G. Shi, Y. Song, N. Garrick, C. Atkinson; data collection: G. Shi; analysis and interpretation of results: G. Shi, Y. Song, N. Garrick, C. Atkinson; draft manuscript preparation: G. Shi, Y. Song, N. Garrick, C. Atkinson. All authors reviewed the results and approved the final version of the manuscript.

DECLARATION OF CONFLICTING INTERESTS

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

DATA ACCESSIBILITY STATEMENTS

The datasets generated and analyzed during the current study are available in the Zenodo repository, https://zenodo.org/records/10628028

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