CPBS
Center for Pedestrian and Bicyclist Safety

A Tier-1 University Transportation Center

Pedestrian vs. Bicyclist Fatality Patterns of Geographic/Demographic Shift

July 2024	A Report From the Center for Pedestrian and Bicyclist Safety

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University of New Mexico

About the Center for Pedestrian and Bicyclist Safety (CPBS)

The Center for Pedestrian and Bicyclist Safety (CPBS) is a consortium of universities committed to eliminating pedestrian and bicyclist fatalities and injuries through cutting-edge research, workforce development, technology transfer, and education. Consortium members include: The University of New Mexico; San Diego State University; The University of California Berkeley; The University of Tennessee Knoxville; and The University of Wisconsin Milwaukee. More information can be found at: https://pedbikesafety.org

Disclaimer

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16. Abstract

Between 2009 and 2022 in the United States (U.S.), pedestrian fatalities increased 82.3% and bicyclist fatalities increased 70.8% according to data from the National Highway Traffic Safety Administration (NHTSA). Where are these fatalities occurring within our regions and what spatial characteristics of these locations could be influencing this trend? Are these issues focused around specific land uses? This project was divided into two main parts. We first analyzed bicyclist fatality data on the national level from the last two decades using NHTSA's Fatality Analysis Reporting System (FARS) in relation to built-environment and socioeconomic characteristics. We then provided an in-depth exploration of pedestrian and bicyclist fatal and serious injury (KA) crashes for the city of Chicago, which allows us to account for more land use and roadway characteristics. The results of this study indicate that both pedestrian and bicyclist KA crashes have trended toward areas with lower population density, suggesting these pedestrian and bicyclist safety issues are migrating from urban to suburban areas, specifically collectors and arterials in post-war suburbs. Additionally, these fatalities are occurring near small-scale commercial land uses and in neighborhoods with high rates of poverty, high proportions of minority residents, and low levels of access to automobiles. A key implication of this work is the need to rethink our suburbs, for which we propose a village model of urbanity where development occurs in self-contained suburban units. In terms of infrastructure, this work identifies the need to better visualize, measure, and implement such VRU networks on a citywide and regional scale with enhanced bicycle level of traffic stress (BLTS) tool for road crossings and intersections and a pedestrian level of traffic stress (PLTS) tool.

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SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

Pedestrian vs. Bicyclist Fatality Patterns of Geographic/Demographic Shift

A Center for Pedestrian and Bicyclist Safety Research Report

July 2024

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Acronyms, Abbreviations, and Symbols

AADT	Annual Average Daily Traffic
ACS	American Community Survey
AIC	Akaike Information Criterion
CDC	Centers for Disease Control and Prevention
EPA	Environmental Protection Agency
FARS	Fatality Analysis Reporting System
GIS	Geographic Information System
IDOT	Illinois Department of Transportation
KA	Fatal and Serious Injury
NHTSA	National Highway Traffic Safety Administration
SLD	Smart Location Database
US	United States
VIF	Variance Inflation Factor
VRU	Vulnerable Road User

Abstract

Between 2009 and 2022 in the United States (U.S.), pedestrian fatalities increased 82.3% and bicyclist fatalities increased 70.8% according to data from the National Highway Traffic Safety Administration (NHTSA). Where are these fatalities occurring within our regions and what spatial characteristics of these locations could be influencing this trend? Are these issues focused around specific land uses? This project was divided into two main parts. We first analyzed bicyclist fatality data on the national level from the last two decades using NHTSA's Fatality Analysis Reporting System (FARS) in relation to built-environment and socioeconomic characteristics. We then provided an in-depth exploration of pedestrian and bicyclist fatal and serious injury (KA) crashes for the city of Chicago, which allows us to account for more land use and roadway characteristics. The results of this study indicate that both pedestrian and bicyclist KA crashes have trended toward areas with lower population density, suggesting these pedestrian and bicyclist safety issues are migrating from urban to suburban areas, specifically collectors and arterials in post-war suburbs. Additionally, these fatalities are occurring near small-scale commercial land uses and in neighborhoods with high rates of poverty, high proportions of minority residents, and low levels of access to automobiles. A key implication of this work is the need to rethink our suburbs, for which we propose a village model of urbanity where development occurs in self-contained suburban units. In terms of infrastructure, this work identifies the need to better visualize, measure, and implement such VRU networks on a citywide and regional scale with enhanced bicycle level of traffic stress (BLTS) tool for road crossings and intersections and a pedestrian level of traffic stress (PLTS) tool.

Executive Summary

Between 2009 and 2022 in the United States (U.S.), pedestrian fatalities increased 82.3% and bicyclist fatalities increased 70.8% according to data from the National Highway Traffic Safety Administration (NHTSA). A total of 7,489 pedestrians and 1,064 bicyclists were killed on American roadways in 2022, representing 19.9% of all roadway deaths. Where are these fatalities occurring within our regions and what spatial characteristics of these locations could be influencing this trend? To what extent is this issue an urban, suburban, or rural issue, and how has that changed over time? Are these issues focused around specific land uses? Answering these spatial questions can help practitioners better understand and address this critical issue.

This project was divided into two main parts. We first analyzed bicyclist fatality data on the national level from the last two decades using NHTSA's Fatality Analysis Reporting System (FARS) in relation to built-environment and socioeconomic characteristics (e.g., street network density, transit access, poverty, and educational attainment) obtained from the U.S. Census and the U.S. Environmental Protection Agency (EPA) Smart Location Database (SLD). We then provided an in-depth exploration of pedestrian and bicyclist fatal and serious injury (KA) crashes for the city of Chicago, which allows us to account for more land use and roadway characteristics.

The results of this study indicate that both pedestrian and bicyclist fatal and serious injury crashes have trended toward areas with lower population density, suggesting these pedestrian and bicyclist safety issues are migrating from urban to suburban areas, specifically collectors and arterials in post-war suburbs. Additionally, these fatalities are occurring near small-scale commercial land uses and in neighborhoods with high rates of poverty, high proportions of minority residents, and low levels of educational attainment.

A key implication of this work is the need to rethink our suburbs. We propose a village model of urbanity where development occurs in self-contained suburban units. Residents can safely and conveniently access what they need by walking and biking within the urban villages, and travel between villages can occur by public transportation, biking, walking, or driving. As much development as possible should occur within these urban villages to preserve green space, recreational uses, or agriculture between urban villages.

In terms of infrastructure, this work identifies the need to better visualize, measure, and implement such VRU networks on a citywide and regional scale. To accomplish this, we propose tools that are based on VRU perceptions and not extant VRU crashes. This tool would build upon the widely-implemented bicycle level of traffic stress (BLTS) tool. The existing BLTS tool, while useful for roadway segments, might be expanded to road crossings and intersections. The BLTS might also be translated to pedestrians to form a pedestrian level of traffic stress (PLTS) tool. These tools will help decision makers understand gaps in the current network and help to enable VRU activity on a city or regional scale.

1. Introduction

Between 2009 and 2022 in the United States (U.S.), pedestrian fatalities increased 82.3% and bicyclist fatalities increased 70.8% according to data from the National Highway Traffic Safety Administration (NHTSA) (**Figure 1**). A total of 7,489 pedestrians and 1,064 bicyclists were killed on American roadways in 2022, representing 19.9% of all roadway deaths. While Centers for Disease Control and Prevention (CDC) data shows that traffic safety in general is a significant concern with car crashes being a leading killer of young and middle-aged Americans, outcomes for the most vulnerable road users (i.e., pedestrians and bicyclists) have been degrading at an especially worrying pace.

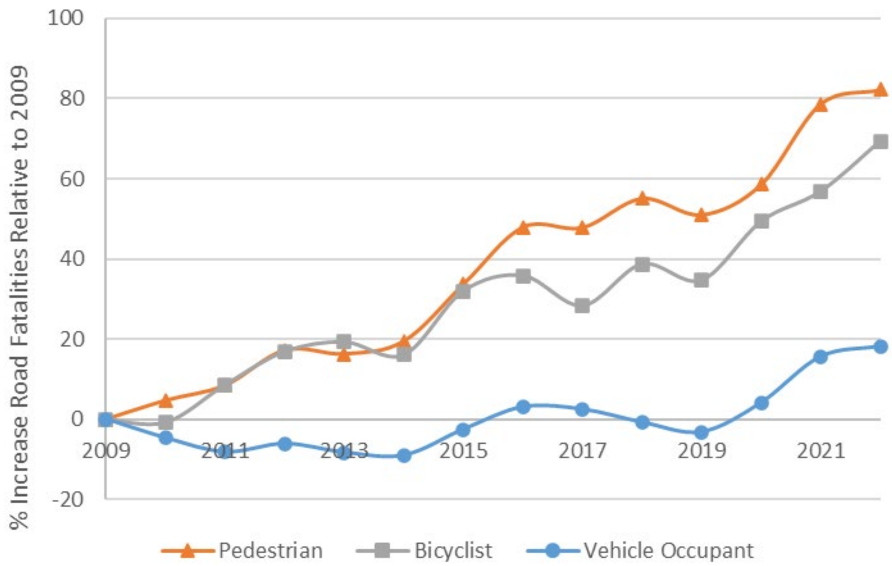


Figure 1. Percent Increase in Road Fatalities Relative to 2009.

Several studies have researched the characteristics of pedestrian and bicyclist crashes such as the people and roadways involved. But where are these fatalities occurring within our regions and what spatial characteristics of these locations could be influencing this trend? To what extent is this issue an urban, suburban, or rural issue, and how has that changed over time? Are these issues focused around specific land uses? Answering these spatial questions can help practitioners better understand and address this critical issue.

This project was divided into two main parts. We first analyzed bicyclist fatality data on the national level from the last two decades using NHTSA's Fatality Analysis Reporting System (FARS) in relation to built-environment and socioeconomic characteristics (e.g., street network density, transit access, poverty, and educational attainment) obtained from the U.S. Census and the U.S. Environmental Protection Agency (EPA) Smart Location Database (SLD). Note that while the results reported in this report are only for bicyclists, similar research focusing on pedestrians has already been published (*Sanchez Rodriguez & Ferenchak, 2023*). Many of the findings for bicyclist trends mirror the pedestrian trends.

For the second part of this research project, we then provided an in-depth exploration of pedestrian and bicyclist fatal and serious injury (KA) crashes for the city of Chicago, which allows us to account for more land use and roadway characteristics. After importing the data into a geographic information system (GIS), we perform logistic regressions using the statistical program R and provide street profiles of segments that had the largest increases in pedestrian and bicyclist KA crashes.

The results of this study indicate that both pedestrian and bicyclist fatal and serious injury crashes have trended toward areas with lower population density, suggesting these pedestrian and bicyclist safety issues are migrating from urban to suburban areas. Additionally, these fatalities are occurring in neighborhoods with high rates of poverty, high proportions of minority residents, and low levels of educational attainment. The results help inform where pedestrian and bicyclist safety issues exist and who is being impacted. Findings will help cities better focus resources to improve vulnerable road user safety, with the critical importance of complete pedestrian and bicyclist networks on citywide or regional scales being a key takeaway of this work.

2. Literature Review

2.1. Background Trends

According to NHTSA data, 7,489 pedestrians were killed on U.S. roadways in 2022. This was the highest number of pedestrian fatalities in over 30 years and represents an 82.3% increase since 2009. According to NHTSA data, 1,064 bicyclists were killed on U.S. roadways in 2022. This was the highest number since federal tracking began in 1975 and represents a 70.8% increase since 2009. While pedestrian and bicyclist fatalities have been increasing relatively consistently since hitting a low point around 2009, past research has shown that vulnerable road user (VRU) safety trends continued to get worse even during COVID when we might have expected vehicle exposure – and therefore risk – to decrease (*Ferenchak, 2023a; Ferenchak, 2023b*).

Several research papers have investigated possible factors related to the increase in pedestrian and bicyclist fatalities since 2009. Findings from past research agree that increased pedestrian and bicyclist fatalities are correlated with infrastructure, vehicle, and person characteristics (*Ferenchak & Abadi, 2021; Schneider, 2020*). We therefore first explore the relationship between VRU safety outcomes and the built environment in Section 2.2, specifically examining both transportation networks and land use. We then explore the relationship between the road safety outcomes and the people involved in Section 2.3.

Another important factor that is not accounted for in this research is lighting condition. About 75% of pedestrian fatalities occur in darkness and nearly 90% of the increase in pedestrian fatalities from 2009 to 2018 occurred in darkness (*Sanders et al., 2022*). Looking beyond just fatalities, past research has found that while the severity of pedestrian collisions has increased during both the day and night, the frequency of pedestrian collisions has increased particularly at night (*Ferenchak et al., 2022*). A key finding of this work will be the importance of road design, and past research has shown that pedestrian fatalities on multilane roads are significantly more likely in darkness (*Sanders et al., 2022*). While we do not parse our analysis by lighting condition, it is important to note its significance.

Furthermore, while we often refer to VRU safety when discussing our analyses of pedestrian and bicyclist KA crashes, we want to note that such reactive crash-based analyses may not fully describe the extent of the VRU safety issue because many pedestrian and bicyclist trips may remain latent, and especially so for more vulnerable road users (*Ferenchak & Marshall, 2019a; Ferenchak & Marshall, 2019b; Ferenchak & Marshall, 2020a*). In other words, crash analyses may not fully identify road safety issues where pedestrian and bicyclist activity has been suppressed because of concerns over perceived traffic safety issues.

It is critical that we improve VRU safety not only directly for the sake of the VRUs that represent 20% of people killed on our roadways, but also because past research has shown that focusing on

VRUs is an effective way of improving overall road user safety and pursuing goals such as Vision Zero (*Ferenchak, 2023c*).

2.2. Road Safety and the Built Environment

2.2.1. Pedestrians

First specifically exploring pedestrian safety trends, pedestrian fatality increases have concentrated on roads with speed limits in the 40–45 mph range, roads identified as arterials, and roads with more than four lanes (*Ferenchak & Abadi, 2021; Long & Ferenchak, 2021; Sanders & Schneider, 2022; Schneider, 2020*). Most pedestrian fatalities occur at midblock locations on these roads. In other words, pedestrian fatalities often involve pedestrians attempting to cross arterials at locations where there are no traffic-controlled pedestrian crossing facilities.

In addition to exploring the relationship between pedestrian safety outcomes and road design, we can also explore the relationship with road networks. Past research has found that higher road network densities are correlated with better traffic safety outcomes (*Marshall & Garrick, 2010*). Also, neighborhoods with higher intersection densities have been found to have fewer crashes across all injury levels, likely because of reduced motor vehicle speeds and the availability of sidewalks and crosswalk assistance (*Marshall & Garrick, 2011a*). Other past research similarly suggested that higher road network densities may be safer because of lower vehicle speeds and shorter trips resulting in lower exposure (*Ewing et al., 2016*).

Higher-density road networks are typically found in areas with higher population densities. Based on the discussion above, we therefore might expect areas with higher population densities to be safer for pedestrians. On the other hand, past research has found that pedestrian safety is very much an urban issue. Ferenchak and Abadi found that 99.7% of additional post-2010 pedestrian fatalities were categorized as urban (*Ferenchak & Abadi, 2021*). But given that FARS only has a simplistic urban/rural dichotomy, the definition is imprecise at best. This work explores the nuance of that density issue.

Developed areas with lower population density, which also might be considered suburban sprawl, have been found to have poorer traffic safety outcomes because of higher vehicle speeds and higher levels of exposure (*Ewing & Hamidi, 2015*). These areas with lower population densities tend to have wider and longer roads which encourage speeding and increase the risk of pedestrian injuries and fatalities (*Ewing et al., 2003*). One paper from 2019 looked at the Philadelphia region and found that denser neighborhoods have fewer collisions, injuries, and fatalities (*Guerra et al., 2019*).

In addition to the density of land use, we also explore different types of land use. Past research that identified pedestrian crash "hot spot" corridors (i.e., 1,000-meter-long sections of roadway where six or more fatal pedestrian crashes occurred during an eight-year period) found that all hot spots had adjacent commercial retail and service land uses and three-quarters were bordered by low-income neighborhoods (*Schneider et al., 2021*). However, once exposure was controlled for, other research found that mixed-use residential neighborhoods experienced lower child pedestrian injury rates than high-density single-use neighborhoods or low-density single-use neighborhoods (*Ferenchak, 2022*).

Another variable worth exploring is access to transit. While we would expect more access to transit in higher-density areas that past research suggests may be relatively safer for pedestrians, we would also expect more pedestrian exposure in areas with high access to transit. Transit activity may be a proxy for pedestrian exposure, although that measure is not available on the national scale. Since linking VRUs to public transportation is an important consideration, we consider the abundance of public transportation in our analyses.

One final variable related to the built environment is the age of the neighborhoods where pedestrian crashes are occurring. Typically, pre-war neighborhoods were built at higher densities because residents had limited mobility options. Neighborhoods built in 1950 and later began to introduce low-density suburban sprawl focused on the automobile. While the underlying mechanisms described above suggest that there may be a relationship between pedestrian safety and neighborhood age, we were unable to identify any past research that explored this relationship.

2.2.2. Bicyclists

Now specifically focusing on bicyclists, although over 80% of pedestrian fatalities occur at midblock locations, that number drops to about 50% at midblock locations for bicyclist fatalities. Bicycling activity may happen more exclusively on roadways with bicycle facilities or lower-volume roadways, again differing from pedestrian activity. For these reasons, we examine how built environment variables are related to bicyclist safety.

First examining roadways, past research found that bicycle routes on arterials were less safe than off-arterial routes (*Chen, 2015*). Additional analysis found that intersections between arterials and local roads were high-risk locations for bicyclists, likely due to high speeds, many conflicting un-signalized turning movements, and typically high traffic volumes (*Wei & Lovegrove, 2013*). Areas with on-street parking were also found to have worse safety outcomes for bicyclists, likely due to the increased points of conflict (*Chen, 2015; Vandenbulcke et al, 2014*).

Past research has found that cities with a high bicycling rate show a lower risk of fatal crashes for all road users (*Marshall & Garrick, 2011b; Ferenchak & Marshall, 2024*). Another paper found that higher bicycling rates were not significantly related to overall traffic safety outcomes, and it was instead the presence of protected bicycle facilities that was related to improved safety outcomes (*Marshall & Ferenchak, 2019*).

Past research showed that industrial and commercial land uses were positively correlated to bicycle injuries, likely attributable to the higher levels of bicycling activity in those areas (*Narayanamoorthy et al., 2013*). The research also found a positive relationship between the number of schools, office intensity, and park areas located in a census tract and the propensity of possible bicyclist injuries, likely because of higher levels of bicycling activity in those areas (*Narayanamoorthy et al., 2013*).

From the research cited above, we identified functional classification, road and intersection density, land use, access to transit, and age of neighborhoods as important variables to explore in our analyses.

2.3. Road Safety and Demographics/Socioeconomics

2.3.1. Pedestrians

Concerning the pedestrians themselves, past research has found important relationships with age and race/ethnicity. Lower-income and minority populations often have fewer mobility options and may need to walk on unsafe roads, resulting in worse safety outcomes. A paper from 2022 analyzing U.S. pedestrian fatalities found critical connections between roadway design and population patterns that disproportionately affect Native American and Black populations (*Sanders & Schneider, 2022*).

The age of pedestrians killed has consistently increased over recent years, possibly because older pedestrians are more susceptible to injury and this age bracket has been growing in the US population at large (*Ferenchak & Abadi, 2021; Sanders & Schneider, 2022*). Past research has also determined that factors such as pedestrian gender and pedestrian group size may be related to utilization of pedestrian crossing treatments (with larger groups being less likely to utilize), although we were not able to explore this individual-level factor given our wide geographic scale (*Ferenchak & Katirai, 2017*).

Increased pedestrian exposure is a possible contributor to the increase in pedestrian fatalities. However, pedestrian exposure data is difficult to obtain. On the national scale, we have access to commuting data on the census tract level, which can help inform broad national trends. But such data may not be appropriate when exploring pedestrian safety on the corridor level in Chicago. First, pedestrian activity may have high variation for different corridors within a census tract. Second, commuting may or may not be a good indicator of overall pedestrian activity. For these reasons, we attempt to account for pedestrian exposure in our analyses but are careful of our interpretation of the results.

2.3.2. Bicyclists

Concerning the bicyclists themselves, past research found that lower-income and non-White neighborhoods are particularly susceptible to traffic fatalities – especially vulnerable road users such as pedestrians and bicyclists (*Ferenchak & Marshall, 2024*). Past research has also found important relationships between age and bicyclist safety outcomes. A paper from 2020 analyzing U.S. bicyclist fatalities found that while child bicyclist fatalities decreased significantly between

1985-2016, adult bicyclist fatalities have increased substantially (*Ferenchak & Marshall, 2020b*). According to NHTSA, the fatality rate for bicyclists aged 45-64 years is the highest among all age groups. Additionally, the fatality rate per 100,000 people was seven times higher for men than women in 2020 (*National Center for Statistics and Analysis, 2022*).

The demographic/socioeconomic distribution of bicycle facilities and bicycle networks is also a concern. While past research found that access to bike networks is lacking relative to access to driving and pedestrian networks, low-income neighborhoods had especially low access, despite the fact that those neighborhoods often have limited mobility options and may have more need for alternatives from driving (*Ferenchak & Barney, 2024*).

From the research cited above, we identified age, race/ethnicity, gender, education, and income as important variables and explore them in our analyses detailed below.

3. Longitudinal Spatial Trends in US Bicyclist Fatalities

3.1. Introduction

According to NHTSA data, 948 bicyclists were killed on U.S. roadways in 2020 (**Figure 2**). This was the highest number in forty years, the third highest count since NHTSA record keeping began in 1975 and represents a 52% increase since 2010. It is vital that we understand the characteristics of and reasons for these fatalities if we wish to improve safety for bicyclists.

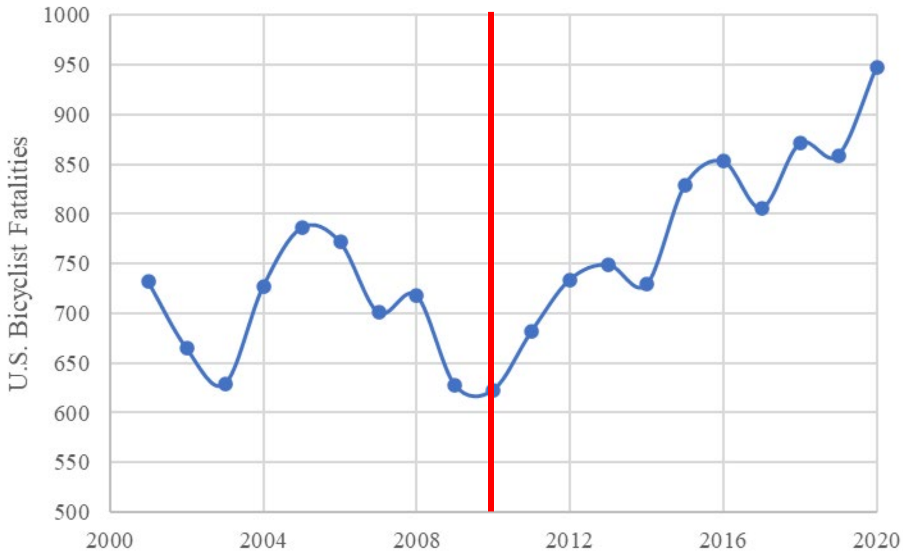


Figure 2. U.S. Bicyclist Fatality Counts (the before/after demarcation of 2010 that we use for this paper is represented by the red vertical line).

Past research has explored the people (*Ferenchak & Marshall, 2020b*), types of streets (*Nicaj et al., 2009*), and vehicles (*Nicaj et al., 2009*) involved in crashes that result in bicyclist fatalities. But where are these crashes occurring and what are the spatial characteristics of the locations of these fatalities? Are bicyclist crashes happening primarily in downtown areas, or has bicycling safety become a suburban issue? The goal of this paper is to provide an important piece of this understanding by performing a longitudinal spatial examination of bicyclist fatalities over the last two decades in terms of socioeconomics, demographics, and urban design.

In this paper, we analyze data from NHTSA's FARS, the U.S. Census, and the U.S. EPA Smart Location Database (SLD) from 2001 through 2020 on the census tract level. After importing the data into a GIS, we plot graphs for longitudinal spatial characteristics of bicyclist fatality locations such as street network density, transit access, poverty, and educational attainment. We then perform a multi-level hierarchical negative binomial regression using the statistical program R on the same variables mentioned above. We use the results from the statistical models to identify how we might better focus resources to improve bicyclist safety.

While we provided a more in-depth literature review at the beginning of this report, we provide a summary here. Several research papers have investigated possible factors related to the recent increase in bicyclist fatalities. Factors that have been identified in past research primarily include bicyclist and infrastructure characteristics. One paper has found that while child bicyclist fatalities have largely decreased over the three preceding decades, adult bicyclist fatalities have continued to see an upward trend (*Ferenchak & Marshall, 2020b*). According to NHTSA, the fatality rate for bicyclists aged 45-64 years is the highest among all age groups. Additionally, the fatality rate per 100,000 people was seven times higher for men than women in 2020 (*National Center for Statistics and Analysis, 2022*). Lower-income and non-White neighborhoods are shown to be particularly susceptible to traffic fatalities – especially for vulnerable road users such as bicyclists (*Ferenchak & Marshall, 2024*). Another paper found that roads with multiple lanes are especially unsafe for bicyclists (*Nicaj et al., 2009*). We go beyond these bicyclist and infrastructure factors to examine the specific knowledge gap of where in our cities bicyclist safety has degraded.

3.2. Data

We used bicyclist fatality data provided by FARS, which has been collected by NHTSA annually since 1975. For a crash to be included in the FARS database, it must involve a motor vehicle traveling on a public roadway and must result in the death of a person within 30 days of the crash. Crashes were queried and entered into ArcGIS Pro, so the numbers in this paper represent counts of crashes where a bicyclist was killed, not the number of bicyclists killed, although this differentiation is marginal as most fatal bicyclist crashes involve a single bicyclist. The timeframe that we chose was 2001 through 2020. The upward trend in bicyclist fatalities started in 2010, giving us 10 years of consistently increasing bicyclist fatalities. We therefore chose to analyze 10 years of before data as well, which gave us a study timeframe of 2001 through 2020.

As described in the Literature Review section, the explanatory variables that we wanted to study generally fell into two categories: 1) built environment and 2) demographics/socioeconomics. Transportation data such as road characteristics including number of lanes and posted speed limits are not available on the national level. To account for characteristics of the transportation system on the national level, we therefore obtained data for road network density (roadway miles per square mile), intersection density (intersections per square mile), and transit access from the EPA SLD (Version 3.0). The SLD is provided by the U.S. EPA Smart Growth Program and uses 2019 census geographies. Road network density and intersection density used 2018 HERE Maps NAVSTREETS highway/streets data as the data source. As a proxy for transit access, we analyzed the proportion of employment within a quarter mile of fixed guideway transit stops which used data from the 2020 General Transit Feed Specification, 2020 Center for Transit Oriented Development database, 2018 U.S. Geological Survey Protected Areas Database of the United States, and Smart Location Database unprotected area polygons as the data sources.

We would have liked to obtain detailed data on land use, but such data is not available on the national level. We therefore used population density and structure age data obtained from the U.S. Census, which serves as a proxy to give us a general idea of the characteristics of the census tracts where bicyclist fatalities occurred. When analyzing the age of the neighborhoods where bicyclists were killed, we used the "year structure built" variable from the census. This variable provided a count of the structures built before 1950 and in each decade after 1950, which we used to derive the average age of structures in each census tract.

We pulled much of the demographic/socioeconomic data from the U.S. Census on the census tract level including age of residents, proportion of residents identifying as White non-Hispanic, educational attainment of residents (proportion of residents with a bachelor's degree), and proportion of residents under the poverty line. We used the Census definition of poverty, which is defined as the proportion of individuals for whom poverty status was determined that are below the federal poverty line.

We used data from the Census on the number of bicyclists commuters per census tract as a proxy for bicyclist exposure. We would expect more bicyclist crashes in locations with more bicyclists, so we wanted to account for that variable in our statistical models. Note that this is just commuting to work data and may or may not represent overall biking activity. However, commuting data is the best bicyclist activity data readily available on the national scale.

3.3. Methods

We first describe our comparison of the characteristics of locations that had bicyclist fatalities to national trends using scatterplot graphs. We then describe our multi-level hierarchical negative binomial regression statistical analysis using the programming language R.

3.3.1. Longitudinal Analysis of Bicyclist Fatality Trends versus National Trends

We longitudinally analyzed the characteristics of locations where bicyclists have been killed in the U.S. from 2001 to 2020 and compared those results with the characteristics of the country as a whole. In ArcGIS Pro, we performed spatial joins to identify the census tract for every bicyclist fatality over our time frame. For each crash, we averaged the values of all census tracts within a 50 ft buffer of the crash location. We used this buffer because major arterials—which are common sites of bicyclist fatalities—often make up boundaries between tracts and we wanted to account for all adjoining tracts.

Since we did not have ACS data for every non-decennial year back to 2001, we joined 2001–2006 crashes to census tracts from the 2000 Census, 2007–2014 crashes to census tracts from the 2010 Census, and 2015–2020 crashes to census tracts from the 2020 Census. We analyzed decennial Census data from 2000–2020 as opposed to American Community Survey (ACS) data because ACS data were only available back to 2009. The benefit of using decennial Census data was that it provides us with a consistent methodology across our study period and larger sample sizes than ACS. We calculated and reported the average value for each explanatory variable for each year for the location of every bicyclist fatality. We visualized the average values on scatterplots so that the longitudinal explanatory variable trends could be visualized. We derived the 95% confidence intervals on the trends and also visualize those on the scatterplots.

We also analyzed the national trends for our explanatory variables to understand whether the bicyclist fatality locations were simply following underlying national trends. For most of our explanatory variables, we reported the national numbers directly from the census on the national level for each study year (e.g., median age, White non-Hispanic, educational attainment, poverty, and bicyclist commute mode share). We did not have longitudinal data on the national level for the EPA SLD variables (i.e., intersection density, road network density, and transit access) and therefore did not report underlying national trends for these explanatory variables. We believe that this should not have materially affected the results, since road networks in individual census tracts most likely would not change significantly over time in the same way as other explanatory variables such as age.

3.3.2. Negative Binomial Regression Analysis in R

After visually analyzing longitudinal trends, we wanted to test the statistical significance of those trends. We completed this statistical analysis on the census tract level. For every census tract, we derived the count of bicyclist fatalities for each study year as well as a value for each explanatory variable for each study year. The approximately 74,000 US census tracts multiplied by 20 years of the study resulted in a total of 1,481,427 lines of data entered into our statistical model.

We first explored the distribution of our dependent variable (i.e., bicyclist fatalities). Most census tracts did not experience a bicyclist fatality in any given study year, creating an over-dispersed dataset with 1,472,309 of the 1,491,566 (98.7%) census tract-years having a value of zero. A negative binomial regression is optimal for analyzing such over-dispersed datasets. In the statistical programming language R, we performed a negative binomial regression test to identify the relationship of our explanatory variables to bicyclist fatalities.

The number of bicyclist fatalities for each census tract and each study year was the dependent variable. Independent variables included many of the variables used in the scatterplot analysis, namely population density, median age, proportion of White non-Hispanic residents, proportion of residents with a bachelor's degree, proportion of individuals below the poverty line, intersection density, transit access, structure age, year, a state code, and number of bicycle commuters.

A state code was entered into the model to control for any differences in bicyclist safety on the state level. For example, it may be that bicyclists are safer in some regions of the country than other regions for cultural and behavioral reasons, regardless of the other variables that we were testing. We therefore included the state code variable in the analysis to control for any possible differences that may exist on the state level. The inclusion of the state code makes the negative binomial regression a multi-level hierarchical statistical model that examines the relationship on the census tract level while also controlling for any relationship on the state level.

Each explanatory variable data was then converted into a Z-score. A Z-score is a statistical measure that relates each sample's value to the mean value of all the samples. In other words, the Z-score can tell us – for each variable – how a value relates to the overall average for that variable in terms of standard deviations. Converting all variables to Z-scores allowed us to compare each variable's estimates that were obtained from the negative binomial regression. Because the dataset exceeded the maximum number of rows allowed by Microsoft Excel at this point, we used Microsoft Access to calculate the Z-scores. The final dataset was then converted into a comma separated value file so it could be read by R. The estimates and p-values obtained from the negative binomial regression were used to identify the direction (i.e., positive or negative correlation) as well as the statistical significance of each variable's relationship with the number of bicyclist fatalities.

Multiple models were run to identify the one with the lowest Akaike information criterion (AIC). The chosen model had the lowest AIC of 204,555. Additionally, variance inflation factors (VIF) were calculated using R to measure the amount of multicollinearity between the independent variables in the negative binomial regression. All variables had VIF values less than two showing low correlation within the variables, so all were kept in the model (**Table 1**).

Table 1. Variance Inflation Factors of variables in Negative Binomial Regression.

Population Density	1.65
Median Age	1.42
Percent of Population that is White	1.87
Percent of Population with Bachelors	1.47
Percent of Population in Poverty	1.76
Intersection Density	1.52
Transit Access	1.38
Structure Age	1.05
Year	1.00
State Code	1.05
Bike Commuting Count	1.21

3.4. Results

The results below are presented in three sections: longitudinal built environment scatterplots, longitudinal demographic/socioeconomic scatterplots, and the negative binomial regression results.

3.4.1. Built Environment

The population density of the average U.S. resident's census tract decreased in the "before" period and increased in the "after" period (**Figure 3**). Locations where bicyclists were being killed stayed relatively stable across the before period (when bicyclist fatality counts were relatively stable) but decreased in the after period (while bicyclist fatality counts were strongly increasing).

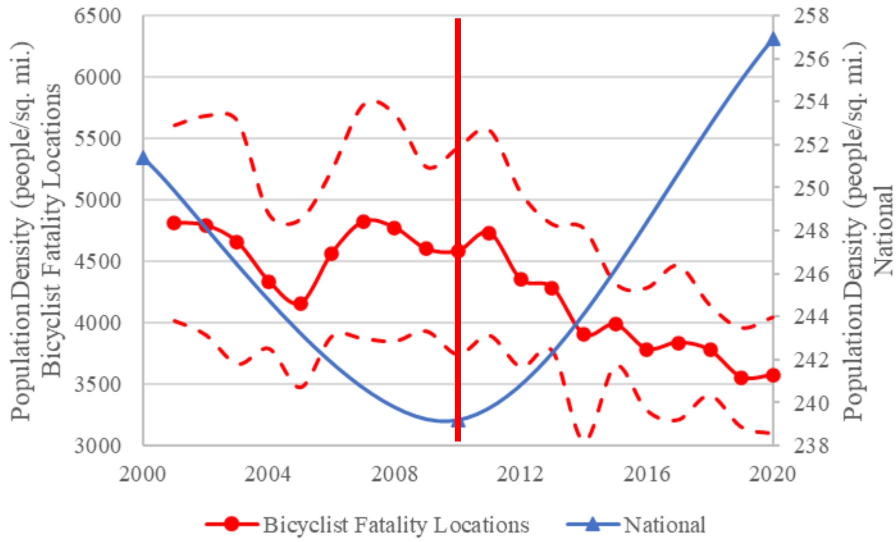


Figure 3. Average population density of bicyclist fatality census tracts.

The intersection density (**Figure 4**) and road network density (**Figure 5**) in locations where bicyclists were being killed dropped slightly in the before period but saw a downward trend in the after period. These results suggest bicyclist fatalities have been occurring in lower-density locations over the last decade as the total number of bicyclist fatalities was increasing significantly. Because we did not have historical transportation network data, these results were obtained by joining crashes for each year with the EPA SLD data from 2019. We did not present national trends as we only had data from 2019. We believe this is fair because we assume that the intersection and road network densities of a census tract would not change significantly over time as road networks are infrequently overhauled.

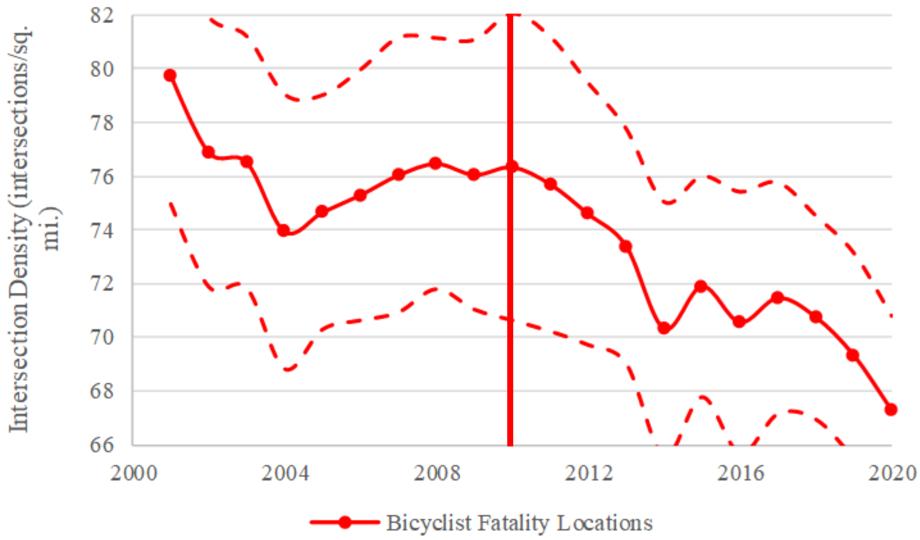


Figure 4. Average Intersection Density of Bicyclist Fatality Census Tracts.

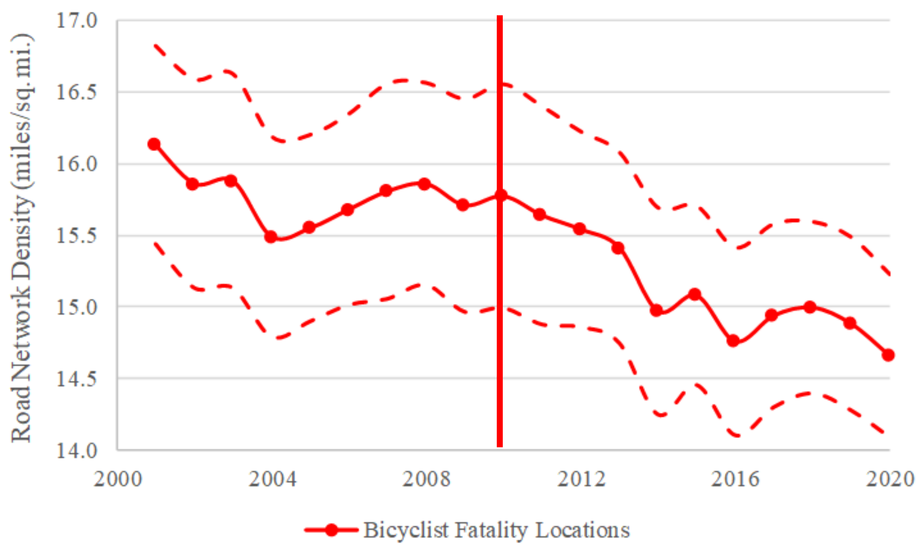


Figure 5. Average Road Network Density of Bicyclist Fatality Census Tracts.

The transit access variable (**Figure 6**) experienced a similar trend with bicyclist fatalities occurring in areas with less access to transit in the after period. This supports the results above that showed that bicyclist fatalities are occurring in places with lower densities, as we would expect areas with lower densities to also have less transit access.

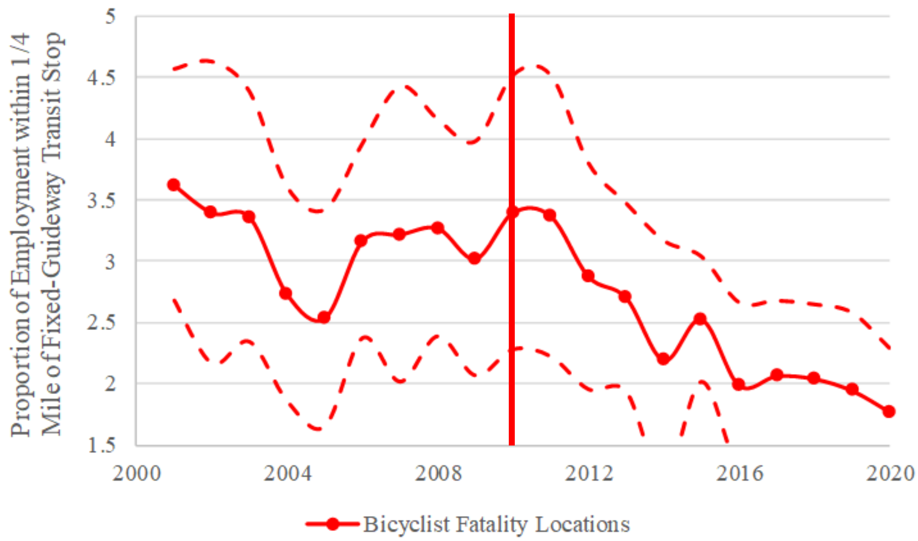


Figure 6. Proportion of Employment Within ¼ Mile of Fixed-Guideway Transit Stop.

3.4.2. Demographic and Socioeconomic Status

By analyzing demographic and socioeconomic trends, we can examine the characteristics of the residents of the lower-density neighborhoods where bicyclists are being killed. In the before period, bicyclists were being killed in areas with bicyclist commute mode shares that were 50% higher than the national average (**Figure 7**). We would expect this, since pedestrian exposure would likely be higher in those areas with more people biking to work. However, over the two decades of this study, bicyclists have become more likely to be killed in areas with lower bicyclist commute mode shares. This resonates with the results above showing that bicyclist fatalities have been recently occurring in lower density areas.

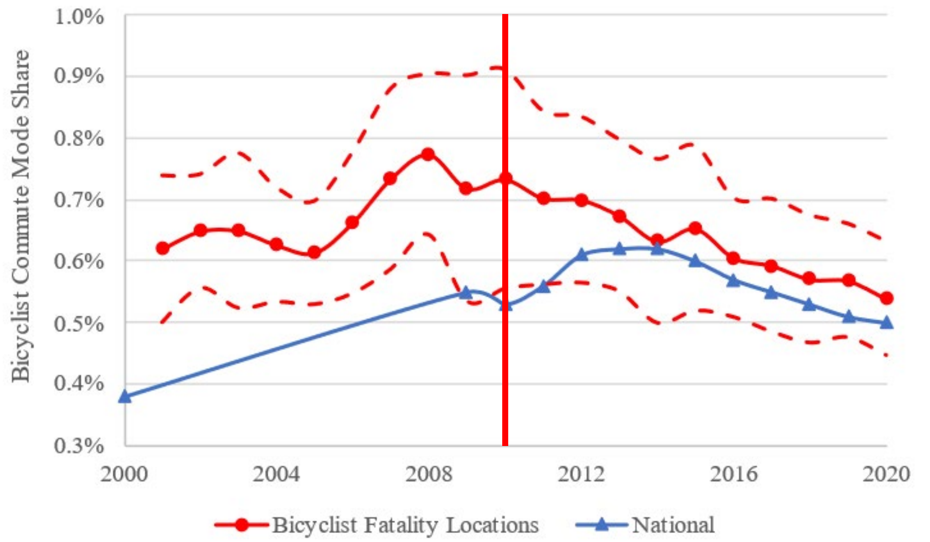


Figure 7. Average bicyclist commute mode share of bicyclist fatality census tracts.

According to historical census data, bicyclists appear to be increasingly killed in census tracts with lower-income populations (**Figure 8**). Census tracts with bicyclist fatalities have always had higher levels of poverty than the nation at large. However, while poverty in census tracts that experienced a bicyclist fatality largely tracked with national trends in the before period, there was a distinct deviation in the after period. While national poverty levels decreased significantly from 2015 through 2019, bicyclists continued to be killed in areas with high levels of poverty during this time.

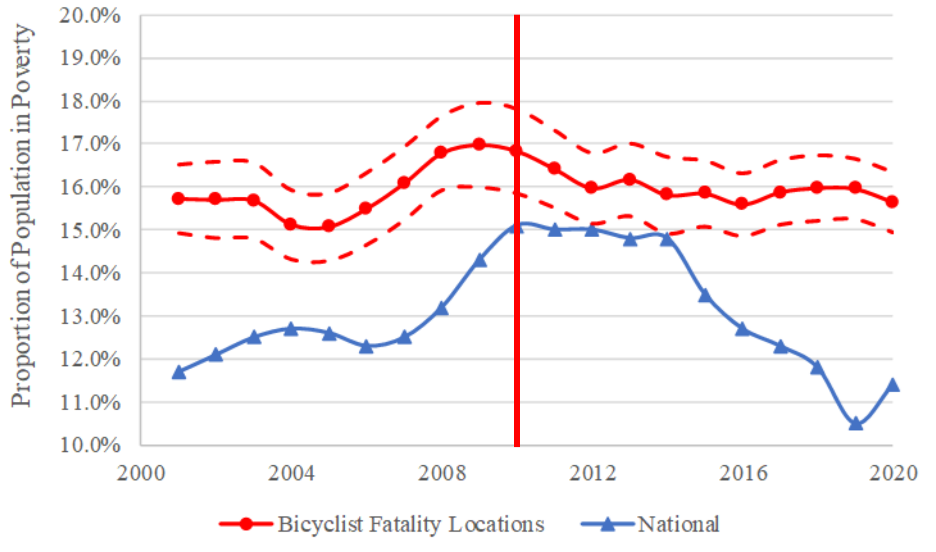


Figure 8. Proportion of Population in Poverty for Bicyclist Fatality Census Tracts.

Bicyclists also appear to be fatally struck in lower-education census tracts (**Figure 9**). While the proportion of the U.S. population with a bachelor's degree increased nationally from about 26% to 37% throughout our twenty-year study period, the areas where bicyclists were killed only saw a slight increase from about 13% to 16%. Census tracts that experienced bicyclist fatalities have significantly lower levels of educational attainment relative to the U.S. as a whole, and that difference has strengthened over the last twenty years.

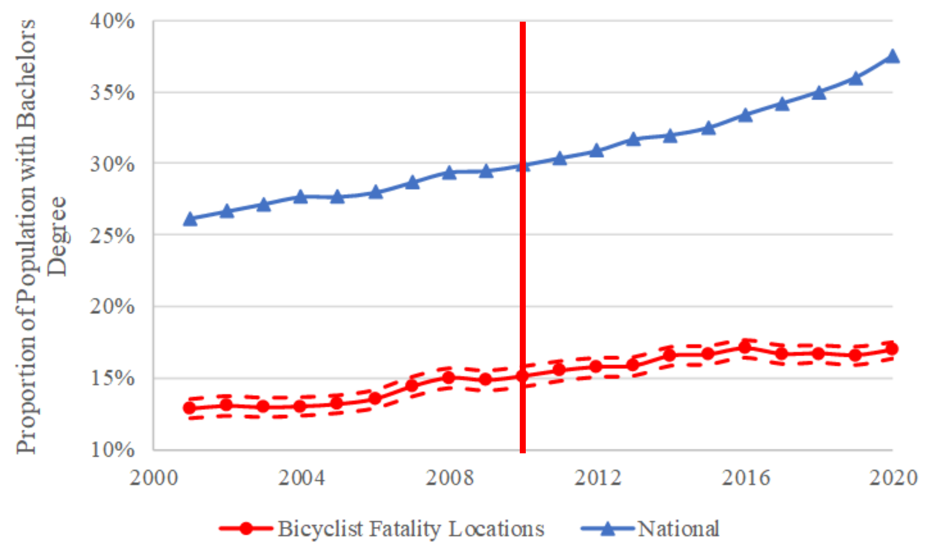


Figure 9. Proportion of Population with Bachelor's Degree for Bicyclist Fatality Census Tracts.

The median age of residents in the census tracts where bicyclists were killed has largely followed the national trend (**Figure 10**). While both areas saw steady increases in age throughout the study period, they began to slightly divert around 2011. The median age of the residents of the locations where bicyclists were killed is now slightly higher than the national average.

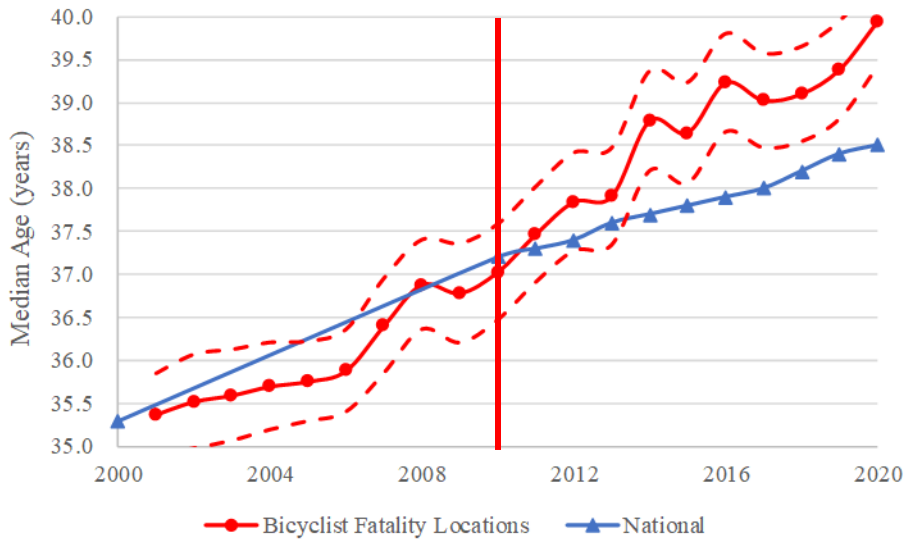


Figure 10. Median Age for Bicyclist Fatality Census Tracts.

Similar to the results above, the proportion of the population that identifies as White non-Hispanic decreased in both locations of bicyclist fatalities and the nation as a whole (**Figure 11**). Areas with fewer White non-Hispanic residents have been consistently more likely to have bicyclist fatalities, although that has not changed significantly over the study period.

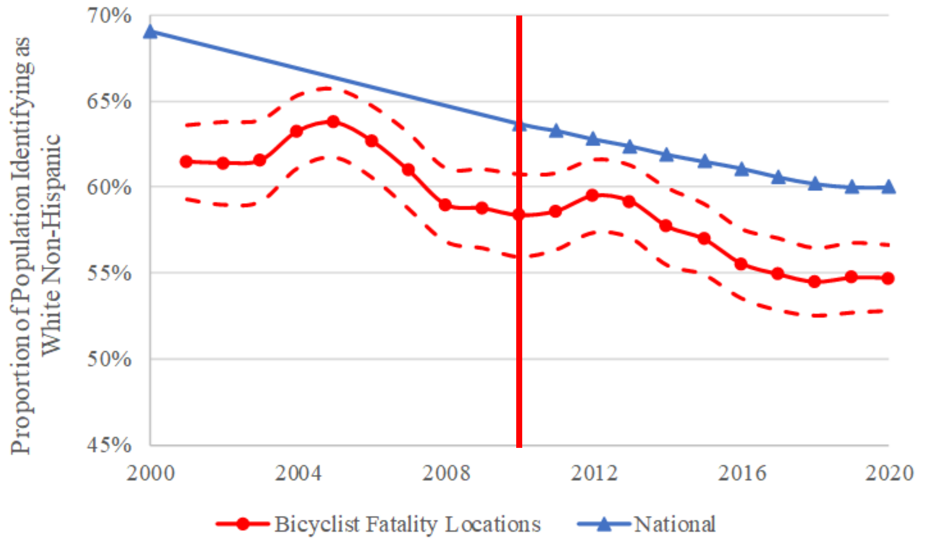


Figure 11. Proportion of Population Identifying as White Non-Hispanic for Bicyclist Fatality Census Tracts.

Overall, the results suggest that over the last ten years as bicyclist fatalities have increased, those bicyclist fatalities have increasingly occurred in areas with lower densities and with more residents that are in poverty, lack college degrees, do not identify as White non-Hispanic, and are slightly older.

3.4.3. Negative Binomial Regression

The estimates of the negative binomial regression allow us to understand the direction of correlation with the dependent variable of bicyclist fatality count (**Table 2**). For example, the population density variable has an estimate that is negative which signifies that if the population density of a census tract is higher than average, then the number of bicyclist fatalities is likely to be lower than average. Since the independent variables were converted to Z-scores, the values of the estimates can also be compared; a larger number (by absolute value) signifies a variable with a stronger relationship to bicyclist fatalities. Finally, the p-values represent the statistical significance of the variables in the test. In general, we identified any variables that had a statistical significance of 95% or greater, which correlated with a p-value of 0.05 or less. However, it should be noted that the poverty variable has a p-value of 0.076 but was still included in the model as it is significant at 90% confidence.

Table 2. Negative Binomial Regression Results (*variables significant at 95% confidence in bold*).

Coefficients	**Estimate**	**Std. Error**	**Pr(>|Z|)**
Built Environment			
Population Density	**-0.132**	**0.012**	**<0.001**
Intersection Density	**-0.039**	**0.009**	**<0.001**
Transit Access	**0.064**	**0.008**	**<0.001**
Structure Year Built	**0.083**	**0.011**	**<0.001**
Demographic/Socioeconomic			
Median Age	**0.019**	**0.008**	**0.023**
Percent Population White non-Hispanic	**-0.202**	**0.009**	**<0.001**
Percent Population with Bachelors	**-0.125**	**0.009**	**<0.001**
Percent Population in Poverty	0.016	0.009	0.076
Other			
Year	**0.030**	**0.007**	**<0.001**
State Code	**-0.020**	**<0.001**	**<0.001**
Bicyclist Commuters	**0.104**	**0.004**	**<0.001**

We first want to note that the number of bicyclist commuters in a census tract had a strong and statistically significant positive relationship with the number of bicyclist fatalities occurring in that census tract (**Table 2**). In other words, census tracts with more bicycle commuters had more bicyclist fatalities, as we would expect. The year variable also had a statistically significant – although relatively weak – positive relationship with bicyclist fatalities, showing that the number of bicyclist fatalities has been increasing over time. The state code was also statistically significant, although not readily interpretable. Although the relationships with the above variables were as expected, they are important to note since those variables are controlled for in the model. For the rest of the results below, the number of bicycle commuters, the year, and any safety differences on the state level have been controlled for in the statistical model.

Population density had a negative correlation to bicyclist fatalities signifying that if a census tract has a higher population density, then it was likely to have fewer bicyclist fatalities (**Table 2**). This agrees with the built environment analysis in **Figures 3-6** that showed that densities in the census tracts with bicyclist fatalities decreased over the study period. The estimate for population density was the second strongest of all the variables and had a high degree of statistical significance, signifying population density had a strong and significant negative relationship with bicyclist fatalities.

All the other built environment variables were statistically significant, although they were not as strong as population density (**Table 2**). Intersection density had a negative correlation with the number of bicyclist fatalities, meaning that census tracts with higher intersection densities were likely to have fewer bicyclist fatalities, which aligns with the population density findings above. Transit access had a positive correlation with the number of bicyclist fatalities, meaning that census tracts with more transit access were likely to have more bicyclist fatalities. This result seems to contradict the results in **Figure 6** that showed that areas with bicyclist fatalities have less transit access. This may be because, after underlying density was controlled for in the negative binomial regression model, the presence of transit may be a proxy for non-commuting bicycling exposure.

The average year that structures were built had a positive and relatively strong correlation with the number of bicyclist fatalities (**Table 2**). If the structure-build year was higher, this signifies a newer development. Therefore, newer developments were correlated with more bicyclist fatalities, after controlling for all other variables. This is especially interesting as one might assume that newer developments would have lower densities than older developments. The results therefore suggest that newer, lower-density areas are home to much of the recent increase in bicyclist fatalities.

In terms of demographic and socioeconomic variables, the strongest variable in the entire analysis was the proportion of the population that identifies as White non-Hispanic. The proportion of White non-Hispanic variable had a strong and statistically significant negative correlation with bicyclist fatalities, signifying that census tracts with more White non-Hispanic residents had fewer bicyclist fatalities, after controlling for all other variables. Said differently, neighborhoods with higher minority populations were more likely to experience bicyclist fatalities.

The proportion of the population with a bachelor's degree also had a negative correlation with bicyclist fatalities and had the third strongest estimate value of all the variables. This suggests that higher-education census tracts experience fewer bicyclist fatalities. Along with the race/ethnicity results above, these results portray a worrying trend of inequitable distribution of bicyclist fatalities.

Median age had a positive but weak correlation with the number of bicyclist fatalities (**Table 2**). This signifies that census tracts with older residents were likely to have more bicyclist fatalities, which aligns with the findings in the scatterplots above. Poverty had a positive correlation with bicyclist fatalities, signifying that census tracts with more poverty also had more bicyclist fatalities, although this variable was only statistically significant at 90% confidence.

3.5. Limitations and Future Research

This paper has identified trends in the locations where bicyclist fatalities are happening on a national level. Future research could dive into specific cities to determine how physical infrastructure could be contributing to better or worse bicyclist safety outcomes. For instance, data on the number of lanes, bike facilities, posted speed limits, and actual vehicle operating speeds are prohibitively difficult to obtain on the national level. Past research has identified cities on opposing sides of the bicyclist fatality spectrum (*Schneider et al., 2017*) which could be used as a good starting point for this deeper dive.

An analysis of land use could also be helpful in identifying if bicyclist fatalities are more likely around residential, commercial, or other types of land uses. It would be interesting to perform a multi-level analysis where we examine both the corridor level (including infrastructure characteristics and land use characteristics) and the neighborhood level (including built environment characteristics such as those investigated in this paper) simultaneously. Doing so would allow us to understand more nuances such as, for example, if bicyclist fatalities are concentrating more on arterials with high speeds and near commercial areas.

Additional research could also analyze crashes across the injury spectrum instead of only fatalities. While fatalities are the most severe crash type and therefore warrant attention, they are also the least common injury severity. Analyzing bicyclist injuries could aid us by providing much larger sample sizes and may reveal alternative trends. For instance, a hypothesis for future work is that while bicyclist fatalities may be more common on higher-speed arterials, bicyclist injuries may be more common on other roadways that typically receive less attention. Identifying the importance of the variables discussed above would not just help us better understand the problem, but better focus on viable solutions.

3.6. Conclusions

This paper has revealed where bicyclist fatalities are concentrating in our cities. The strongest and most consistent finding was that bicyclist fatalities are occurring in less dense areas of our cities. These decreasing densities were detected across several variables that included overall population density as well as transportation network density. Bicyclist fatalities have also been statistically linked with newer neighborhoods, which aligns with the density finding as newer neighborhoods are typically lower density, or at least in lower density areas as they are more likely on the outer edges of our cities. It is important to note that the low-density finding does not necessarily mean that bicycle safety has become a rural issue so much as a suburban issue. This is an important finding as bicycle infrastructure is often installed in downtown areas (*Ledsham et al., 2023*), but the findings suggest that cities might be wise to ensure that safe bicycle networks extend into and connect suburban areas as well. More attention should be paid to building bicycle networks that connect entire regions as opposed to focusing solely on a single downtown or commercial area.

When exploring who is living in these neighborhoods, we identified that areas experiencing bicyclist fatalities are overrepresented by minority populations with lower incomes and lower levels of education. This is troublesome as these populations may have limited mobility options and may have the most need for safe facilities for biking. More research is needed to understand this equity issue which has been widely reported in the academic literature. Three main hypotheses (which are not mutually exclusive) as to why these neighborhoods have poor bicyclist safety outcomes to be explored with future research include: 1) infrastructure in these neighborhoods is less safe than in high-income neighborhoods, 2) exposure is higher because of more non-automobile mode share by residents of these neighborhoods, and/or 3) more unsafe behavior (both by drivers and bicyclists) by people living in or travelling through these neighborhoods.

A Complete Streets approach of providing transportation systems that work for everyone starts with improving the safety of our vulnerable road users. Policymakers, planners, and engineers should work together to ensure the road safety of our less-dense, lower-income minority neighborhoods if we wish to halt the increase in bicyclist fatalities.

4. Longitudinal Pedestrian/Bicyclist Safety Trends in Chicago

4.1. Introduction

Pedestrians and bicyclists across the United States continue to see worsening safety outcomes, with both seeing their highest number of fatalities in over 35 years from motor vehicle crashes in 2020. If we wish to improve these poor outcomes, it is important to understand where in our cities these vulnerable road users are being most affected. Chicago, IL, is the third most populous city in the United States and can provide insight into what characteristics could be influencing this trend. This analysis examines pedestrian and bicyclist fatalities and serious injuries and attempts to identify the types of functional classifications, spatial demographics, and land uses most associated with poor safety outcomes for vulnerable road users (VRU).

4.2. Data

The timeframes we chose to analyze were three-year periods from 2009-2011 for the 'before' period and 2018-2020 for the 'after' period. This allowed us to compare VRU crashes from just prior to the significant increase in VRU fatalities over the last twelve years to the most recent data available at the time of this writing.

We used pedestrian and bicyclist serious injury and fatal (KA) crash data from the Chicago Data Portal. The data collected shows information about each traffic crash on streets under the jurisdiction of the Chicago Police Department within Chicago city limits for both of our study periods. Injury severity was estimated by police officers responding to the scene of the crash. It is important to note that only the VRU crashes that were reported to the police and that had crash reports completed are in the database; any unreported VRU crashes are not included in this analysis.

As described in the Literature Review section, our explanatory variables generally fell into two categories: 1) built environment and 2) demographics/socioeconomics. We pulled much of the explanatory variable data from the U.S. Census on the census tract level including population, area, average year structures built, commute mode share, resident age, proportion of residents identifying as White non-Hispanic, educational attainment, and poverty. We derived population density by dividing each Census tract's population by its area of land. We used the Census definition of poverty, which is defined as the proportion of individuals for whom poverty status was determined that are below the federal poverty line.

We used roadway segment data from the Illinois Highway Information System, which collects roadway information for all public roadways in Illinois. The roadway information is collected largely by the Illinois Department of Transportation (IDOT), with local road information coming from IDOT or non-IDOT agencies such as the county, township, or municipality. We filtered the dataset for roads within Chicago City limits which was nearly 23,000 segments. This dataset included attribute data such as the functional classification, number of lanes, and the speed limit of the segments.

We used land use data from the Chicago Metropolitan Agency for Planning, which serves seven counties in northeast Illinois. The land use inventory is on the parcel level and is updated every five years, with the 2018 version being used as it was the most recent at the time of this writing. We filtered this data for commercial land uses to identify any safety outcome trends relative to these specific land uses. Since nearly every road had several residential parcels on it, we instead wanted to identify roads in close proximity to commercial parcels as we hypothesized these would be related to VRU crashes because of higher exposure levels. We were not able to obtain this land use data longitudinally, but we would not expect parcels to change between commercial and residential land uses very often, or at least not to the degree that it would substantially alter our findings.

We used the EPA SLD (version 3.0) for road network density, intersection density, and transit access data. The SLD is provided by the U.S. EPA Smart Growth Program and uses 2019 census geographies. Road network density and intersection density used 2018 HERE Maps NAVSTREETS highway/streets data as the data source. As a proxy for transit access, we analyzed the proportion of employment within a quarter mile of fixed guideway transit stops which used data from the 2020 General Transit Feed Specification, 2020 Center for Transit Oriented Development database, 2018 U.S. Geological Survey Protected Areas Database of the United States, and SLD unprotected area polygons as the data sources.

4.3. Methods

We performed two separate analyses: 1) a crash-level analysis and 2) a segment-level analysis. For the first analysis, we joined every pedestrian and bicyclist fatal and serious injury (KA) crash to its closest census tract and calculated the distance from each crash to different land uses. Every row in our dataset represented an individual crash. For the second analysis, we derived the count of pedestrian and bicyclist KA crashes that occurred on each road segment and compared those counts to characteristics of the segment and surrounding neighborhoods. Every row in our dataset represented an individual road segment.

4.3.1. Crash-Level Analysis Methods

For the crash-level analysis, we performed spatial joins using ArcGIS Pro to join every crash to its closest census tract. This approach combined the attribute data of the crashes and the census tracts into a single table. Additionally, we calculated the distance from each crash to several types of commercial land uses and 'downtown' Chicago. We defined 'downtown' as the Chicago Loop and traced that area with a polygon in ArcGIS Pro. We performed basic descriptive statistics to preliminarily understand how the characteristics of pedestrian and bicyclist KA crashes changed over the study period. We utilized a 50-foot buffer so that if a crash occurred on a roadway that made the boundary of a census tract, all adjoining census tracts would be averaged.

4.3.2. Segment-Level Analysis Methods

For the segment-level analysis, we calculated the number of bicyclists or pedestrians killed or seriously injured in both our before and after periods on each road segment in Chicago. We then calculated the change in pedestrian and bicyclist KA counts between the before and after periods for each road segment so we could determine which segments had the largest increases (or decreases) over the study period. We then created one new column to designate whether a crash increase was experienced on each road segment and a second additional column to designate whether a large crash increase was experienced on each road segment. We defined large crash increases as an increase of three or more pedestrian KA crashes or an increase of two or more bicyclist KA crashes.

The road segments that met the criteria for either an increase or a large increase received a score of one while road segments that did not meet the criteria received a score of zero. These dichotomous crash-increase variables were treated as our dependent variables. This statistical approach allowed us to answer the research question: which types of roads in which contexts were home to most of the increase in pedestrian and bicyclist KA crashes?

In terms of independent variables, each road segment had roadway design characteristics associated with it such as functional classification, number of lanes, and speed limit. We joined each road segment to adjoining census tracts to estimate the population density, total population, road network density, households without access to an automobile, proportion of residents who identified as White non-Hispanic, and proportion of residents that identified as male. For any road segment that intersected with two or more census tracts, we calculated the average of all the intersecting census tracts. We used a spatial join to derive a count of the number of parcels of each type of commercial land use within 100 feet of each road segment. We also calculated the distance to downtown Chicago from the center point of each road segment.

In the statistical programming language R, we derived a logistic regression to identify the relationship of our explanatory variables to our dichotomous dependent variable of whether or not there was an increase in pedestrian or bicyclist KA crashes. We generated four logistic regressions for the following dependent variables: 1) increase in pedestrian KA crashes; 2) large increase (3+ crashes) in pedestrian KA crashes; 3) increase in bicyclist KA crashes; and 4) large increase (2+ crashes) in bicyclist KA crashes. The estimates and p-values from the logistic regressions helped to identify the direction (i.e., positive or negative correlation) as well as the statistical significance of each explanatory variable.

Variance inflation factors (VIF) were calculated using R to measure the amount of multicollinearity between the variables in the logistic regressions (**Table 3**). Since all independent variables (except the functional classification categories) had VIF values less than four showing low correlations with other variables, all independent variables remained in the models.

Table 3. Variance Inflation Factors for variables in Logistic Regressions.

	Ped Increase	Large Ped Increase	Bike Increase	Large Bike Increase
Roadway Characteristics				
Functional Classification				
Principal Arterial	11.62	7.00	10.87	5.80
Minor Arterial	17.18	13.82	15.81	9.72
Major Collector	16.86	10.96	20.26	18.70
Minor Collector	2.43	1.51	2.64	1.00
Local Road or Street	25.39	12.41	25.03	15.40
Number of Lanes	1.98	1.54	1.79	1.47
Speed Limit	2.05	1.62	1.90	1.53
Land Use				
Distance to Downtown	1.62	1.66	1.71	1.79
Shopping Mall	1.01		1.00	
Regional/Community Retail Center	1.02	1.05	1.02	1.02
Single Large-Site Retail	1.01		1.01	
Urban Mix	1.83	3.59	2.19	3.56
Urban Mix w/ Residential	1.75	3.38	2.08	3.28
Cultural/Entertainment	1.03	1.07	1.04	1.07
Hotel/Motel	1.08	1.25	1.08	1.10
Population Density	1.50	1.75	1.49	1.48
Road Network Density	1.37	1.34	1.40	1.39
Total Population	1.32	1.32	1.31	1.31
Demographics & Socioeconomics				
% Households with Zero Cars	1.49	1.47	1.63	1.73
% Population White non-Hispanic	1.66	1.97	1.53	1.53
% Population that is Male	1.20	1.25	1.17	1.14

4.4. Results

4.4.1. Crash-Level Analysis Results

We first analyzed the distance to downtown to understand where in our cities the pedestrian and bicyclist KA crashes were occurring. We divided the city into three zones: 1) downtown and within one mile of downtown; 2) a middle ring between one mile and seven miles from downtown; and 3) the outer edge of the city being seven or more miles (to a maximum of about 17 miles) from downtown.

There was an increase in bicyclist KA crashes on the fringes of the city seven or more miles away from downtown (**Table 4**). Pedestrian KA crashes saw an increase in the middle zone of the city between one and seven miles away from downtown. Most pedestrian and bicyclist KA crashes occurred in the middle zone of Chicago and both modes saw decreases within a mile of downtown. These results suggest that pedestrian and bicyclist safety is not primarily a downtown issue and many VRU safety issues can be found in the inner suburbs.

Table 4. Distance to Downtown for Pedestrian and Bicyclist KA Crashes (*proportional increases in bold*).

Bicyclist	Before		After	
Distance (d) from downtown (miles)	#	%	#	%
0≤d<1	62	13.7%	84	12.8%
1≤d<7	280	61.7%	393	59.7%
7≤d	112	**24.7%**	181	**27.5%**
TOTAL	454	100.0%	658	100.0%
Pedestrian	Before		After	
Distance (d) from downtown (miles)	#	%	#	%
0≤d<1	157	11.8%	196	9.7%
1≤d<7	715	**53.5%**	1172	**58.2%**
7≤d	464	34.7%	646	32.1%
TOTAL	1,336	100.0%	2,014	100.0%

The average population density of neighborhoods that experienced pedestrian and bicyclist KA crashes decreased for both modes in the after period, but only decreased by about 1% (**Table 5**). This finding agrees with the distance results above that showed that pedestrian and bicyclist KA crashes are migrating away from downtown slightly. KA crashes for both VRU types were frequently located near land uses including Urban Mix (i.e., small retail trade and services such as grocery stores, eating and drinking establishments, and gasoline service stations) and Urban Mix with Residential (i.e., Urban Mix parcels where there is a likelihood of one or more residential units on the upper floors of the building). Because pedestrian and bicyclist KA crashes were much less likely to occur around other types of commercial land uses and there were no significant changes in those other land uses over the study period, the other commercial land uses are not detailed in **Table 5**. Because we do not have pedestrian or bicyclist exposure data for these areas, we are not necessarily trying to show that one area is less safe than any other area in relative terms, but instead simply identifying areas where many of the VRU KA crashes are occurring.

Table 5. Population Density and Proximity to Land Uses for Pedestrian and Bicyclist KA Crashes.

		Number of Crashes	Population Density	% within 100 feet of Urban Mix	% within 100 feet of Urban Mix w/ Residential
Bike	Before	454	34.4	48.7%	38.8%
	After	660	33.4	50.6%	36.7%
	Difference		**-1.0**	**1.9%**	**-2.1%**
Pedestrian	Before	1,336	31.8	56.4%	35.5%
	After	2,023	30.1	57.2%	31.2%
	Difference		**-1.6**	**0.9%**	**-4.2%**

4.4.2. Segment-Level Analysis Results

4.4.2.1 Pedestrian Increase

In terms of roadway functional classification, all categories were statistically significant when analyzing pedestrian KA crash increases (**Table 6**). Each functional classification was analyzed relative to the benchmark category of Interstate Highway. These results can therefore be interpreted as all other functional classifications in Chicago had a higher likelihood of experiencing an increase in pedestrian KA crashes than interstate highways, with minor arterials and major collectors being the most likely to experience an increase. Note that pedestrian exposure was not directly accounted for in the statistical model because it was not available for each of the almost 23,000 road segments analyzed. These results can therefore be interpreted as identifying the roadways that were most likely to experience an increase in pedestrian KA crashes, as opposed to the roadways with the largest increases in rates of KA crashes per pedestrian present.

Neither the number of lanes nor the posted speed limit of the road segments had a statistically significant relationship with the chance of a roadway experiencing an increase in pedestrian KA crashes (**Table 6**). However, it is important to note that even though the number of lanes and speed limit did not have statistically significant relationships, the functional classifications of minor arterial and major collector had the strongest positive correlations, meaning that these often relatively wide and fast road types saw a disproportionate amount of the safety issues that developed over the study period. In other words, functional classification is likely serving as a proxy for number of lanes and speed limits.

Table 6. Pedestrian Logistic Regression Models (*results statistically significant at 95% confidence in bold*).

	Pedestrian KA Increase			Large Pedestrian KA Increase		
Coefficients	**Estimate**	**SE**	**p-value**	**Estimate**	**SE**	**p-value**
Roadway Characteristics						
Functional Classification						
Principal Arterial	**0.549**	**0.076**	**<0.001**	0.418	0.261	0.109
Minor Arterial	**0.663**	**0.082**	**<0.001**	**0.550**	**0.265**	**0.038**
Major Collector	**0.635**	**0.081**	**<0.001**	0.323	0.265	0.223
Minor Collector	**0.177**	**0.031**	**<0.001**	0.025	0.130	0.845
Local Road or Street	**0.564**	**0.119**	**<0.001**	0.037	0.383	0.922
Number of Lanes	-0.025	0.038	0.514	**-0.416**	**0.165**	**0.012**
Speed Limit	-0.044	0.045	0.330	0.093	0.172	0.588
Land Use						
Distance to Downtown	**-0.198**	**0.032**	**<0.001**	-0.223	0.144	0.122
Shopping Mall	0.005	0.021	0.805			
Regional/Community Retail Center	**0.085**	**0.017**	**<0.001**	0.083	0.060	0.166
Single Large-Site Retail	-0.015	0.024	0.531			
Urban Mix	**0.330**	**0.024**	**<0.001**	**0.252**	**0.064**	**<0.001**
Urban Mix w/ Residential	0.014	0.023	0.539	0.025	0.066	0.705
Cultural/ Entertainment	0.007	0.022	0.737	**0.101**	**0.051**	**0.046**
Hotel/Motel	0.023	0.017	0.171	**0.117**	**0.028**	**<0.001**
Population density	**0.228**	**0.023**	**<0.001**	**0.249**	**0.088**	**0.005**
Road Network Density	**-0.065**	**0.027**	**0.017**	-0.127	0.131	0.334
Demographics & Socioeconomics						
% Households w/ Zero Cars	**0.185**	**0.028**	**<0.001**	**0.290**	**0.112**	**0.010**
% Population White non-Hispanic	**-0.261**	**0.031**	**<0.001**	**-0.464**	**0.149**	**0.002**
% Population that is Male	-0.023	0.027	0.404	-0.020	0.115	0.864

Table 7. Bicyclist Logistic Regression Models (*results statistically significant at 95% confidence in bold*).

	Bicyclist KA Increase			Large Bicyclist KA Increase		
Coefficients	**Estimate**	**SE**	**p-value**	**Estimate**	**SE**	**p-value**
Roadway Characteristics						
Functional Classification						
Principal Arterial	**0.481**	**0.112**	**<0.001**	0.202	0.368	0.582
Minor Arterial	**0.574**	**0.119**	**<0.001**	0.310	0.386	0.422
Major Collector	**0.692**	**0.117**	**<0.001**	**0.690**	**0.371**	**0.063**
Minor Collector	**0.190**	**0.044**	**<0.001**	-1.322	0.928	0.984
Local Road or Street	**0.527**	**0.171**	**0.002**	0.200	0.552	0.716
Number of Lanes	**-0.119**	**0.054**	**0.029**	-0.157	0.185	0.396
Speed Limit	-0.004	0.063	0.948	0.081	0.184	0.660
Land Use						
Distance to Downtown	**-0.269**	**0.046**	**<0.001**	**-0.457**	**0.184**	**0.013**
Shopping Mall	-0.315	5.725	0.956			
Regional/Community Retail Center	0.000	0.030	0.998	-0.121	0.149	0.416
Single Large-Site Retail	0.022	0.027	0.410			
Urban Mix	**0.200**	**0.030**	**<0.001**	**0.271**	**0.069**	**<0.001**
Urban Mix w/ Residential	**0.062**	**0.026**	**0.019**	0.083	0.052	0.106
Cultural/ Entertainment	**0.049**	**0.024**	**0.044**	-0.095	0.119	0.424
Hotel/Motel	-0.025	0.026	0.339	-0.085	0.099	0.393
Population density	**0.180**	**0.030**	**<0.001**	0.050	0.102	0.622
Road Network Density	-0.001	0.034	0.970	0.058	0.109	0.598
Demographics & Socioeconomics						
% Households w/ Zero Cars	0.024	0.043	0.582	0.207	0.160	0.196
% Population White non-Hispanic	**0.124**	**0.041**	**0.003**	**0.530**	**0.158**	**<0.001**
% Population that is Male	0.005	0.041	0.910	0.038	0.165	0.818

A roadway's distance to downtown had a statistically significant and negative relationship with pedestrian KA crash increases (**Table 6**). The negative estimate value signifies that as a roadway's distance from downtown increases, there was less of a chance that the roadway experienced a pedestrian KA crash increase. However, this result may reflect the fact that a majority of pedestrian KA crashes occurred in the "inner suburbs" of the city rather than on the outskirts, so this relationship would not necessarily be linear, as illustrated in **Table 4**. Also, we would expect larger road segment sample sizes as the distance to downtown increases, so although many of the pedestrian KA crash increases occurred miles from downtown, the proportion in these locations may have been relatively low.

The land use types that were statistically significant included Regional/Community Retail Center (i.e., retail centers between 100,000 and 750,000 square feet; typically developments with at least one big box store and several other smaller stores) and Urban Mix (**Table 6**). Both land use types had a positive estimate which signifies that roadways with more of these types of land uses were more likely to experience an increase in pedestrian KA crashes. The Urban Mix land use had the second largest estimate value (behind the functional classification categories) signifying that this was the strongest land use relationship and one of the strongest variables overall. It is interesting that the land use category Single Large-Site Retail (i.e., a stand-alone big box store) was not statistically significant. This may be because these types of commercial developments are more likely to be accessed by driving trips than walking or biking trips whereas Regional/Community Retail Centers and Urban Mix may be more engrained into a neighborhood and accessed by the immediately surrounding community. Shopping Malls were relatively rare in Chicago; none were in downtown or the inner suburbs and the variable did not reach statistical significance.

Road network density was statistically significant and had a negative correlation to pedestrian KA crash increases, signifying that roadways in denser networks were less likely to experience a pedestrian KA crash increase (**Table 6**). Population density was statistically significant but contradicts what we would expect since it had a positive estimate, signifying a higher likelihood of a pedestrian KA crash increase in areas with higher population densities. This result may be because of higher levels of pedestrian exposure in these areas.

The percentage of households with zero cars was statistically significant and had a positive correlation, signifying that roadways in neighborhoods with higher proportions of households without access to an automobile had a higher likelihood of experiencing a pedestrian KA crash increase (**Table 6**). The proportion of population that identifies as White non-Hispanic was statistically significant with the negative correlation signifying that roadways in neighborhoods with higher proportions of White non-Hispanic residents had a lower likelihood of experiencing a pedestrian KA crash increase. The race/ethnicity variable had the third largest estimate value signifying that it had an especially strong relationship with pedestrian safety. Said differently, neighborhoods with higher minority populations and less access to automobiles were more likely to experience increases in pedestrian KA crashes. The proportion of male residents was not statistically significant.

4.4.2.2. Large Pedestrian Increase

The results for large increases (3 or more) in pedestrian KA crashes mirrored the previous results while highlighting the most significant metrics that may be contributing to worse pedestrian safety outcomes. The only significant functional classification was minor arterials, with principal arterials also having a strong estimate and nearly 90% statistical significance (**Table 6**). The number of lanes was significant for large pedestrian KA crash increases with a negative correlation. While this relationship is counterintuitive, it may signify that most of the pedestrian KA crash increases occurred on roads with relatively few lanes (e.g., minor arterials with three lanes), while larger roads such as highways with seven or more lanes have relatively little pedestrian activity and did not experience many of the pedestrian KA crash increases.

The land use types that were statistically significant included Urban Mix, Cultural/Entertainment, and Hotel/Motel (**Table 6**). These three land uses had positive estimate values signifying that roadways with more of these land uses had a higher likelihood of experiencing a large pedestrian KA crash increase, with Urban Mix being the strongest. Note that we had to remove two land uses from this statistical model because there were no large pedestrian KA instances on roadways with these land uses and the statistical model was therefore giving an error. Population density was statistically significant with a positive estimate, which we again suspect was because it is functioning as a proxy for pedestrian exposure.

Both the households with zero cars and White non-Hispanic variables were again statistically significant (**Table 6**). These demographic and socioeconomic variables saw even stronger correlations than in the previous model, illustrating the importance of these pedestrian safety equity issues.

Between the two pedestrian models, the importance of variables across our roadway, land use, and demographic/socioeconomic categories becomes clear. In both models, minor arterials were the strongest roadway characteristic with other principal arterials and major collectors also being strong predictors of pedestrian KA increases (**Table 6**). Roadways that had Urban Mix on them were also a strong predictor and roadways in census tracts with higher population density were likely to experience pedestrian KA crash increases, likely acting as proxies for pedestrian exposure. Access to an automobile and race/ethnicity were also strong variables, and especially so for large pedestrian KA crash increases. These results therefore suggest that larger roadways (although not highways) with smaller commercial establishments on them and in lower-income or minority neighborhoods in the inner suburbs were host to much of the increase in pedestrian KA crashes in Chicago.

4.4.3.1. Bicyclist Increase

Table 7 analyzes the significance of the same metrics as in **Table 6** but now with a dependent variable of bicyclist KA crash increases. Similar to the results above, all functional classifications were statistically significant when analyzing bicyclist KA increases, signifying that all functional classifications had a better chance of experiencing a bicyclist KA increase relative to interstate highways. The order for bicyclists was similar to that for pedestrians with minor arterials and major collectors being the strongest predictors. It is interesting that major collectors now have the strongest correlation for bicyclists (as opposed to minor arterials for pedestrians) as bicyclists may be less likely to use arterials if they do not have safe, protected bike facilities. The number of lanes was statistically significant for bicyclist KA crashes with a negative correlation possibly suggesting that bicyclists do not ride as much on wider roads (such as highways with five or more lanes).

The distance to downtown was again statistically significant with a negative estimate value, possibly suggesting that a majority of bicyclist KA crash increases occurred in the "inner suburbs" of the city rather than on the outskirts (**Table 7**). The land uses that were statistically significant included Urban Mix, Urban Mix w/ Residential, and Cultural/Entertainment. These three land uses had a positive estimate which signifies that roadways with more of these types of land uses on them were more likely to experience bicyclist KA crash increases. Urban Mix was the strongest for both bicyclists and pedestrians. Population density was statistically significant with a positive estimate, although this may again be a result of higher levels of bicyclist exposure in these areas (**Table 7**).

The percent of White non-Hispanic was again statistically significant. However, the correlation was positive for bicyclists, signifying that as the proportion of the White non-Hispanic population increased, the likelihood of a roadway experiencing an increase in bicyclist KA crashes also increased. While this finding is counter to what much of the literature suggests about inequitable distributions of bicyclist safety problems, it may be indicative of exposure as bicycling in Chicago appears to be predominantly an activity pursued in White non-Hispanic neighborhoods. **Figure 12** compares the 2020 census tracts by percentage of White non-Hispanic population (on the left) to the heatmap of bicyclist KA crash increases in Chicago from 2018-2020 (on the right). The north end of Chicago has a large White non-Hispanic population and sees the largest concentration of bicyclist KA crash increases. This supports the results above that the locations where bicyclist KA crashes are occurring have larger White non-Hispanic populations, possibly because of higher bicycling activity levels.

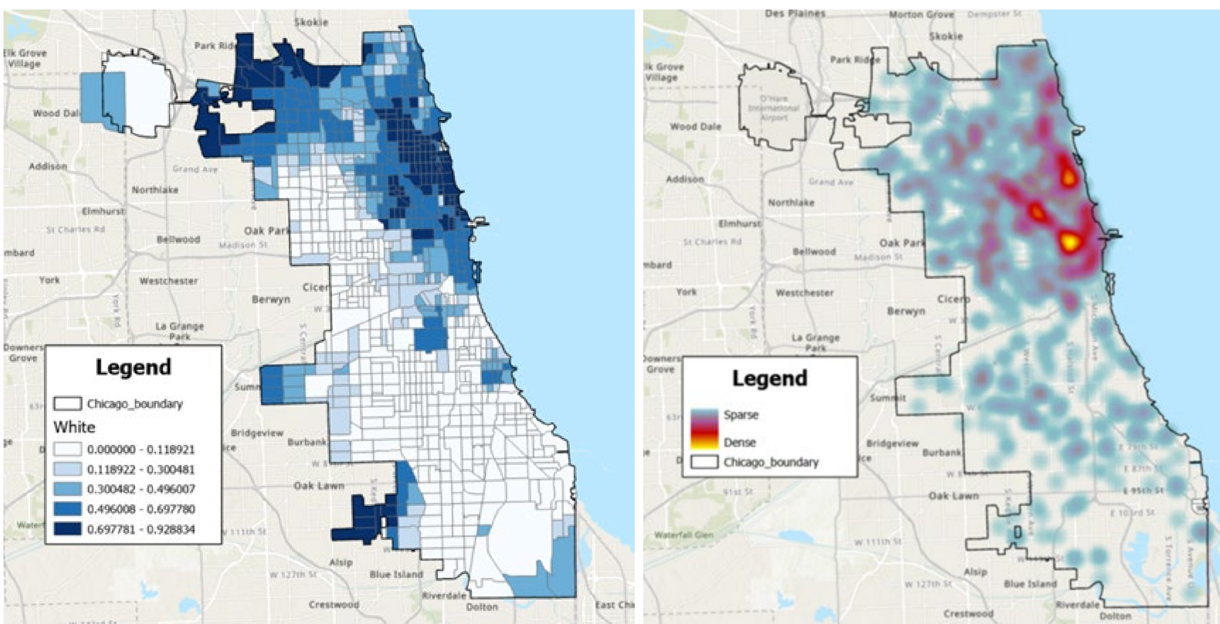


Figure 12. Percent White non-Hispanic Map (left) vs Bicyclist KA crash increases (right) in Chicago.

4.4.3.2. Large Bicyclist Increase

Only the strongest variables from the bicyclist KA crash increase model above remained statistically significant in the model for large bicyclist KA crash increases (**Table 7**). Those significant variables included roads that were major collectors, distance to downtown, roads with Urban Mix on them, and proportion of residents identifying as White non-Hispanic. The direction of the correlations remained the same for all these variables and the race/ethnicity variable increased substantially in strength for the large bicyclist KA crash increase model.

These results suggest that larger roadways (although not highways) with smaller commercial establishments on them and in White non-Hispanic neighborhoods in the inner suburbs were host to much of the increase in bicyclist KA crashes in Chicago over the study period. The bicyclist roadway and land use contexts are similar to those for pedestrians. The significant differences between the two types of VRUs was that pedestrian safety issues have a strong suggestion of equity issues while bicyclist appear to occur in more affluent and White neighborhoods.

4.4.4. Road Segment Examples

Now that we have identified general characteristics of roadways that saw increases in pedestrian and bicyclist KA crashes, we profile the three roadways that saw the largest increases for each VRU type to better understand the road design and land use context. **Figure 13** shows the locations of the three road segments that saw the largest increases in pedestrian KA crashes over the study period. Interestingly, these segments are similar distances from downtown – although in different directions – and are near the boundary between the “inner suburb” zone discussed earlier and the outer parts of the city, typically about five to nine miles from downtown. Additionally, all the profiled roadways are in different parts of the city and the three roadways are located in neighborhoods with different race/ethnicity majorities, namely White non-Hispanic, Black, and Hispanic neighborhoods.

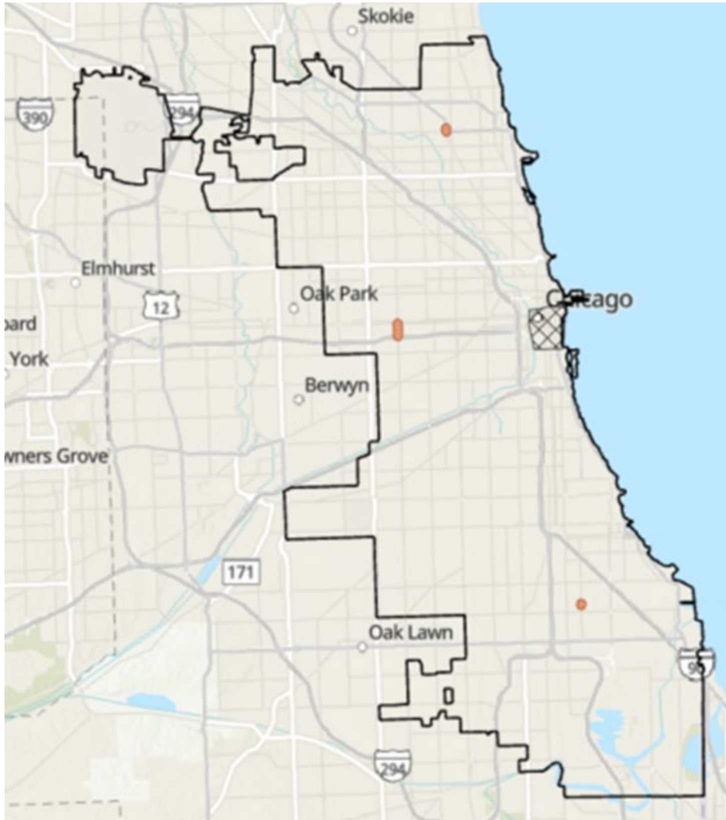
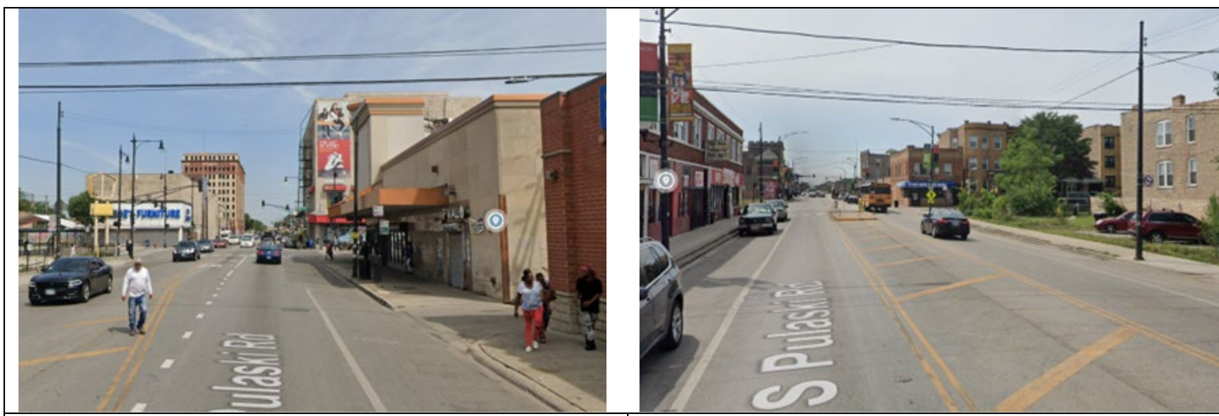


Figure 13. Road Segments with Largest Increases in Pedestrian KA Crashes.

Figures 14-16 highlight some of the common characteristics of the roadways that saw the largest increases in pedestrian KA crashes over the study period. All these segments are minor arterials that have Urban Mix or Urban Mix w/ Residential parcels and high-density residential along them. Two segments have ground floor commercial uses with residential floors above them. Aligning with the negative relationship that the number of lanes variable had in our statistical models, two of these segments are relatively narrow with only two lanes and a center turn lane. All the profiled roadways have sidewalks, but traffic-controlled pedestrian crossings are relatively rare. The posted speed limits are reasonable at 30 mph or 35 mph, but we were not able to obtain data on the operating speeds of the corridors. Vehicle volumes are not exceedingly high, with a daily volume of 8,150 annual average daily traffic (AADT) at Location #3. While pedestrian exposure data was not available, the presence of pedestrians in many of the street images suggests that pedestrian exposure is relatively high, although the areas are likely to still be primarily auto-oriented (*Ferenchak & Marshall, 2018*)

LINCOLN AVENUE Ped KA Increase: 5 Speed Limit: 35 MPH Func Class: Minor Arterial	Lanes: 2 AADT: 15,500

Figure 14. Road Profile of Large Increase in Pedestrian KA Crashes (Location #1).



PULASKI ROAD Ped KA Increase: 9 Speed Limit: 30 MPH Func Class: Minor Arterial	Lanes: 2 AADT: 15,500

Figure 15. Road Profile of Large Increase in Pedestrian KA Crashes (Location #2).

COTTAGE GROVE AVENUE Ped KA Increase: 4 Speed Limit: 30 MPH Func Class: Minor Arterial	Lanes: 4 AADT: 8,150

Figure 16. Road Profile of Large Increase in Pedestrian KA Crashes (Location #3).

Figure 17 shows the locations of the three road segments that saw the largest increases in bicyclist KA crashes over the study period. Interestingly, these segments are all located in the north/northwest part of Chicago, which aligns with the positive White non-Hispanic correlations in **Table 7** and the locations of predominant White populations shown in **Figure 12**. These roadways are also in the “inner suburb” area of the city.

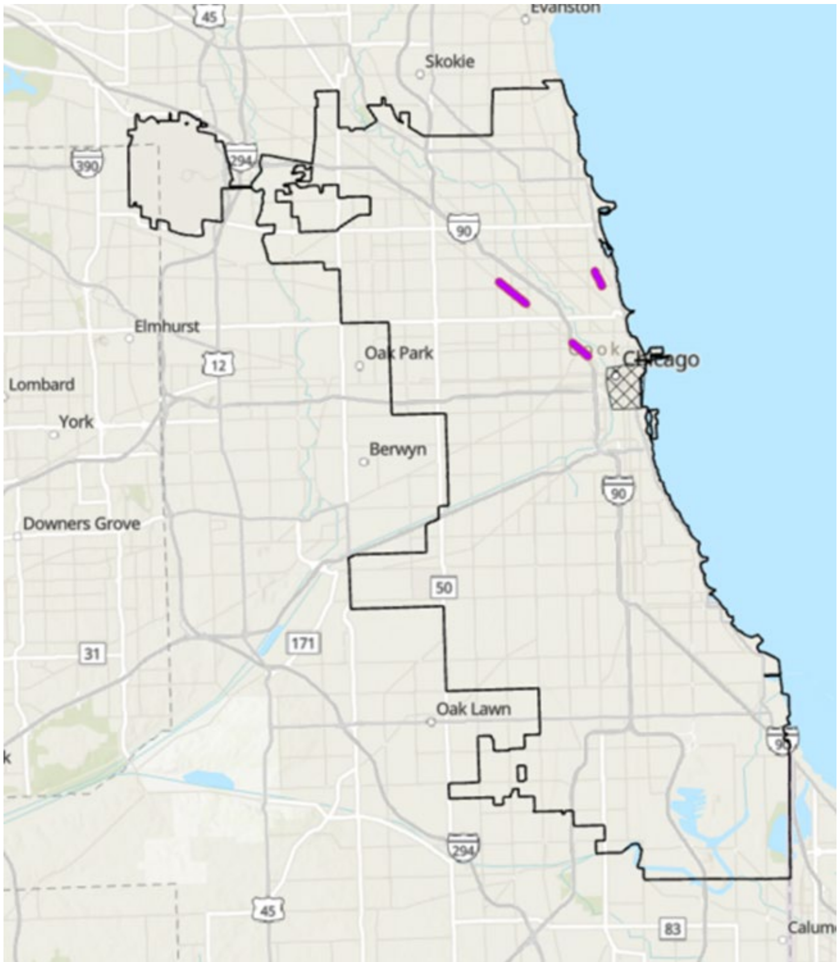
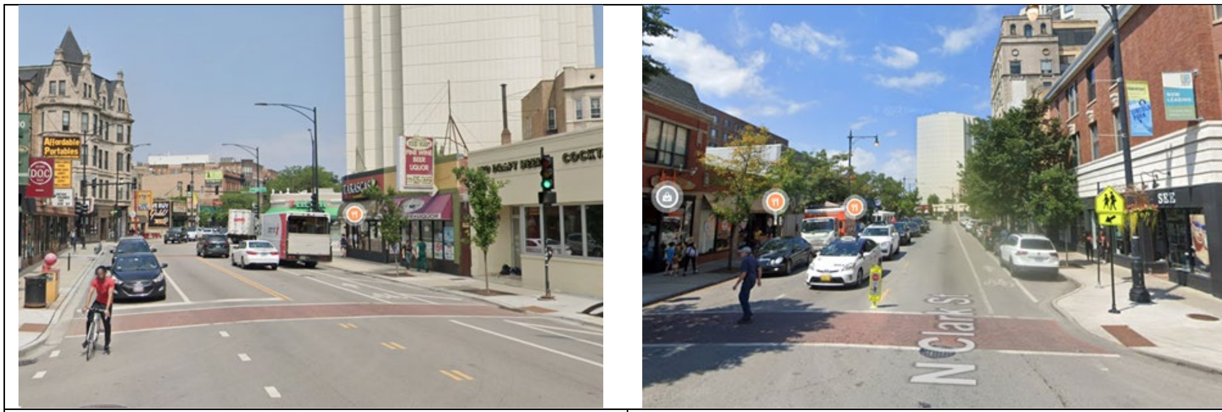


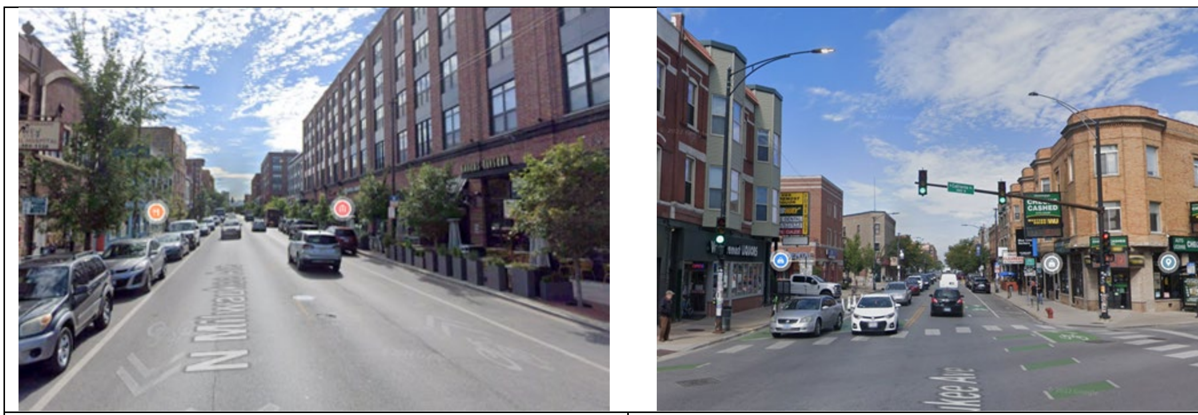
Figure 17. Road Segments with Largest Increases in Bicyclist KA Crashes.

Figures 18-20 highlight some of the common characteristics of the roads that saw the largest increases in bicyclist KA crashes over the study period. All these road segments are major collectors that have Urban Mix w/ Residential parcels along them. These road segments have relatively moderate posted speed limits at 30 mph or 35 mph, although we were not able to obtain data on actual operating speeds. The roadways all have two travel lanes, which aligns with the negative correlation with the number of lanes variable seen in **Table 7**. The vehicle volumes are not particularly high, which may induce more VRU activity.



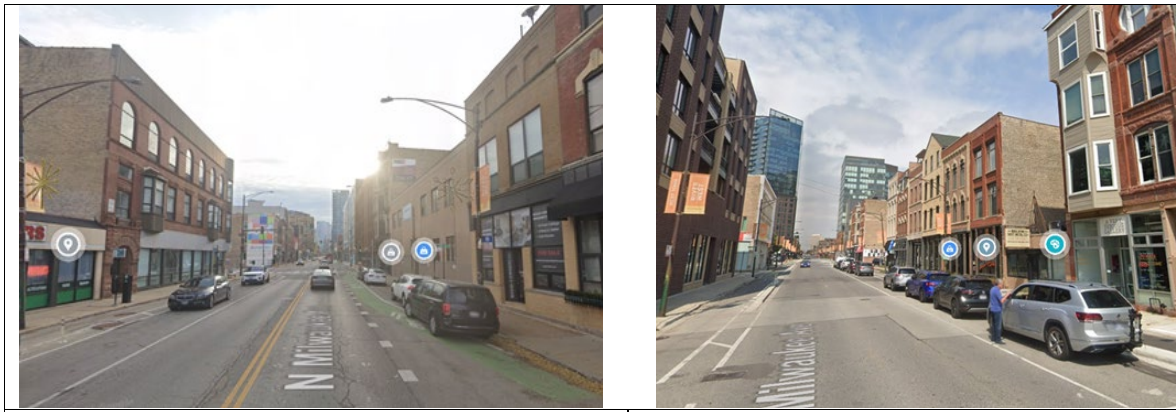
CLARK STREET Bike KA Increase: 5 Speed Limit: 30 MPH Func Class: Major Collector	Lanes: 2 AADT: 11,100

Figure 18. Road Profile of Large Increase in Bicyclist KA Crashes (Location #1).



MILWAUKEE AVENUE Bike KA Increase: 7 Speed Limit: 35 MPH Func Class: Major Collector	Lanes: 2 AADT: 12,400

Figure 19. Road Profile of Large Increase in Bicyclist KA Crashes (Location #2).



MILWAUKEE AVENUE Bike KA Increase: 3 Speed Limit: 35 MPH Func Class: Major Collector	Lanes: 2 AADT: 12,100

Figure 20. Road Profile of Large Increase in Bicyclist KA Crashes (Location #3).

Although bicycle facilities exist along these segments, it is often simple striping and sharrows rather than protected bike infrastructure. On-street parking can be seen in many of the pictures, along with a vehicle parked in the bike lane in **Figure 20**. We do not want to insinuate that the bicycle infrastructure on these corridors makes them unsafe. First, the bike lanes were installed before the study period, so their installation should have had no causality relationship with the increases seen over the study period. Furthermore, we would expect that if we could obtain the data, we would find that bicyclist exposure is relatively high on these corridors because of the bike facilities that are provided. The bike facilities that exist in these locations may provide enough of a false sense of security to attract bicyclists, while they are not safe enough to avoid bicyclist KA crash increases. It is interesting that while many protected bike lanes were installed over the study period and we might expect them to be heavily used, none of them resulted in significant bicyclist KA crash increases.

4.5. Limitations and Future Research

While this analysis provides insight into the variables affecting VRU safety in Chicago, there exists opportunities to drive the research further. Firstly, other cities could be analyzed to see if they host similar patterns. Research could identify cities that have improved their VRU safety outcomes to understand what changes (engineering, planning, education, enforcement, or otherwise) correlated with crash reductions, and how they prioritized the application of those successful strategies in their cities.

Future work might explore pedestrian and bicycle infrastructure to compare any changes between before and after periods to identify whether KA crashes shifted along with the infrastructure and which type of infrastructure has better or worse safety outcomes. Examples could include road diets that reduce the number of lanes of a roadway, additional/upgraded bicycle infrastructure, or pedestrian crossings. To perform such an infrastructure-specific analysis would necessitate better exposure data and therefore likely a smaller scale for the study.

One significant limitation of the current work is the lack of VRU exposure data. Our statistical examination of specific corridors necessitated a relatively wide geographic area so we could have a large enough sample size to obtain meaningful results. However, that large sample size of corridors precluded obtaining VRU exposure data for both the before and after periods and for all the corridors. On one hand, this lack of exposure data limited us so we could not create KA rates to understand relative safety outcomes. On the other hand, we were still able to answer our research question of: which roads and what land use contexts harbored the recent increase in VRU KA crashes? If the roads that saw the largest increases in VRU KA crashes over the last decade also happened to have high levels of exposure, do they not still deserve to be identified and addressed?

4.6. Conclusions

Where have VRU KA crashes been increasing in Chicago? They have been moving away from downtown areas with the majority happening in the middle zone of the city (between one and seven miles from downtown). The roadways are frequently arterials or collectors and frequently have Urban Mix, Urban Mix w/ Residential, or Regional/Community Retail Center land uses on them. While past research has identified larger roadways such as arterials and collectors as prime safety issues, this work is some of the first to substantiate that these roadways often have commercial land uses and are in the inner suburbs.

The results also highlight the importance of who is being impacted, especially in terms of pedestrians. Pedestrian KA increases were predominantly in minority neighborhoods with limited car access. An equity issue was identified in the bicyclist statistical models, but it was counter to much of the previous academic literature, with the only significant demographic/socioeconomic variable showing that bicyclist KA increases were most likely to occur in White neighborhoods. This might suggest that while walking is a mode of necessity, biking is more likely a mode of choice and is utilized in neighborhoods where residents have access to automobiles.

5. Discussion

A key implication of this work is the need for complete VRU networks as opposed to simply focusing on individual pieces of infrastructure. Past research that explored different types of VRU treatments found that appropriate facilities – such as protected bike lanes and road diets – can improve safety for VRUs (*Ferenchak & Marshall, 2019c; Harris et al., 2013; Marshall & Ferenchak, 2019; Venegas et al., 2022*). However, while many of those treatments have traditionally clustered around downtown or other high-density areas (*Ledsham et al., 2023*), our research suggests that VRU safety issues have been migrating into lower-density suburban areas. That suburban migration may play an important role in the recent increase in VRU KA crashes because, while downtown and other high-density areas may be relatively concentrated, suburban areas are expansive.

Given the migration into expansive suburbs, how do we look beyond individual treatments and begin to form complete VRU systems and networks that serve entire cities and regions? What do those VRU systems look like not only from a planning/engineering perspective, but also from land use, development, funding, and policy perspectives? These are critically important and novel questions because we may have forgotten – or never known in the modern context – how to create such VRU systems and networks. Other than a few exceptions, the last time we built places in the US with the assumption that most people might want to make comfortable and convenient walking trips was before the widespread implementation of the automobile. That may never have occurred for bicycles, other than a very few examples such as Davis, CA.

While some may propose that this will simply necessitate the installation of more VRU treatments, the solution may not be that simple. As identified in this paper, land use is critically important and we need to re-think our suburbs. Long travel distances introduced by suburban sprawl are a primary barrier to walking and biking and necessitate large, fast roadways which simultaneously introduce the second primary barrier to VRU activity: road safety issues.

Assuming, then, that American cities will continue to grow outward, how can we approach that suburban growth in a sustainable manner? We propose a village model of urbanity where development occurs in self-contained suburban units. Residents can safely and conveniently access what they need by walking and biking within the urban villages, and travel between villages can occur by public transportation, biking, walking, or driving. As much development as possible should occur within these urban villages to preserve green space, recreational uses, or agriculture between urban villages.

Second, we need to fundamentally rethink our approach to infrastructure, at least within the urban villages where we would anticipate most VRU activity. For example, a common current approach to improve pedestrian safety on wide, fast arterials is to add spot treatments such as pedestrian hybrid beacons (PHBs) to enable pedestrian crossings between signalized intersections. However, since the roadways within urban villages should be designed for short internal trips as opposed to long and fast external trips between villages, we can eliminate the wide and fast roadways altogether within the urban villages. If the roads within urban villages have a maximum of two travel lanes and low speed limits, walking and biking will be enabled.

With this urban village land use schematic and associated infrastructure improvements, we eliminate the primary barrier of distance for many trips (by clustering origins and destinations) and we eliminate the primary barrier of road safety within the urban villages by fundamentally shifting infrastructure to serve pedestrians and bicyclists as opposed to high-volume and fast motor vehicle travel.

In conjunction with the infrastructure recommendations made above, this work identifies the need to better visualize, measure, and implement such VRU networks on a citywide and regional scale. To accomplish this, we propose tools that are based on VRU perceptions and not extant VRU crashes. Basing decisions on crash locations is a more reactive approach that does not capture latent safety issues, while a proactive tool might better ensure safe and comfortable conditions for all users. This tool would build upon the widely-implemented bicycle level of traffic stress (BLTS) tool. The existing BLTS tool, while useful for roadway segments, might be expanded to road crossings and intersections. The BLTS might also be translated to pedestrians to form a pedestrian level of traffic stress (PLTS) tool. These tools will help decision makers understand gaps in the current network and help to enable VRU activity on a city or regional scale.

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