CPBS
Center for Pedestrian and Bicyclist Safety

A Tier-1 University Transportation Center

Exploring the Role of Arterial Roads' Characteristics on Pedestrian and Cyclist Crashes

July 2024

A Report From the
Center for Pedestrian and Bicyclist Safety

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16. Abstract
Pedestrians and bicyclists, termed Vulnerable Road Users (VRUs), are disproportionately affected in crashes. The impact of arterial roads on crashes is well-documented, especially concerning VRUs. Prior research highlights factors such as access management, built environment, land use, and socioeconomic conditions as significant contributors to VRU crash frequency. However, limited research has explored these relationships between arterial roads' features and its surroundings with the occurrence of pedestrian and bicyclist crashes in New Mexico, a proper case study for this research given its high rates of fatality per capita for bicyclist and pedestrians compared to any other state in the U.S. Hence, this study aims to answer the following research questions: 1) Are high-speed, high-access roads more likely to experience crashes than roads with better access management and/or slower speeds? The findings from this inquiry will enlighten the subsequent questions: 2) Do more driveways per mile correlate to more non-motorized crashes per mile? and 3) What other factors related to arterials-built environment, characteristics, and demographics correlate with a higher likelihood of pedestrian and bicycle crashes? 4) What are the spatial patterns of pedestrian and bicyclist crashes and their associated factors (e.g., road characteristics, land use, and sociodemographic)? Using two years (2018-2019) of crash data from the NMDOT, along with data on arterial features, surrounding land uses, and socioeconomic variables, this study identifies key factors influencing VRU crashes. The findings underscore the importance of access management in reducing crashes and highlight the most critical arterial road features and socioeconomic factors contributing to VRU crashes. Additionally, the study identifies the most critical corridors in Albuquerque, characterizing them with the variables impacting VRU crash frequency. These insights can inform future planning and intervention strategies to effectively implement crash mitigation measures.

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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)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		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)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		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

Exploring the Role of Arterial Roads' Characteristics on Pedestrian and Cyclist Crashes

A Center for Pedestrian and Bicyclist Safety Research Report

July 2024

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Acronyms, Abbreviations, and Symbols

ABQ	City of Albuquerque
AIC	Akaike Information Criterion
ANOVA	Analysis of Variance
CPBS	Center of Pedestrian and Bicyclist Safety
DOT	Department of Transportation
FDR	False Discovery Rate
FHWA	Federal Highway Administration
HAHS	High Access and High-speed segments
HALS	High Access and Low-speed segments
KED	Kernel Estimation Density
GIS	Geographic Information System
IPUMS	Integrated Public Use Microdata Series
LISA	Local Indicator of Spatial Association
MAUP	Modifiable Areal Unit Problem
MRCOG	Mid-Region Council of Governments
NHTSA	National Highway Traffic Safety Administration
NMDOT	New Mexico Department of Transportation
PCI	Pedestrian Composite Index
TAZ	Traffic Analysis Zones
UMA	Urban Minor Arterial
UPA	Urban Primary Arterial
VIF	Variance Inflation Factor
VRU	Vulnerable Road User
WMA	Well-Managed Access
ZIP	Zero Inflated Poisson
ZINB	Zero Inflated Negative Binomial

Abstract

Pedestrians and bicyclists, termed Vulnerable Road Users (VRUs), are disproportionately affected during crashes. The impact of arterial roads on crashes is well-documented, especially concerning VRUs. Prior research highlights factors such as access management, built environment, land use, and socioeconomic conditions as significant contributors to VRU crash frequency. However, limited research has explored these relationships between arterial roads' features and its surroundings with the occurrence of VRU crashes in New Mexico. Hence, this study aims to answer the following research questions: 1) Are high-speed, high-access roads more likely to experience crashes than roads with better access management and/or slower speeds? The findings from this inquiry will enlighten the subsequent questions: 2) Do more driveways per mile correlate to more non-motorized crashes per mile? and 3) What other factors related to arterials-built environment, characteristics, and demographics correlate with a higher likelihood of pedestrian and bicycle crashes? 4) What are the spatial patterns of pedestrian and bicyclist crashes and their associated factors? Using two years (2018-2019) of crash data from the NMDOT, along with data on arterial features, surrounding land uses, and socioeconomic variables, this study identifies key factors influencing VRU crashes. The findings underscore the importance of access management in reducing crashes and highlight the most critical arterial road features and socioeconomic factors contributing to VRU crashes. Additionally, the study identifies the most critical corridors in Albuquerque, characterizing them with the variables impacting VRU crash frequency. These insights can inform future planning and intervention strategies to effectively implement crash mitigation measures.

Executive Summary

This report investigates the factors contributing to VRU (Vulnerable Road User) crashes on arterial roads in Albuquerque. The study aims to identify the key characteristics of these roads and their surroundings that impact VRU safety, and to pinpoint the most critical corridors in the city regarding VRU crashes. To achieve this, we conducted a background literature review to identify key factors influencing arterial VRU crashes. From this review, we identified the impact of access management and speed on the frequency of VRU crashes, along with other important characteristics detailed in this report. Subsequently, a novel method to evaluate access management was implemented, along with a statistical model to identify characteristics impacting VRU crashes in Albuquerque, New Mexico. Additionally, a spatial analysis to identify corridors with the highest VRU density was performed. The spatial analysis created both a statistical and visual representation of the crucial corridors. This report's objectives were fulfilled using two years (2018-2019) of crash data from the NMDOT, supplemented by data on arterial features, surrounding land uses, and socioeconomic variables from various sources. The findings provide actionable recommendations to mitigate VRU crash frequency. Among the key findings of the study are:

- A high number of accesses and greater speed presented a higher mean number of overall crashes.
- Driveway and signalized intersection density were significant predictors of VRU crashes when access was the sole explanatory factor. However, only access (herein understood as driveways, signalized, and unsignalized intersections) does not adequately predict VRU crashes, and more variables were explored.
- The resulting negative binomial regression model from this study provides evidence that well-managed driveways and lower traffic volumes (less than 20,000), the presence of schools, higher residential areas, and populations with associate degrees are associated with fewer crash frequency.
- Higher VRU exposure and road features such as larger segment length, greater number of lanes, and higher density of off-street parking and fuel stations, the presence of left turns, VRU facilities, such as crosswalks, sidewalks, and bus lanes, were connected to increase VRU exposure and conflicts, subsequently, the frequency of crashes.
- Variables associated with land use and sociodemographic surroundings, such as number of jobs, population below the poverty line, and Black or Afro-American population, were correlated with a higher frequency of crashes.
- The study identified 18 critical arterial corridors in Albuquerque with the highest density of VRU crashes. After characterizing these corridors, the findings validated the results from the statistical model.

- Integrating spatial analysis in safety analyses is a powerful tool for researchers to understand and visualize the crashes better and for authorities to implement crash mitigation measures effectively.

The findings from this report provide several recommendations to improve the safety of pedestrians and bicyclists in Albuquerque:

- Local agencies should adhere to spacing and design standards of access during city expansions to ensure safer roadways.
- Introducing measures like road diets, complete streets, and enhanced pedestrian and bicycle facilities may improve the safety of pedestrians and bicyclists.
- Education campaigns targeting younger individuals may establish safer habits among future generations to use adequately the infrastructure for VRU.
- Prioritize safety measures and regulations in areas with high commercial activity, dense populations below the poverty line, and significant Black or Afro-American populations may have a positive impact in reducing VRU crashes.

Implementing these strategies will require coordinated efforts between urban planners, local authorities, and community stakeholders.

Introduction

Walking and biking are sustainable modes of transportation that offer numerous benefits to individuals' health and the environment by alleviating traffic congestion and pollution and reducing the likelihood of non-communicable diseases. Nevertheless, these modes are also prone to higher fatality rates in the event of a crash. Consequently, bicyclists and pedestrians are often denominated as Vulnerable Road Users (VRU) since their protection is negligible or nonexistent in traffic crashes compared to other road users, making them more vulnerable when a crash occurs (Siddiqui et al., 2012). According to the Pedestrian and Bicycle Information Center, non-motorist fatalities in the United States have risen by 49% from 2012 to 2021, whereas traffic fatalities only increased by 27% in the same period ("Pedestrian & Bicycle Information Center," 2023). Hence, ensuring the safety of non-motorized users is a significant challenge as injuries and fatalities increase across the country.

The US Department of Transportation (DOT) and its recently funded Center for Pedestrian and Bicyclist Safety (CPBS) are actively working to implement measures that prioritize the protection of VRUs and promote the usage of these environmentally friendly modes of mobility. However, achieving these objectives requires a deeper understanding of the aspects contributing to VRU collisions, and arterial roads are crucial for identifying those factors. Several studies reported that the crash risk for pedestrians and bicyclists increases as the miles of arterials increase (Dumbaugh & Li, 2010; Nashad et al., 2016). In 2018, arterial roads accounted for 59% of pedestrian crashes in the U.S. (FHWA, 2020). As for bicyclists, 65% of their fatalities in the U.S. occurred on arterials (League of American Bicyclists, 2024). Overall, arterials have a higher probability of traffic events occurrence because of the high speeds (Chakraborty & Gates, 2022; Dumbaugh & Li, 2010; Su et al., 2021a), larger speed distributions (especially on roads with higher vehicle speeds), and the unrestricted entry for non-motorized road users (Huang et al., 2010; Ming Ma et al., 2010). Hence, understanding what makes arterials prone to a higher likelihood of crashes is critical to advancing safety for VRU in the U.S.

Previous studies have examined arterials, identifying the features that render these roads more susceptible to crashes. Among these characteristics, access and speed have been included in these analyses and found to be associated with a higher frequency of crashes. This is attributed to the complex interactions between road users generated by these features (Chakraborty & Gates, 2022; Dai & Dadashova, 2021; Ming Ma et al., 2010). Moreover, other road characteristics, particularly those related to VRUs, have been identified in previous studies as significant factors contributing to crashes. These include the built environment, VRU facilities, land use, and sociodemographic factors. Consequently, there is a need to comprehensively study arterials and their surrounding features to understand their impact on the safety of all road users.

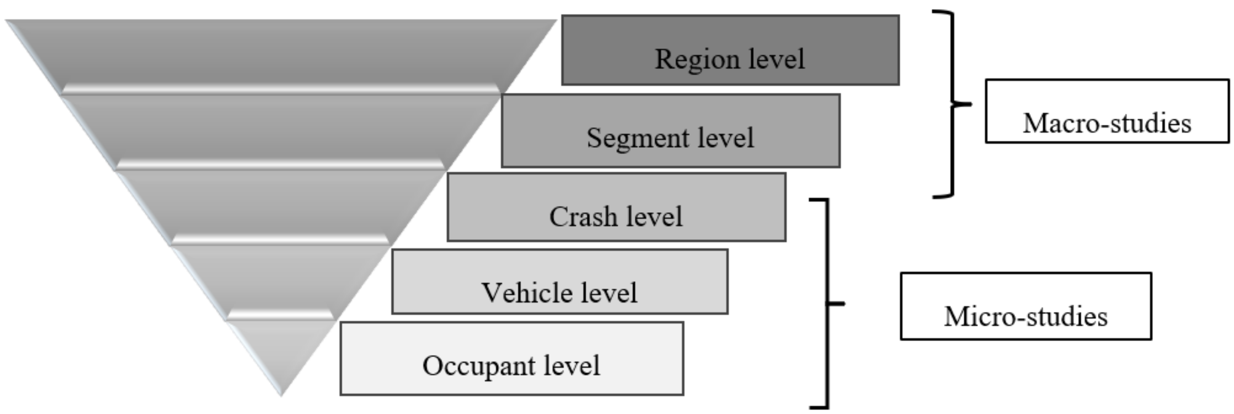
The field of safety in transportation has increasingly recognized in the last decades the importance of spatial analysis, particularly in the study of crashes, applying different modeling approaches to include the spatial component in crash analysis. One significant application of this type of analysis is geospatial statistics, which identifies critical locations that require interventions to reduce crash frequency, supported by statistical analysis (Ziakopoulos & Yannis, 2020). By pinpointing these areas, local agencies and authorities can strategically allocate resources to impact communities positively (Anderson, 2009).

With these goals in mind, this study addresses four fundamental questions regarding non-motorized traffic events in the largest urban area of New Mexico, Albuquerque. i) whether high-speed, high-access arterial roads are more likely to experience crashes than roads with better access management. The findings from this inquiry informed the two subsequent questions: ii) Do more driveway access and intersections per mile in arterials correlate to more non-motorized crashes? iii) What other factors related to the built environment correlate with a higher likelihood of pedestrian and bicycle crashes on arterial roads? The findings from the latest inquiry informed the subsequent question iv) What are the spatial patterns of pedestrian and bicyclist crashes and their associated factors (e.g., road characteristics, land use, and sociodemographic)? The Mid-Region Council of Governments (MRCOG), City of Albuquerque (ABQ), and New Mexico Department of Transportation (NMDOT) databases were used to conduct this analysis, providing diverse information from the metropolitan area of Albuquerque. This range of data allowed the study to obtain a deeper comprehension of the factors that impact the safety of pedestrians and bicyclists by implementing statistical models such as One-way Analysis of Variance (ANOVA), negative binomial regression to understand the influence of various factors on non-motorized crashes, and spatial analysis techniques such as Kernel Estimation Density (KED), Global and Local Moran's I, and Local Gi* statistics to identify the most critical corridors.

This report makes several notable contributions. Firstly, this study develops a novel methodology to evaluate access management in urban arterials, a feature that is related to crash frequency. In addition, this research assesses how other numerous factors, including the built environment, land use, and socioeconomic conditions, impact VRU crashes in Albuquerque, NM. New Mexico stands out as it registered the highest rate of pedestrian fatalities in recent years, with a rate of 4.82 per 100,000 habitants in 2021, according to NHSTA statistics (U.S. DOT, 2021). It also ranks among the highest rates for bicyclists, with a rate of 0.38 fatalities per 100,000 people in 2020 (NHTSA, 2024). While previous studies have explored pedestrian crashes in Albuquerque (Bia & Ferenchak, 2022; Long & Ferenchak, 2021); none has studied pedestrian and bicyclist crashes together in one analysis. In addition, it is crucial to recognize that although statistical models have been developed to identify arterial features associated with VRU crashes in existing studies, they do not comprehensively cover all the variables examined in our research (51 variables). Specifically, we investigate the influence of access management, built environment, land use, and socioeconomic conditions, focusing on arterial roads—known to pose the highest crash risk for non-motorized users. To address this gap, we also analyze road features such as width and number of lanes, sociodemographic factors, and intersection density, offering a holistic perspective on VRU crashes. Finally, we utilize a novel index for VRU exposure—the number of boardings per stop—which has not been previously explored in this context. Finally, the spatial analysis methodology can serve as a blueprint for other cities to employ a similar approach, enabling them to allocate resources effectively by identifying the patterns and features that affect road safety.

Background Literature Review

In the event of a crash, various characteristics describe the incident, which can be classified into five levels of information: occupant level, vehicle level, crash level, segment level, and region level. This hierarchical structure enables the classification of safety studies in macro and micro studies, depending on the considered levels. The occupant level includes characteristics of the road user(s) involved in the crash, such as age, gender, and any other behavioral or perceptional factors that impacted the occurrence of the crash. The vehicle level describes features such as model, year, speed, and type of vehicle. The crash level describes attributes related to location, time, weather conditions, and lighting conditions present at the incident. The segment level describes the surrounding road features at the crash location. Finally, the region level describes the sociodemographic features and land use of the area in which the crash occurred. Each level may contain additional features relevant to the crash, enhancing the understanding of the incident and correlations among the crashes (Haghighi et al., 2018; Huang & Abdel-Aty, 2010). These levels facilitate the classification of safety studies in two ways depending on the levels considered in the analysis: micro and macro studies, which intersect at the crash level. Micro-studies focus on the occupant, vehicle, and crash levels, identifying the individual or vehicle features associated with a higher likelihood of a crash. Macro studies analyze the crash, segment, and region level, identifying the road or crash features related to a higher crash likelihood. Figure 1 describes this structure.



Adapted from: Huang, H., & Abdel-Aty, M. (2010). Multilevel data and Bayesian analysis in traffic safety. Accident Analysis & Prevention, 42(6), 1556–1565. https://doi.org/10.1016/j.aap.2010.03.013

Figure 1. Structure of a crash analysis.

Considering the previous description regarding micro and macro studies, this study aims to develop a safety macro-study for VRUs. The following sections will describe some of the features within the crash and segment levels identified in previous studies that affect the frequency of VRU crashes. In addition, this study will present the statistical models and spatial analysis that have been employed in prior studies to analyze crashes.

Factors affecting safety

Previous literature has identified numerous factors that significantly influence the frequency of crashes and the safety of road users, especially pedestrians and bicyclists. For this section, the study will provide a detailed literature review focusing on access and speed separately from the other road features. These two characteristics serve as the main independent variables for addressing research questions 1 and 2. Additionally, other factors to be analyzed in this literature review include other road characteristics, land use, and sociodemographics.

Access

This study will incorporate the term “access” to encompass various elements facilitating the entry and exit of vehicles, pedestrians, and bicyclists from a roadway. Within this context, “access” will encompass features such as driveways leading to residences, commercial establishments, and other buildings, as well as intersections, both signalized and unsignalized.

Access is a significant factor often considered in vehicles, bicyclists, and pedestrians crash models. Numerous studies have explored the impact of driveway density and intersections on traffic incidents, revealing that higher access density is associated with a higher likelihood of collisions (Avelar et al., 2013; Brown & Tarko, 1999; Caliendo et al., 2007; Chakraborty & Gates, 2022; Dai & Dadashova, 2021; Ming Ma et al., 2010; Sawalha & Sayed, 2001; Siddiqui et al., 2012; X. Wang et al., 2018; Wei & Lovegrove, 2013; Zhang et al., 2015a). This has been attributed to the increasing conflicts between road users within the road network, which are exacerbated in larger road segments (Zhang et al., 2015a). When access points are situated in close proximity to each other, the conflicts they generate interact with one another, compounding into larger conflicts (Avelar et al., 2013; Brown & Tarko, 1999; Chakraborty & Gates, 2022). Consequently, adopting access management measures, such as controlling the density of access per mile, use of medians, and internal access lanes, emerges as a crucial factor affecting casualties, particularly in high-traffic scenarios since it is directly related to crash frequency (Avelar et al., 2013; Brown & Tarko, 1999; Dumbaugh & Rae, 2009a; Karlaftis & Golias, 2002; Sawalha & Sayed, 2001).

Regarding pedestrians, intersections and driveways have a higher pedestrian exposure, thereby they are linked to higher risk of crashes involving pedestrians due to the raised traffic conflicts caused by the interaction between pedestrians and vehicles (Dumbaugh & Rae, 2009b; Zhang et al., 2015a; Zhu et al., 2022). Even though intersections may have traffic lights to avoid those conflicts, several studies have found that intersections with this type of traffic control have a higher risk of crashes than intersections with stops, yield, or no signals to control the traffic (Avelar et al., 2013; Jaber et al., 2021; J. Lee et al., 2015). Intersections also are correlated with a higher likelihood of bicycle crashes but not the severity, which is more significant in segments due to the higher vehicle and bicyclists speed (Bíl et al., 2010; Dai & Dadashova, 2021; Kapousizis et al., 2021; Ming Ma et al., 2010; Wei & Lovegrove, 2013; Zhang et al., 2015a).

Speed

Previous assessments have indicated that speeding is directly linked to the frequency and seriousness of traffic crashes across all types of road users (Avelar et al., 2013; Chakraborty & Gates, 2022; Dai & Dadashova, 2021; J. Lee et al., 2015; Merlin et al., 2020; Ming Ma et al., 2010). This relationship is also influenced by speed variance (Arias et al., 2021). Numerous studies have consistently highlighted pedestrians and bicyclists as the most vulnerable road users in incidents caused by speeding, primarily due to the higher vehicle energy and lack of protection that VRUs possess (Amoh-Gyimah et al., 2016; Arias et al., 2021; Jaber et al., 2021; Zhang et al., 2015a). Research has revealed that pedestrians involved in collisions at a speed of 15 mph have a considerably higher probability of survival and prevent serious injuries than events at 40 mph (Tefft, 2013). In the case of bicyclists, there is no clear reduction of crashes at low velocities but the severity since most of the fatalities occurred at high speeds (Bíl et al., 2010; Dai & Dadashova, 2021; Kröyer, 2015). As previous studies have noted, speed affects the frequency of crashes. However, speed is contingent on road functionality and features. In the following section, we will examine the road characteristics identified in previous papers as contributing factors to crash occurrence.

Road-related characteristics

Numerous analyses have concentrated on identifying the features impacting road safety, concluding that road configuration significantly relates to crashes. Some studies have identified several characteristics and their influence on the occurrence of collisions in general, while others have focused their analysis on non-motorized crashes primarily. To the author's knowledge, only Ma et al. combined vehicles, bicyclists, and pedestrian crashes in one evaluation on arterials (Ming Ma et al., 2010). The road features analyzed in previous studies are presented in the table below. Some road facilities have been shown to have positive and negative influences on incidents involving non-motorized users. Streetlamps, for instance, have been associated with reducing pedestrian and bicyclist crashes during the evenings and early in the morning (Bíl et al., 2010; Jaber et al., 2021; Zhu et al., 2022). On the other hand, transportation facilities such as bus lanes have been associated with higher non-motorized incidents (Kapousizis et al., 2021; Zhang et al., 2015a). Similarly, metro stations and bus stops relate to a higher probability of pedestrian collisions, as these locations experience higher pedestrian exposure. Additionally, there are behavioral factors involved, such as pedestrians crossing in front of the bus stops instead of using the facilities designated for this purpose (Chakraborty & Gates, 2022; Dai & Dadashova, 2021; Kapousizis et al., 2021; Ming Ma et al., 2010; Pljakić et al., 2022; Su et al., 2021b; Zhu et al., 2022).

Even though VRU facilities, such as crosswalks and sidewalks, are designed to eliminate conflict between these users and vehicles at intersections or access points, they have a counterintuitive effect as they increase the risk of pedestrian crashes due to the exposure of pedestrians and bicyclists at these locations and the conflicts with other users. However, this effect is not related to the infrastructure itself or its purpose (Chakraborty & Gates, 2022; Merlin et al., 2020; Ming Ma et al., 2010; Sawalha & Sayed, 2001; Tokey et al., 2023a; Zhu et al., 2022). Separated bicycle facilities and lane barriers at intersections may be related to reducing the frequency of incidents. Still, bicycle or track lanes with poor geometric characteristics do not provide the same level of protection (Avelar et al., 2013; Chakraborty & Gates, 2022; Dai & Dadashova, 2021; Kapousizis et al., 2021; Merlin et al., 2020; Ming Ma et al., 2010). Road features vary depending on urban locations since residential zones may have different facilities than commercial or mixed areas. Therefore, given the significance of land use in comprehending the factors influencing crash frequency, this aspect is further examined in the subsequent section.

Land use

Land use has a well-documented influence on crash occurrences. Prior studies found that urban areas experience more collisions than rural areas because of road users' exposure (Jaber et al., 2021; Merlin et al., 2020). Commercial and business land uses are related to traffic incidents occurrence due to the high activity in those areas, affecting especially pedestrians and bicyclists because there is more VRUs activity in those zones (Avelar et al., 2013; Brown & Tarko, 1999; Chen, 2015; Dumbaugh & Li, 2010; Huang et al., 2010; Merlin et al., 2020; Ming Ma et al., 2010; Siddiqui et al., 2012; Su et al., 2021b; Zhang et al., 2015a). However, industrial areas do not have a significant impact on non-motorized users' incidents (Amoh-Gyimah et al., 2016; Chen & Zhou, 2016). Residential and mixed land uses are strongly related to pedestrians and bicycle crashes, particularly for pedestrians, due to the increasing conflict between non-motorized users and vehicles in densely populated areas (Amoh-Gyimah et al., 2016; Chen, 2015; Chen & Zhou, 2016; Ming Ma et al., 2010; Siddiqui et al., 2012; Su et al., 2021b; Tokey et al., 2023a). Since population density may be related to land use and crash frequency, reviewing the socio-demographic factors affecting crashes is critical to this study.

Socio-demographics

Several demographic factors impact road safety, particularly for non-motorized users. Population density has a positive correlation with crash occurrences as it increases the exposure of pedestrians and bicyclists (Zhang et al., 2015a) . Age is another variable that affects collision frequency. The older population faces a higher risk of being involved in traffic events as both pedestrians and bicyclists, while young people (before 19 years) increase primarily the risk of pedestrian crashes (Amoh-Gyimah et al., 2016; Dai & Dadashova, 2021; Su et al., 2021b). Education and household income are related factors that influence crash occurrences by affecting non-motorized users' behaviors, perceptions, and attitudes (Siddiqui et al., 2012; Su et al., 2021b). Populations with low levels of education often have low household incomes, forcing these individuals to walk or bike through inadequate pedestrians and bicycle facilities, which are often prevalent in low-income neighborhoods (Dai & Dadashova, 2021; Yu, 2014). Consequently, vulnerable populations are more likely to be involved in collisions (Yu, 2014).

Table 1. Factors affecting VRU safety mentioned in previous literature.

Used in Crashes models for				References
	General	Bicycle	Pedestrian	
Access				
Access	x	x	x	(Avelar et al., 2013; Brown and Tarko, 1999; Caliendo et al., 2007; Chakraborty and Gates, 2022; Dai and Dadashova, 2021; Dumbaugh and Rae, 2009a; Jaber et al., 2021; Kapousizis et al., 2021; Karlaftis and Golias, 2002; Ming Ma et al., 2010; Sawalha and Sayed, 2001; Siddiqui et al., 2012; Su et al., 2021b; Wang et al., 2018; Wei and Lovegrove, 2013; Zhang et al., 2015
Speed				
Speed Limit	x	x	x	Amoh-Gyimah et al., 2016; Arias et al., 2021; Avelar et al., 2013; Chakraborty and Gates, 2022; Dai and Dadashova, 2021; Jaber et al., 2021; Lee et al., 2015; Merlin et al., 2020; Ming Ma et al., 2010; Zhang et al., 2015
Road Features				
Traffic volume	x	x	x	Caliendo et al., 2007; Chakraborty & Gates, 2022; Dai and Dadashova, 2021; Ma et al.,2010; Sawalha & Sayed, 2001;
Ped Exposure		x	x	Amoh-Gyimah et al., 2016; Jaber et al., 2021; Su et al., 2021
Segment length	x	x	x	Avelar et al., 2013; Caliendo et al., 2007; Dai and Dadashova, 2021; Ma et al.,2010; Sawalha & Sayed, 2001; Siddiqui et al., 2011; Wang et al., 2018, Zhu et al. 2022
Number of traffic lanes	x	x	x	Avelar et al., 2013; Dai and Dadashova, 2021; Ma et al.,2010; Jaber, 2021; Sawalha & Sayed, 2001; Zhang et al., 2015
Directionality	x	x	x	Ma et al.,2010; Zhu et al. 2022

	Used in Crashes models for			References
	General	Bicycle	Pedestrian	
Road width	x	x	x	Avelar et al., 2013; Chakraborty & Gates, 2022; Jaber et al., 2021; Kapousizis et al., 2021; Potts et al., 2007; Zhu et al. 2022
Road Network (Grid, Tree-like)	x	x	x	Wang et al., 2018
Horizontal curves	x			Caliendo et al., 2007; Chakraborty & Gates, 2022
Presence of an outside shoulder	x			Brown & Tarko, 1999
Shoulder width	x			Potts et al., 2007
Presence of a two-way left-turn lane	x			Brown & Tarko, 1999
Presence of a median	x			Brown & Tarko, 1999; Dai and Dadashova, 2021; Jaber et al., 2021; Zhu et al. 2022
Roadside hazard	x			Potts et al., 2007
Signal density	x			Brown & Tarko, 1999; Sawalha & Sayed, 2001; Wang et al., 2018
Type of median	x	x		Avelar et al., 2013; Ma et al.,2010; Sawalha & Sayed, 2001
On-street parking presence	x	x		Avelar et al., 2013; Chakraborty & Gates, 2022; Kapousizis et al., 2021; Sawalha & Sayed, 2001
Road surface		x		Jaber et al., 2021
Longitudinal slope		x		Jaber et al., 2021; Caliendo et al., 2007; Kapousizis et al., 2021
Marking		x		Jaber et al., 2021
Fuel station presence		x		Kapousizis et al., 2021
Parking lot		x		Kapousizis et al., 2021
Facilities for non-motorized users				

	Used in Crashes models for			References
	General	Bicycle	Pedestrian	
Streetlamps		x	x	Bíl et al., 2010; Jaber et al., 2021; Zhu et al., 2022
Bus lane		x	x	Kapousizis et al., 2021; Zhang et al., 2015
Bus/metro stop presence	x	x	x	Chakraborty and Gates, 2022; Dai and Dadashova, 2021; Kapousizis et al., 2021; Ming Ma et al., 2010; Pljakić et al., 2022; Su et al., 2021b; Zhu et al., 2022
Pedestrian-crossing facilities (bridge-tunnel, crosswalk)	x	x	x	Chakraborty and Gates, 2022; Merlin et al., 2020; Ming Ma et al., 2010; Sawalha and Sayed, 2001; Tokey et al., 2023; Zhu et al., 2022
Sidewalk presence	x		x	Avelar et al., 2013; Chakraborty & Gates, 2022
Bicycle Facility	x	x		Avelar et al., 2013; Chakraborty and Gates, 2022; Dai and Dadashova, 2021; Kapousizis et al., 2021; Merlin et al., 2020; Ming Ma et al., 2010
Division type between roadway and bikeway		x	x	Kapousizis et al., 2021; Ma et al.,2010
Land use				
Commercial/business/ industrial areas	x	x	x	Amoh-Gyimah et al., 2016; Avelar et al., 2013; Brown and Tarko, 1999; Chen, 2015; Chen and Zhou, 2016; Dumbaugh and Li, 2010; Huang et al., 2010; Jaber et al., 2021; Merlin et al., 2020; Ming Ma et al., 2010; Siddiqui et al., 2012; Su et al., 2021b; Zhang et al., 2015
Mixed land areas	x		x	Amoh-Gyimah et al., 2016; Chen, 2015; Chen and Zhou, 2016; Ming Ma et al., 2010; Siddiqui et al., 2012; Su et al., 2021b; Tokey et al., 2023
Residential areas	x	x	x	Amoh-Gyimah et al., 2016; Ming Ma et al., 2010; Siddiqui et al., 2012; Su et al., 2021b; Tokey et al., 2023
Socio-demographics,				
Demographics		x	x	Amoh-Gyimah et al., 2016; Dai and Dadashova, 2021; Siddiqui et al., 2011; Su et al. 2021; Yu - 2014; Zhang et al., 2015

Used in Crashes models for				References
	General	Bicycle	Pedestrian	
Population		x	x	Zhang et al., 2015
Age		x	x	Amoh-Gyimah et al., 2016; Dai and Dadashova, 2021; Su et al., 2021b
Population poverty level		x	x	Dai and Dadashova, 2021; Yu, 2014
Education attainment		x	x	(Siddiqui et al., 2012; Su et al., 2021b)

After reviewing the literature, we identified gaps that our study addressed. Firstly, this research analyzes access management in arterials and studies Albuquerque, a location that has not been previously examined regarding these features (Avelar et al., 2013; X. Wang et al., 2018). In addition, this study includes the impact of road width and the number of lanes on VRU crashes (Zhu et al., 2022). Additionally, we study the influence of detailed roadway characteristics and sociodemographic factors on pedestrian and bicyclist safety, together (Arias et al., 2021). Furthermore, we incorporate intersection density as another variable in our analysis to assess its impact on pedestrian and bicyclist crashes (Merlin et al., 2020). It is important to mention that our study focuses on both pedestrians and bicyclists, considering that some research studies concentrate solely on one type of user. Studies of this type require models able to account for the count nature of the data.

Traffic Crash Models

Since crashes are denominated as count data, consisting of non-negative integer values, crash prediction models should use proper methods to model count data to obtain consistent results. The most popular model used for this purpose is the Poisson regression, from which several regression techniques have been developed. In this study, we will discuss the most popular statistical methods. Note that we are following the notation from Statistical and Econometric Methods for Transportation Data Analysis (Washington et al., 2010).

Poisson Regression Model

This model serves as the foundational framework for crash prediction. It considers the annual probability of crashes occurring at an intersection or segment 'i', denoted by a nonnegative integer 'n', through the following equation:

$$P(y_i) = \frac{EXP\,(-\lambda_i)\lambda_i^{y_i}}{y_i!}$$

In this context, P(yi) represents the likelihood of roadway entity 'i' encountering 'yi' crashes annually. The parameter λi corresponds to the Poisson parameter applicable to the intersection or segment 'i'. This parameter is equivalent to the anticipated count of crashes for the given segment or intersection, denoted as E[yi], within a defined time frame. The estimation of Poisson regression models involves determining the Poisson parameter λi, which signifies the projected count of events per designated period, in relation to explanatory factors. Among these relationships, the most prevalent is the log-linear model:

$$\lambda_i = EXP(\beta X_i) \text{ or equivalently } LN(\lambda_i) = \beta X_i$$

Here, Xi represents a collection of explanatory variables, and β stands for a set of parameters open to estimation.

Nonetheless, a constraint exists within this model, requiring the mean to align with the variance. This implies that when data displays over-dispersion or under-dispersion, the model's effectiveness diminishes.

Although this author did not find recent crash studies using this model, it has served as a foundation for several numerical techniques that have improved the model performance and the analysis of crash data.

Poisson Gamma or Negative Binomial Regression Model

This regression model addresses the issue of overdispersion observed in the Poisson model.

$$\lambda_i = EXP(\beta X_i + \varepsilon_i)$$

EXP(εi) represents a disturbance term that follows a Gamma distribution with an average of one and a variance of α. It introduces an unobserved heterogeneity term, denoted as α and commonly known as the overdispersion parameter. Incorporating this term enables the variance to deviate from the mean, leading to the following distinction:

$$VAR[y_i] = E[y_i] + \alpha E[y_i]^2$$

Numerous studies have applied this model for crash prediction (Arias et al., 2021; Avelar et al., 2013; Brown & Tarko, 1999; Dumbaugh & Li, 2010; Su et al., 2021b). Due to crash data's nature as a non-negative count variable and its tendency toward overdispersion, this model has found extensive use in both micro and macro crash analyses. Nevertheless, various supplementary techniques have been developed to address distinct challenges within crash prediction, such as under dispersion and small samples (Lord & Mannering, 2010a).

Zero-inflated models

Instances of zero-crash observations are frequently encountered within crash data. Two distinct qualitative conditions contribute to the emergence of such observations. The first condition materializes when an event never occurs due to an absolute occurrence probability of zero (typical count scenario). The second scenario arises when an observation does not materialize in the period of observation, which, while not exactly zero, is negligible. In such cases, the event might still occur outside the timeframe of observation (Zero-Inflated).

As a result, the dataset tends to exhibit a higher frequency of zeros due to these zero-count observations. Zero-inflated models were developed to effectively handle many zero-crash observations. These models achieve this by identifying whether the two aforementioned conditions are present within the estimation process. This methodology boasts distinct extensions for both the Poisson distribution (ZIP) and the Negative Binomial distribution (ZINB).

Within the ZIP model, it is assumed that the events, denoted as Y = (y1, y2, …, yn), are independent, and the model is articulated as:

$$y_i = 0 \ \ with\, probability \ \ p_i + (1 - p_i)EXP(-\lambda_i)$$

$$y_i = y \ \ with\, probability \ \ \frac{(1 - p_i)EXP(-\lambda_i)\lambda_i^y}{y!}$$

In this context, 'p_i' signifies the probability of being in the zero state, while 'y' represents the count of events occurring within a given period.

The ZINB regression model adheres to a comparable structure, wherein the events Y = (y1, y2, …, yn) are assumed to be independent, and the model unfolds as follows:

$$y_i = 0 \ \ with\, probability \ \ p_i + (1 - p_i)EXP(-\lambda_i)$$

$$y_i = y \ \ with\, probability \ \ (1 - p_i)\left[\frac{\Gamma\left(\left(\frac{1}{\alpha}\right)+y\right)u_i^{\frac{1}{\alpha}}(1-u_i)^y}{\Gamma\left(\frac{1}{\alpha}\right)y!}\right], \ y = 1,2,3,\ldots$$

where $u_i = (1/\alpha)/\,[(1/\alpha) + \lambda i\,]$.

$pi_i = (\lambda i)/\,[(1+ \lambda i]$.

Maximum likelihood methods are used to estimate the parameters of a ZINB and ZIP regression models.

These two models have been employed in multiple studies to analyze VRU crashes (Pour et al., 2012; Raihan et al., 2019; Shankar et al., 2003; Sun et al., 2021). They are well-suited for handling datasets with an excess of zeros, a common occurrence in areas with minimal or no activity involving VRUs. Despite the low activity levels, these areas still require detailed analysis, making these models essential tools for comprehensive examination.

Multilevel models

Whitin safety analysis, certain unobserved temporal and spatial factors affect crash occurrence. These factors encompass aspects like the proximity of crashes and the characteristics of the road. Neglecting to incorporate these elements into statistical models can result in parameter estimations that are both erratic and inefficient (Castro et al., 2013). Multilevel models, also known as hierarchical, random effects, and random parameter models, simulate multilevel or hierarchical data structures often encountered in road safety and crash analysis to specify and estimate properly the data (Huang & Abdel-Aty, 2010).

This model accounts for spatial correlations (Data from adjacent road entities), temporal correlations (Data from the same location for several months or years), or the combination of both, alongside with the unobserved heterogeneity in crashes analyses. This statistical technique considers random and fixed effects (parameters) models for this purpose.

$$\lambda_{ij} = EXP\left(\beta X_{ij}\right) EXP\left(\eta_j\right) \text{ or equivalently } LN\left(\lambda_{ij}\right) = \beta X_{ij} + \eta_j$$

In this context, 'λij' represents the anticipated count of events for observation 'i' within group 'j'. 'Xij' denotes a vector comprising explanatory variables, 'β' signifies a vector of parameters available for estimation, and 'ηj' stands as a random effect associated with observation group 'j'. The variance-to-mean ratio is now adjusted to 1 + λij / (1/α).

Several studies have employed this model extensively, primarily due to its advantages in spatial and temporal analysis (Amoh-Gyimah et al., 2016; Castro et al., 2013; Chen & Zhou, 2016; Huang et al., 2010; J. Lee et al., 2015). These models implement hierarchical levels for the data, enhancing their robustness and efficiency in predicting crash occurrences (Dupont et al., 2013; Jones & Jørgensen, 2003). Another method to understand crashes is by applying spatial analysis. This approach combines statistical methods with geographical visualizations, providing deeper insights into safety issues.

Spatial analysis

As Geographic Information System (GIS) technologies have proliferated in recent decades, the spatial analysis of crashes has become increasingly prevalent. Several approaches have been developed to understand better the crashes, including mathematical models to explore the spatial relationship between different variables impacting the frequency of crashes and geographical tools to identify and visualize areas with high risk of crashes (Anderson, 2009; Lee & Abdel-Aty, 2017; Lord & Mannering, 2010b).

Among the statistical models used to address the spatial correlation of crashes are random-effects and hierarchical-multilevel models, which have been employed in prior crash studies (Jones & Jørgensen, 2003; MacNab, 2004). These methods explore the different crash levels (region, segment, crash, vehicle, and occupant level) by employing different regression models to identify unobserved spatial correlations, offering insight into other crash-related variables. However, the results of these models may not always be straightforward to interpret and visualize (Lord & Mannering, 2010).

On the other hand, geospatial analysis employed statistical approaches to identify variables associated with crash frequency by pinpointing specific locations of incidents based on their spatial patterns. This enables local authorities to implement targeted measures effectively to mitigate crashes (Xie & Yan, 2008). Among the techniques used to conduct these analyses are density and cluster analysis, which provide different spatial outcomes that allow researchers to understand a phenomenon better (Amiri et al., 2021; Berhanu et al., 2023; Pljakić et al., 2019; Qinglu Ma et al., 2021; Tola et al., 2021). Density analysis reveals the distribution of points within the examined area, highlighting regions with the highest point density. In contrast, cluster analysis identifies spatial autocorrelation among these points, indicating the presence of hotspots and cold spots. Over the last decade, numerous methods for conducting density and cluster analysis have emerged, and they are available in GIS software. Among the most widely used are Kernel Density, Moran's I, Local Moran's I, and the Local G statistic. These methods will be described in more detail in the following sections.

Density analysis

This analysis has been employed to visualize point patterns, aiding in the identification of hot spots. One technique available in ArcGIS Pro is KED. Gatrell et al. describe KED as a method that utilizes a three-dimensional mathematical function to estimate the intensity of events per unit area at specific locations (x) within a defined radius or bandwidth (h). Each point is weighted based on its distance from the location x, ensuring that the distance analyzed does not exceed the bandwidth h. The bandwidth serves as the criterion defining the smoothness of the estimated surfaces. (Gatrell et al., 1996). The KED can be calculated with the following equation:

$$f_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - x_i)$$

Where n is the number of observations, and Kh represents the kernel weighting nonnegative function.

This method has been extensively utilized to analyze crashes ((Amiri et al., 2021; T. Anderson, 2007; T. K. Anderson, 2009; Katanalp & Eren, 2022; Steenberghen et al., 2004; H. Wang et al., 2019; Xie & Yan, 2008), encompassing segments or areal units as the units of study and examining all crashes or pedestrian and bicyclist crashes individually. However, none of these studies integrated pedestrians and bicyclists into one model.

Cluster analysis.

This spatial analysis technique has been used to illustrate the spatial associations among variables within a georeferenced area. One of the commonly employed methods is the Global Moran's I statistic, which integrates spatial and statistical theories to address overall patterns across an entire region. This method utilizes a combination of Moran's I index, p-value, and z-score to define whether the data exhibits a random, clustered, or dispersed pattern (Amiri et al., 2021; Getis, 2008). The Moran's I index ranges from -1 to +1. Upon obtaining a significant p-value, values nearing -1 signify strong dispersion or high negative autocorrelation, while values approaching +1 indicate strong clustering or high positive autocorrelation. Values near 0 suggest no spatial autocorrelation. This method is represented by the following mathematical expression:

$$Global\ Moran's\ I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij})(\sum_{i=1}^{n}(x_i - \bar{x})^2}$$

Where n is the number of observations and $\bar{x}$ is the mean of the variables, x_i and x_j are the variable value at a particular location i≠j, and W_{ij} is the weight indexing location of I relative to j.

The concept of Global Moran's I is extended to local conditions by employing local statistics that aid in identifying local clusters. Two of the most widely used methods are Local Moran's I, also known as Local Indicator of Spatial Association (LISA), and local G_i^* statistic (Getis, 2008). These methods assess the similarity or dissimilarity of a variable at a specific location compared to its neighboring.

Local Moran's I is given by the expression:

$$I_i = z_i \sum_{j \neq i} W_{ij} z_j$$

where $z_i = \frac{(y_i - \bar{y})}{S}$ and W is a matrix row standardized.

Local G statistics or Getis-Ord is given by the expression:

$$G_i = \frac{\sum_{j=1} W_{ij} x_j - x \sum_{j=1}^{n} W_{ij}}{S\sqrt{\frac{\left[n \sum_{j=1}^{n} W_{ij}{}^2 - (\sum_{j=1}^{n} W_{ij})^2\right]}{n-1}}}$$

where n is the number of features in the dataset, x_j are the attribute value for feature j, and W is a matrix row standardized.

These two methods identify the locations of hot spots (clusters of high values), cold spots (clusters of low values), outliers, and non-significant observations. This information cannot be derived from the application of Global Moran's I alone.

The three methods, Global Moran's I, Local Moran's I, and local Gi* statistics, have been extensively employed to analyze the spatial correlation between different variables and crashes. Global Moran's I has often been utilized in prior studies to confirm the presence of global autocorrelation among crashes (Flahaut et al., 2003; M. Lee & Khattak, 2019; Pljakić et al., 2019; Shbeeb, 2023; Tola et al., 2021; Zahran et al., 2021). However, it has been augmented or substituted by local spatial autocorrelation measures such as Local Moran's I (Shbeeb, 2023) and, more often, local Gi* statistics, which has been one of the most often employed techniques (Amiri et al., 2021; Berhanu et al., 2023; M. Lee & Khattak, 2019; Tola et al., 2021). The advantage of these local methods is they offer specific locations, enabling a more precise visualization of crash patterns.

Unit of study

In addition to the selection of the modeling approach, spatial analysis has another concern related to the Modifiable Areal Unit Problem (MAUP), and safety is not exempt from this issue (Fotheringham & Wong, 1991; I. Thomas, 1996). Prior studies have widely conducted a spatial analysis of VRU crashes in different units, including census blocks, which are the smallest areal units, Census Tracts, Traffic Analysis Zones (TAZ), and counties; census tracts and TAZ are the most often units used (Cai et al., 2017; Siddiqui et al., 2012; Tokey et al., 2023b; Zhang et al., 2015b). Segment units have also been analyzed in prior studies, but not as often as the mentioned areal unit, and most of these studies have not focused on VRU but all road users (Barua et al., 2015; Ming Ma et al., 2010). Thus, it is crucial to recognize that VRU crashes occur on roads spatially connected to a network. This fact introduces various considerations related to the transportation system because it traverses a road network and influences human behavior and activities (Yamada & Thill, 2007). As a result, careful consideration is required in the analysis of VRU's road safety.

After reviewing prior studies on spatial analysis in crashes, this study aims to address a gap highlighted by Ziakopoulos and Yannis, emphasizing the significance of conducting more crash studies on segment units rather than areal units is essential. Additionally, we are addressing another gap by focusing on measuring the spatial autocorrelation for specific road users, particularly pedestrians and bicyclists, who have not often been studied together in the same analysis. This will be achieved by combining three geospatial methods to comprehend crash patterns and identify the necessity for safety measures.(Ziakopoulos & Yannis, 2020).

Data and Methodology

Considering the features previously studied and the research questions outlined earlier, this section presents the variables that form our database and the sources of this information, ranging from local agencies to open databases. Figure 2 illustrates the general methodology used to construct this report. Additionally, we provide a detailed description of the methodology used to address each research question, including the processes, statistical methods, and software employed.

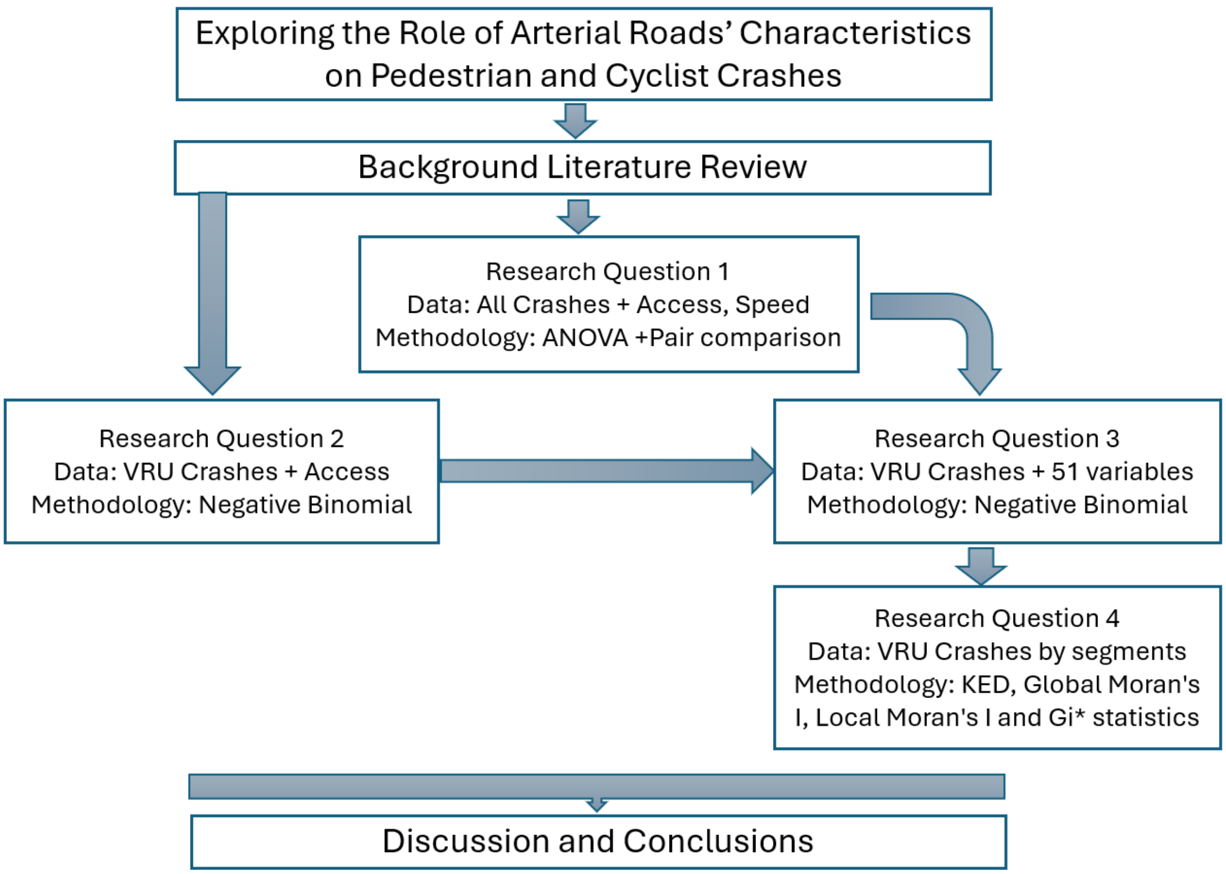


Figure 2. General research process

Data Collection and Sources

New Mexico is situated in the southwestern region of the United States, and its largest metropolitan area, Albuquerque, is located in central New Mexico. Albuquerque spans 189.5 square miles and is home to over half a million residents. Notably, this city has seen a concerning trend in recent years, registering the highest rate of pedestrian fatalities per 100,000 inhabitants, reaching an alarming 3.75% in 2020, according to NHSTA statistics (U.S. DOT, 2021). Additionally, Albuquerque ranks among the top for bicyclist fatalities per 100,000 people, with a rate of 0.38%.

Figure 3 shows a map of the city highlighting VRU crashes and the arterial road network, which serves as the primary focus of this study. These statistics position Albuquerque as an ideal case study for analyzing the road features that impact VRU crashes. Therefore, all the data required for this study was collected exclusively from this city provided by its different agencies and authorities.

Figure 3. VRU crashes and Arterial Network in Albuquerque, NM

As the initial step in model development and addressing the research questions, the authors gathered data from diverse sources, including the Mid-Region Council of Governments of New Mexico, City of Albuquerque, and New Mexico Department of Transportation. Some additional factors that can affect crash frequency were gathered separately from the databases. These were sourced from the Integrated Public Use Microdata Series (IPUMS), an open database containing data from the United States Census and other surveys on various topics (Kugler & Fitch, 2018). All the information was available in GIS format, facilitating the spatial joins and other analysis based on spatial location. The variables obtained are listed below, identifying the source and the criteria adopted by the authors for the analysis and model inputs.

Arterial segments (Source: MRCOG): We obtained road segmentation data for Albuquerque from MRCOG, including each segment's length and functionality classification. Given the focus of our study, we specifically took functionalities 2 and 3, corresponding to primary and minor arterials. We create a buffer of these segments 45 feet wide to each side, a total of 90 feet. The mean of the total road width was 51 feet, so with 90 feet, we ensured to include all the relevant variables for analysis. Consequently, we linked all the variables to this buffer area to construct our dataset.

Total Crashes (Source: NMDOT): We had the total unit of crashes for all vehicles from 2012 to 2021. However, due to the pandemic's impact on traffic patterns and the lack of traceability regarding modifications in the built environment within the segments from 2012 to 2020, we opted to focus on crashes occurring specifically in 2018 and 2019 to have a representative sample of the incidents.

Vulnerable Road User Crashes (Source: NMDOT): We filtered the total crashes to get only the VRU crashes, maintaining consistency with the same timeframe used for the total crashes in our analysis. VRU were those who were pedestrians or bicyclists at the time of the crash since data on scooter and other devices was not available in the database.

Average Daily Traffic (Source: MRCOG): We had the Average Annual Daily Traffic data for each year. Consequently, we selected 2018 and 2019 and computed their average to obtain a singular value for each segment.

VRU exposure (ABQ Transit Ride and IPUMS): This variable limits our study as the number of pedestrians and bicyclists is unavailable. Thus, we used two proxies for this variable: the average number of boardings per stop and the population that walked or biked to work in the adjacent census tracks of the segment. As indicated in several guides of different states and in a National Cooperative Highway Research Program (NCHRP) report, the average number of boarding passes per stop served as a proxy for VRU exposure as their locations are related to the high activity of these road users (NCHRP, 2015; NYDOT, 2016; L. Thomas et al., 2016; U.S. DOT, 2021b). To obtain this data, we aggregated the boardings for each route, getting the total boardings per stop. Subsequently, we cross-verified this value with the available data from the Albuquerque Ride website, finding a close match (ABQ Ride, 2018). It is pertinent to mention that the city possesses ridership statistics per route per fiscal year, which are collected using “fareboxes.” These “fareboxes” are activated automatically or by the bus driver, providing essential data for analysis. Then, we performed a spatial join in ArcGIS to assign the stop points to the segments, summing up the stops in the same segment.

The second index, the number of people who walk or bike to work, was obtained in the U.S. Census Bureau-IPUMS NHIS for the area of Albuquerque using census blocks as the geographical unit. The shape file from this database was spatially joined to the census blocks containing the sociodemographic information. Since numerous segments served as the boundaries of these census blocks, we conducted a spatial join with the road buffer. This process involved determining the average values from the intersected census blocks to derive the average population who walk or bike data for the respective segments.

Speed Limit (Source: MRCOG): We got the speed limit for each segment without doing any additional analysis from MRCOG.

Driveways density (Source: MRCOG): We obtained a shape file containing polygons representing access points for the Mid Region of New Mexico. Initially, we narrowed down the focus to Albuquerque and clipped the access points, specifically on the Arterials. Subsequently, we isolated only the driveways and driveway intersections since they shared the same locations, separating them from road intersections. Using these access areas, we dissolve the boundaries of the polygons to get a unique polygon for each access. These polygons were then converted into points to calculate the access density. Finally, we joined the points to each segment by counting the access within a buffer along arterial roads, obtaining the number of accesses per segment, subsequently converting to access per mile according to the segment's length.

Controlled and uncontrolled Intersection Density (Source: ABQ City - MRCOG): We employed a shapefile featuring points representing stop-controlled intersections from Albuquerque City and another shapefile with intersections controlled by lights and uncontrolled intersections from MRCOG. The intersections from MRCOG were categorized into those controlled by lights and those without control. Subsequently, we selected and joined the points of each category to the road buffer, counting the number of intersections per segment. The intersections controlled by stop and those controlled by lights were combined to create a distinct category for controlled intersections, while uncontrolled intersections formed another category. Finally, we determined the density of controlled and uncontrolled intersections per mile.

Road width and number of lanes (Source: ABQ City – MRCOG - Team-collected data): We utilized a shapefile containing street data from ABQ city. Some streets were represented by a single line encompassing data from both directions, while others had separate lines for each direction. To obtain the width and number of lanes, we segregated these segments. For the roads with only one line, we took the width and the number of lanes indicated in the spatial join with the road buffer. For roads represented by a single line, we extracted width and lane data from the spatial join with the road buffer. For roads with two lines, one for each direction, we conducted a spatial join to obtain lane and width information for one roadway, then multiplied these values by two to encompass the entire section. The data regarding the width and number of lanes for each segment were consolidated into a single column. As the shapefile lacked information on all arterials, we supplemented the lane data using a database from MRCOG, which contained the lane counts for the analyzed segments. When width information was missing, we utilized the minimum width recommended in the FHWA and multiplied this value by the number of lanes. (FHWA, 2024)

Left turns (Source: ABQ City – MRCOG): We utilized a shapefile containing the locations of left turns represented as lanes in the Mid Region of Council Government area. These lanes were spatially joined with the road buffer, enabling us to count the number of left turns per segment and calculate the density of left turns per segment.

Directionality (Source MRCOG): We got the directionality for each segment without doing any additional analysis.

Medians presence (Source: ABQ City- Team-collected data): We used a shapefile containing the locations of medians represented as polygons in Albuquerque. However, certain segments were missing, so we completed the medians' information for all the segments under analysis. The additional data on medians were represented as lines in the last file. We conducted separate spatial joins with the road buffer for each file and then consolidated the tables in Excel to obtain a unified count of medians. This approach enabled us to determine the number of medians per segment and calculate the density of medians per segment.

Crosswalk Presence (ABQ city): We utilized a shapefile containing crosswalk locations represented as lines. As the file also included other pavement stripping details, we specifically selected the crosswalks and created a separate layer with these items. These lines were then spatially joined with the road buffer, enabling us to count the number of crosswalks per segment. We categorized this variable as either 'yes' (for segments with more than 0 crosswalks) or 'no' (for segments with 0 crosswalks).

Bike lane Presence (ABQ city): We used a shapefile containing bike lane locations represented as lines. As the file also included trails and walk sides, we specifically selected the bike lanes and paved multiple-use trails, creating a separate feature with these items. These lines were then spatially joined with the road buffer, enabling us to count the number of bike lanes per segment. We categorized this variable as either 'yes' (for segments with more than 0 bike lanes) or 'no' (for segments with 0 bike lanes).

Sidewalk Presence (MRCOG): We utilized a shapefile containing sidewalk locations represented as lines within the Mid Region of Council Government area. To focus specifically on sidewalks along major roads in Albuquerque, we clipped the data accordingly. These lines were then spatially joined with the road buffer, enabling us to count the number of sidewalks per segment. We categorized this variable as either 'yes' (for segments with more than 0 sidewalks) or 'no' (for segments with 0 sidewalks).

Speed bumps presence (ABQ City): We employed a shapefile containing speed bump locations in ABQ city, represented as points. These points were spatially joined with the road buffer, allowing us to count the number of bumps per segment. We categorized this variable as either 'yes' (for segments with more than 0 bumps) or 'no' (for segments with 0 bumps).

Streetlamps (MRCOG): We utilized a shapefile containing streetlamp locations in Albuquerque, represented as points. We specifically chose the streetlamps classified as operational and then conducted a spatial join with the road buffer. Through this process, we counted the number of streetlamps per segment and categorized the variable as either 'yes' (for segments with more than 0 streetlamps) or 'no' (for segments with 0 streetlamps).

Bus stop presence (ABQ Transit Ride): We employed a shapefile featuring bus stop locations in Albuquerque, represented as points. Using a spatial join with the road buffer, we tallied the number of buses stops per segment. The variable was then categorized as ‘yes’ (for segments with more than 0 bus stops) or ‘no’ (for segments with 0 stops).

Bus lanes (ABQ Transit Ride): We utilized a shapefile containing bus stop locations in Albuquerque, treating them as lanes. Employing a spatial join with the road data, we determined the number of bus lanes per segment. The variable was then categorized as ‘yes’ (for segments with more than 0 bus lanes) or ‘no’ (for segments with 0 lanes).

Exclusive bus lanes (Team-collected data): We examined the bus lanes data to identify lanes exclusive to bus operations, creating a separate shapefile for this information. Subsequently, we conducted a spatial join to count the number of exclusive bus lanes per segment, categorizing the variable as 'yes' (for segments with more than 0 exclusive bus lanes) or 'no' (for segments with 0 exclusive lanes).

School zone presence (Team-collected data): We generated a shapefile indicating schools near arterial roads, represented as points. However, these points were situated within structures. To resolve this, we performed a spatial join with the road buffer, utilizing a larger geodesic distance, approximately 1,000 feet from the road. Consequently, we calculated the number of schools per segment, categorizing the variable as 'yes' (for segments with more than 0 schools) or 'no' (for segments with 0 schools).

Gas stations (Team-collected data): We generated a shapefile indicating fuel stations along arterial roads, represented as points. However, these points were positioned inside structures. To resolve this, we performed a spatial join with the road buffer, utilizing a larger geodesic distance, approximately 300 feet from the road. Consequently, we calculated the number of fuel stations per segment, categorizing the variable as 'yes' (for segments with more than 0 fuel stations) or 'no' (for segments with 0 fuel stations).

Parking on and off street (Team-collected data – ABQ City): We generated a shapefile indicating off-street parking lots along arterial roads, represented as points. However, these points were situated within the parking lots. To address this, we performed a spatial join with the road buffer, employing a larger geodesic distance, approximately 300 feet from the road. Additionally, we utilized a shapefile from ABQ City containing on-street parking spaces in Albuquerque. We also conducted a spatial join for these points and the road buffer as well. After counting both types of parking lots, we combined the data to create a unified field categorizing the variable as 'yes' (for segments with more than 0 parking spaces) or 'no' (for segments with 0 parking spaces).

Area (ft^2) of commercial and of residential properties and jobs density (MRCOG): We utilized a shapefile containing the areas of residential and commercial properties and other file for jobs in Albuquerque. Employing a spatial join, we first joined these areas and the jobs to the corresponding census block, adding all the ft^2 and number of each type of land use. As numerous segments served as the boundaries of these census blocks, we conducted a spatial join with the road buffer. This process involved determining the average values from the intersected census blocks to obtain the average ft^2 of residential and commercial properties and the jobs related to each arterial.

All the following demographic information was represented by density per census block. As numerous segments served as the boundaries of these census blocks, we conducted a spatial join with the road buffer. This process involved determining the average values from the intersected census blocks to obtain comprehensive demographic data for the respective segments.

- Population (MRCOG): Density of population
- Population below poverty (MRCOG): Density of population below poverty

- Population between 10-17 years (MRCOG): Density of population between 10- 17 years old.
- Population >65 years (MRCOG): Density of population older than 65 years old.

Educational attainment (IPUMS): We obtained the educational attainment of individuals over 25 years old in Albuquerque, categorized into no schooling at all, K0-K12, associate, undergraduate, and graduate, as per U.S. Census definitions. This data was acquired using census blocks as the geographical unit. The shape file from this database was spatially joined to the census blocks containing the sociodemographic information. As numerous segments served as the boundaries of these census blocks, we conducted a spatial join with the road buffer. This process involved determining the average values from the intersected census blocks to obtain the average educational attainment data for the respective segments. Subsequently, we aggregated the education into the following categories: no schooling, elementary schooling or under, middle schooling or under, high schooling or under, associate degree, undergraduate, and graduate levels.

Ethnicity (IPUMS): We collected data on ethnicity for the Albuquerque area, using census blocks as the geographical unit. The shape file from this database was spatially joined to the census blocks containing the sociodemographic information. As numerous segments served as the boundaries of these census blocks, we conducted a spatial join with the road buffer. This process involved determining the average values from the intersected census blocks to obtain the average of the ethnicity data for the respective segments. Subsequently, we aggregated the ethnicity data based on categories such as White, Black or Afro-American, Asian, Indian Alaskan, Hawaiian, other races, more than one race, and Hispanic-Latino.

Methodology

After obtaining the data to include in the analysis, we answered the research questions mentioned at the beginning of the document using the following methodology.

Research Question One: Are high-speed, high-access arterial roads more likely to experience crashes than roads with better access management?

To answer this question, we first established the criteria for access classification by referring to the NMDOT State Access Management Manual (NMDOT, 2001). We compared the spacing of driveways, signalized and unsignalized intersections to the spacings suggested in that manual for the same categories of access, which classified them by Urban Primary Arterials (UPA) and Urban Minor Arterials (UMA) (Table 2). This table indicates the minimum spacing required between access points for each category of access, signalized and unsignalized intersections, and driveways, across different speed limits.

The spacing of driveways is divided into two categories, depending on the presence of traversable medians in the road. There is only one spacing type for roads with traversable medians, as indicated in Table 2. However, for roads without traversable medians, the manual indicates two spacing categories: one for full access and the other for partial access. In the manual, full access is defined as access where no turning movement is restricted, while partial access has some restricted movements.

We classified driveways by considering the spacing for traversable medians specified in the manual, which allows roads with a higher density of driveways. Since we only have data on raised medians without specifying if they have full or partial access, for roads with non-traversable medians, we compared the driveway spacing to the full access criteria specified in the manual, which permits the lowest driveway density, and the partial access, which allows the same density as the traversable medians. This sensitivity analysis will indicate how full and partial access spacing impacts access classification. It is worth mentioning that driveway spacing for non-traversable medians with partial access and traversable medians was the same in the manual. This is why the sensitivity analysis is focused on those segments with full and partial access.

Table 2. NMDOT Access Management Manual

Access Category	Posted Speed (mph)	Intersection Spacing (feet)		Driveway Spacing (feet)		
				Non-Traversable Median		Traversable Median
		Signalized	Unsignalized	Full Access	Partial Access	
UPA	≤30	2640	1320	1320	200	200
	35 to 40	2640	1320	1320	325	325
	45 to 50	2640	1320	1320	450	450
	≥ 55	5280	1320	1320	625	625
UMA	≤30	1760	660	660	175	175
	35 to 40	1760	660	660	275	275
	45 to 50	2640	660	660	400	400
	≥ 55	5280	1320	1320	600	600

Source: NMDOT State Access Management Manual

We converted the minimum separation specified in Table 2 above into access points per mile for each type of access (driveways, signalized, and unsignalized intersections), comparing this density with the density obtained for each arterial segment from the data collected in this research. This comparison resulted in classifications for the three types of access as well-managed when the access density of the corridor was lower than the one indicated in the manual; otherwise, it was classified as high access. We classified a segment as having well-managed access only when all three classifications indicated effective management according to the manual thresholds. Otherwise, it was classified as high access. Since we considered two criteria for driveways, with full and partial access, we conducted two separate analyses for the classifications of the segments in each case.

For speed classification, we referred to previous studies demonstrating the impact of speed on the increased risk of fatality for pedestrians involved in crashes (Rosén et al., 2011). These consistently indicated that higher speeds correlate with a greater risk of pedestrian fatality or severe injury. Therefore, we analyzed three posted speed limits: 30 mph, 35 mph, and 40 mph. Segments with speeds exceeding these cutoff points were classified as high-speed roads. For example, in the first scenario, segments with speeds higher than 30 mph were classified as high speed.

It is worth noting that, due to the limited number of observations for roads with well-managed access, we opted not to differentiate between low and high speeds to ensure a representative sample to apply statistical analyses. After completing the classification by access and speed, we combined these two classifications to obtain three categories for the arterial roads: high-access, high-speed; high-access, low-speed; and segments with good access management.

We utilized the One-way Analysis of Variance (ANOVA) method in R to compare the means and determine which road had a higher mean of all road users' crashes, representing the road with a greater likelihood of crashes. We used this technique because it allows us to compare more than one mean at a time, capturing the significant difference across the means. One of the conditions for applying ANOVA in statistical inference is normality. As the data did not meet this assumption, we transformed the crash counts to their square root to satisfy this condition. However, the results are presented without this transformation for ease of interpretation. We applied this procedure separately for the two cases obtained in the driveways classification (full and partial access) and for each speed analyzed (30 mph, 35 mph, 40 mph), resulting in three pairs of mean crash comparisons. It is worth mentioning that this question considered all types of crashes (VRU and motor vehicles), regardless of whether they resulted in an injury or fatality outcome.

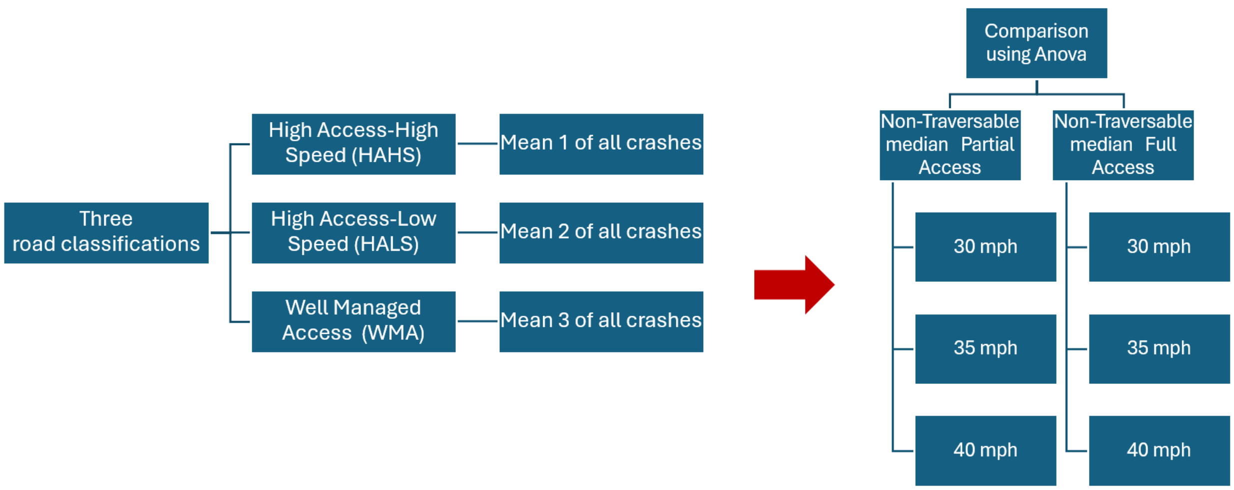


Figure 4. Methodology Question 1

Research Question Two: Do more driveway access and intersection per mile correlate to more non-motorized crashes per mile?

This question analyzes the influence of driveways and intersection density on VRU crashes only. We used the same density measure obtained in question one for driveways and controlled and uncontrolled intersections. Initially, we conducted an exploratory analysis using GIS software to assess whether linear models provided by the software adequately explained the relationship between VRU crashes and the density of intersections. However, the exploratory analysis using GIS software yielded a poor R^2 coefficient, prompting us to explore other models that might better fit the dataset. We turned to R software, which offers a broader range of statistical modeling options. First, we plotted the data to visualize its distribution. After exploring the distribution and considering crashes as count data, we evaluated the Poisson, Quasi-Poisson, and Negative Binomial models to fit the data. The first two models resulted in an overdispersion higher than two (2), while Negative binomial model yielded an overdispersion close to 1, as the results section will show.

Additionally, we checked the excess of zero in the data to see if this was a case for a zero-inflated model. Still, it was unnecessary as the negative Binomial model adequately predicted the zeros of the data in the allowed ratio between 0.95 and 1.05. To select the most suitable model, we compared the overdispersion, the Akaike information criterion (AIC) factor, and the Bayesian information criterion BIC, choosing the model with the lower factors, in this case, the Negative Binomial model.

To predict VRU crashes, we included the three densities mentioned above as variables of the model, identifying their significance in predicting VRU crashes. Even though we evaluated different models, we will present only the results of the negative binomial model, as it was observed to better represent the relationship between VRU crashes and the various access variables.

Table 3. Descriptive statistics of access density model

Variable	N	Mean	Min	Max	Sd
VRU Crashes	845	2.10	0	41	3.16
Driveways Density	845	17.11	0	150	20.46
Unsignalized Intersections	845	6.91	0	85.71	8.99
Signalized Intersections	845	15.45	0	242.42	16.09

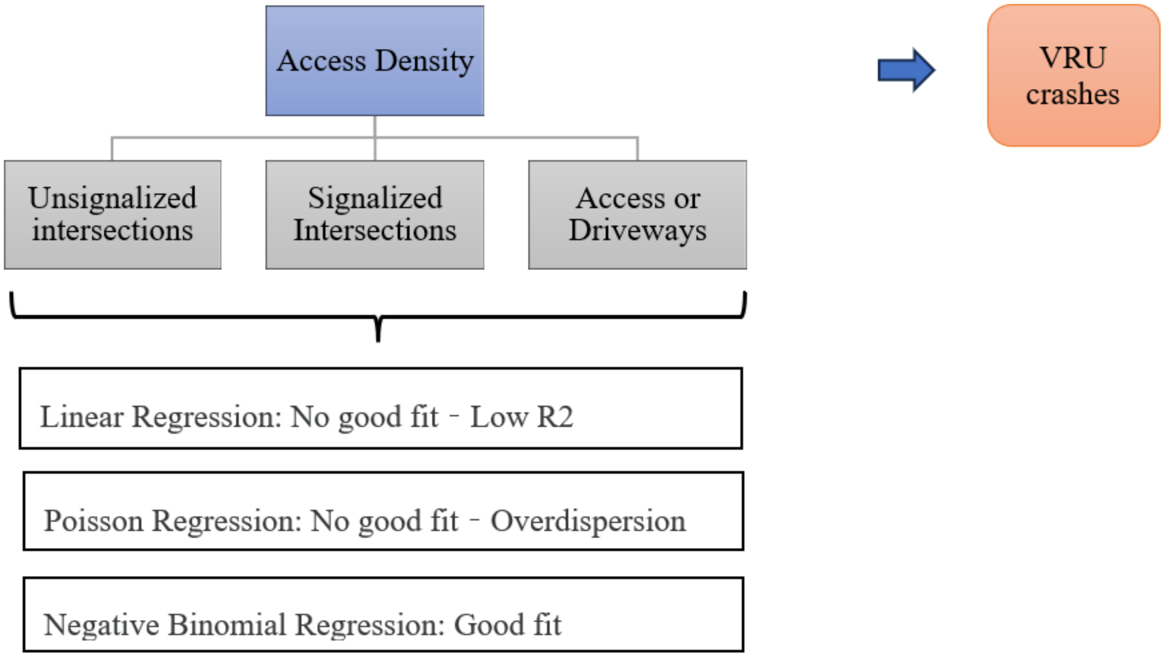


Figure 5. Summary of Methodology Strategy for Question 2

Research Question Three: What other factors related to the built environment correlate with a higher likelihood of pedestrian and bicycle crashes?

To address this question, we developed a statistical model aimed at identifying the most significant factors for predicting VRU crash frequency. As the crash data for this question is the same as question 2, we used Negative Binomial model to fit the data. We considered all variables mentioned in the previous sections, Research questions one and two, in constructing this model. To provide greater detail, we disaggregated certain variables, including traffic volume (ADT) into a range based on the number of vehicles, speed limit into segments with speeds equal to or under 35 mph to ensure a balanced distribution of segments, and segment classifications based on access type for 35 mph (Used in the analysis of Question 1). The variables included in the model are presented in Table 4.

Table 4. Variables included in the NB model

#	Variable	Units	Mean	Sd	Min	Max
	VRU crashes	Unit	2.10	3.16	0.00	41.00
1	Segment length	Miles	0.44	0.37	0.03	4.58
2	ADT	Vehicles	19294.03	12048.93	0.00	89045.00
3	ADT less than 20K	Y/N			0.00	1.00
4	VRU exposure boardings	Boardings per stop/hour	16.99	68.60	0.00	959.67
5	VRU exposure work	Population	745.10	239.62	234.00	1892.00
6	Speed limit	mph	37.89	6.97	25.00	60.00
7	speed less than 35mph	Y/N			0.00	1.00
8	Well-managed access	Y/N			0.00	1.00
9	Well-managed driveways	Y/N			0.00	1.00
10	Well-managed unsignalized intersections	Y/N			0.00	1.00
11	Well-managed signalized intersections	Y/N			0.00	1.00

#	Variable	Units	Mean	Sd	Min	Max
12	Driveways density	Driveways/mile	17.11	20.46	0.00	150.00
13	Light intersections density	Light int/mile	6.83	7.79	0.00	38.46
14	Stop intersections density	Stop int/mile	8.62	13.79	0.00	212.12
15	Unsignalized intersections density	Unsignalized int/mile	6.91	8.99	0.00	85.71
16	Width	Feet	51.71	15.84	10.00	116.00
17	Number of lanes	Unit	4.29	1.42	1.00	9.00
18	Presence of left-turns	Y/N	0.85	0.36	0.00	1.00
19	Directionality	1 or 2 directions	1.96	0.20	1.00	2.00
20	Presence of raised medians	Y/N			0.00	1.00
21	Presence of crosswalks	Y/N			0.00	1.00
22	Presence of bike lane	Y/N			0.00	1.00
23	Presence of sidewalk	Y/N			0.00	1.00
24	Streetlamps density	streetlamps/mile	61.00	67.06	0.00	405.80

#	Variable	Units	Mean	Sd	Min	Max
25	Bus stops density	bus stops/mile	8.89	10.36	0.00	80.00
26	Presence of bus lanes	Y/N			0.00	1.00
27	Schools' density	schools/mile	2.19	6.13	0.00	44.78
28	Fuel station's density	fuel station/mile	1.30	3.96	0.00	78.95
29	Off-parking's density	off parking/mile	12.40	16.84	0.00	102.94
30	Residential area	ft^2	1216792.80	488885.55	268112.00	3655219.00
31	Commercial area	ft^2	2382981.79	4243778.40	1713.00	18616181.00
32	Population density	population/mile square	3761.65	2143.14	43.00	14380.00
33	Jobs density	jobs/mile square	5008.72	8214.24	4.00	43317.00
34	Gross activity density	(population + jobs)/mile square	8770.37	8384.50	116.00	49238.00
35	Density of population below the line of poverty	population/mile square	773.02	786.94	0.00	7960.00
36	Density of Population between 10-17 years	population/mile square	352.54	296.50	0.00	1883.00

#	Variable	Units	Mean	Sd	Min	Max
37	Density of Population older than 65 years	population/mile square	572.68	381.57	3.00	1696.00
38	White population	population	524.89	261.20	51.00	1572.00
39	Black or Afro-American population	population	46.61	41.84	0.00	311.00
40	Indian-Alaskan population	population	62.42	80.03	0.00	1116.00
41	Asian population	population	0.38	2.19	0.00	40.00
42	Another race	population	9.92	24.67	0.00	246.00
43	More than one race	population	36.04	28.34	0.00	343.00
44	Hispanic-Latino population	population	800.68	378.78	129.00	2156.00
45	Population over 25 with no schooling	population	12.86	14.58	0.00	94.00
46	Population over 25 with elementary school	population	7.22	19.88	0.00	122.00
47	Population over 25 with middle school	population	21.53	27.13	0.00	188.00

#	Variable	Units	Mean	Sd	Min	Max
48	Population over 25 with high school	population	536.42	188.54	121.00	1072.00
49	Population over 25 with associate degree	population	91.19	50.39	5.00	350.00
50	Population over 25 with bachelor's degree	population	226.91	130.31	0.00	643.00
51	Population over 25 with graduate degree	population	168.97	111.11	0.00	724.00

The first step in filtering these variables involved ensuring that each variable had sufficient observations, accounting for at least 10% of the total observations (845 arterial segments). Variables such as on-street parking, exclusive bus lanes, and Hawaiian were excluded as they did not meet this requirement. Following this initial filter, we created a matrix plot with all remaining variables to identify and eliminate collinear variables that could affect the model's performance. Variables presenting a correlation coefficient greater than ±0.7 were removed. Subsequently, we executed the Negative Binomial model using the stepAIC function in R to identify significant variables with the lowest AIC factor and overdispersion. We only retained the model with the significant variables. A second verification of correlation between variables was conducted using the function variance inflation factor (VIF), eliminating the variables with a VIF higher than 2.

Research Question Four: What are the spatial patterns of pedestrian and bicyclist crashes and their associated factors (e.g., road characteristics, land use, and sociodemographic)?

We utilized various spatial analysis techniques using GIS software (ArcGIS Pro) to perform an exploratory analysis and evaluate spatial patterns and autocorrelations of crashes involving VRUs. Arterial segments were chosen as the unit of study, and we calculated the density of crashes per mile on each segment, including the two years of crash data. To achieve this, we conducted a spatial join of crashes occurring within a 90-foot buffer, which covers the average width of the arterials, adding the total crashes that occurred in a segment. Then we computed a field representing the number of crashes per segment divided by the length of the segment in miles, yielding the density of crashes per mile per segment. This data was used in the analyses of density and clusters. The following sections provide an overview of the techniques employed for each study: density and hot spots.

Kernel Estimation Density (KED)

This analysis utilized the tool of planar Kernel Density, which partitions the analysis area into multiple small squares known as cells. It estimates the crash density within each cell inside a specified search radius, resulting in a map depicting the hot spots of crashes. A crucial aspect of this process is determining the bandwidth or search radius and the cell size (Thakali et al., 2015; Xie & Yan, 2008). Prior studies have noted that cell size can be chosen based on population density, as higher population densities may warrant smaller standard deviations compared to less dense areas (Rushton & Lolonis, 1996).

Given Albuquerque's urban nature and high population density, we opted for a cell size of 90 by 90 feet (27.5 m by 27.5 m), consistent with the approach utilized in previous studies analyzing crashes in urban areas, where cell sizes of 25 and 20 meters have been used, demonstrating good visualization of crash concentrations (M. Lee & Khattak, 2019; Steenberghen et al., 2004). For the bandwidth or search radius, we employed two distinct approaches: the average arterial segment length of 2300 feet (700 m) to observe general patterns in the city and ten times the cell size based on prior research, 900 feet (275 m), to investigate local patterns more closely (M. Lee & Khattak, 2019; Xie & Yan, 2008). After defining this criterion, we used the KED tool in ArcGIS, with the shape of the arterial segments and the density of crashes as our input features. The population field was set to the crash density column for this analysis. Since our units are in miles, we set the area units to square miles. The output cell values were densities, and the method used was planar. This analysis will provide us with the areas with the highest crash densities, which are expected to change depending on the search radius.

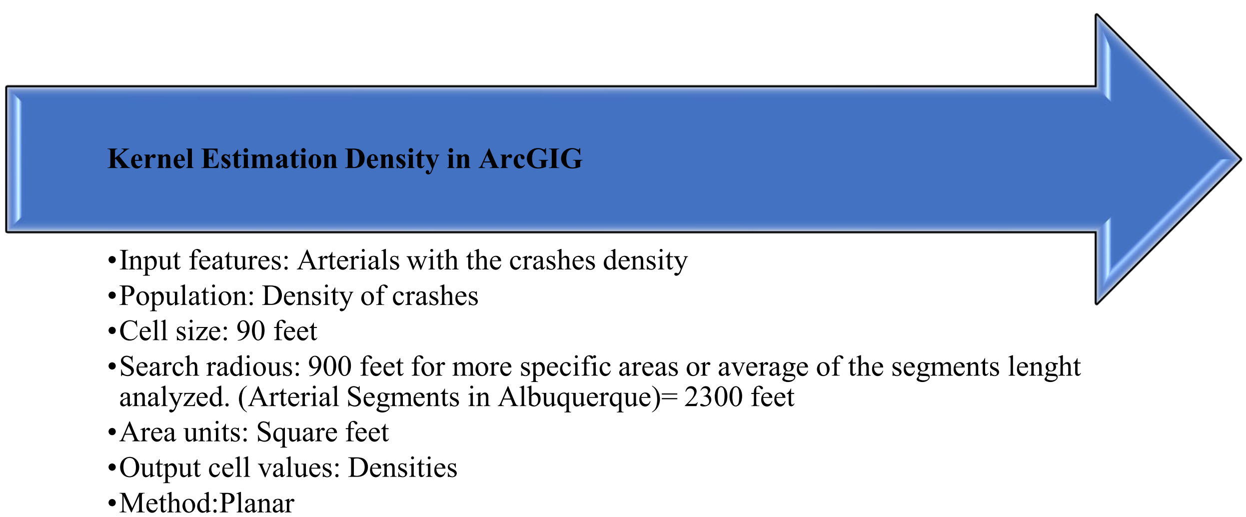


Figure 6. Methodology for Kernel Estimation Density

Global Moran's I

To identify the spatial correlation of segments with high crash rates, we employed the Spatial Autocorrelation tool (Global Moran's I). A critical criterion in this process is defining the distance band or threshold distance. The tool can provide a default distance band, which in our case was 14,372 feet. However, this default value may not form the most pronounced clusters of crashes.

To verify this, we applied a method used in previous studies that calculates the distance threshold yielding the highest z-score from the analysis that provides most of the clusters in the data (M. Lee & Khattak, 2019). Firstly, we used the "Calculate Distance Band from Neighbor Count" tool to determine the average distance needed to find at least one neighbor in the cluster analysis. This distance was found to be 1,385 feet (422 meters). For the analysis, we rounded this value to 1,300 feet (396 meters) to ensure coverage of the minimum distance required to find at least one neighbor.

This distance was input as the starting and increment distance in the GIS tool "Incremental Spatial Autocorrelation" to obtain the highest z-score and identify the distance band where most clusters are found. In our case, this distance was 13,000 feet. Once this threshold was identified, we applied the Spatial Autocorrelation tool (Global Moran's I), using the "Zone of Indifference" to specify spatial relationships and the Euclidean method to determine if the segments were spatially correlated. The results of this analysis will define whether segments are spatially correlated or not to apply the hot spots analysis.

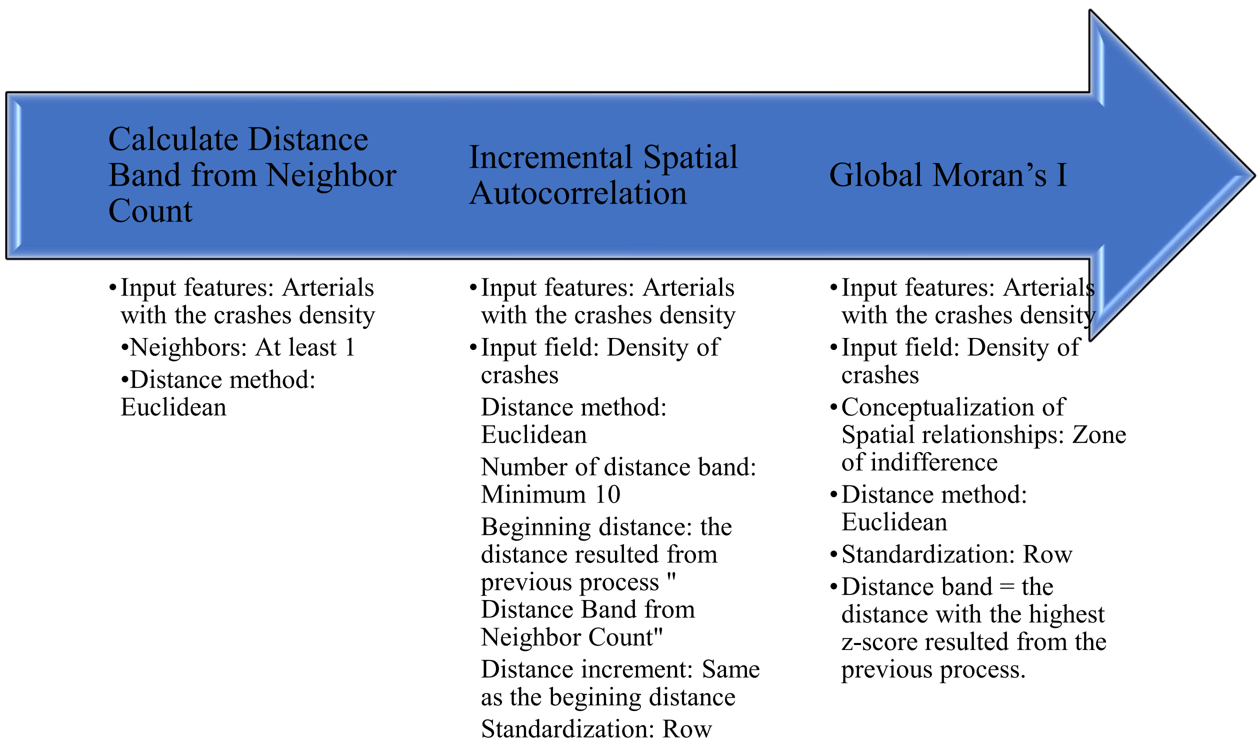


Figure 7. Methodology for Global Moran's I in ArcGIS

Local Moran’s I and G statistics

These methods are employed if spatial autocorrelation is detected based on Global Moran’s I results. Each method has a corresponding tool in GIS software, with similar specifications to Global Moran’s I, “Cluster and Outlier Analysis (Anselin Local Moran’s I)” and “Hot Spot Analysis (Getis-Ord Gi*).” Therefore, we will apply the same spatial relationship (Zone of Indifference) and method (Euclidean). However, for the distance band, the study will utilize three different distances based on the methods applied in the previous sections. These distances are: 1300 feet, corresponding to the average distance to obtain at least one neighbor, 2300 feet, corresponding to the average segment length, and 13000 feet, corresponding to the distance where most clusters are encountered. We applied the false discovery rate (FDR) correction using 199 and 999 permutations to define the permutations for Local Moran’s I analysis. The results were similar for both permutations, varying only in one segment for the smaller bandwidths and the same number of segments for the biggest bandwidth. Therefore, we will show the results of the 199 permutations.

After applying these techniques and identifying the hot segments of VRU crashes, we will characterize each segment or corridor based on the features that impact VRU crashes. These features were determined using a negative binomial statistical model in the same study area conducted for the author's thesis under evaluation. This approach allows us to prioritize not only the corridors that need intervention but also the specific features that need to be addressed in order to reduce crashes effectively.

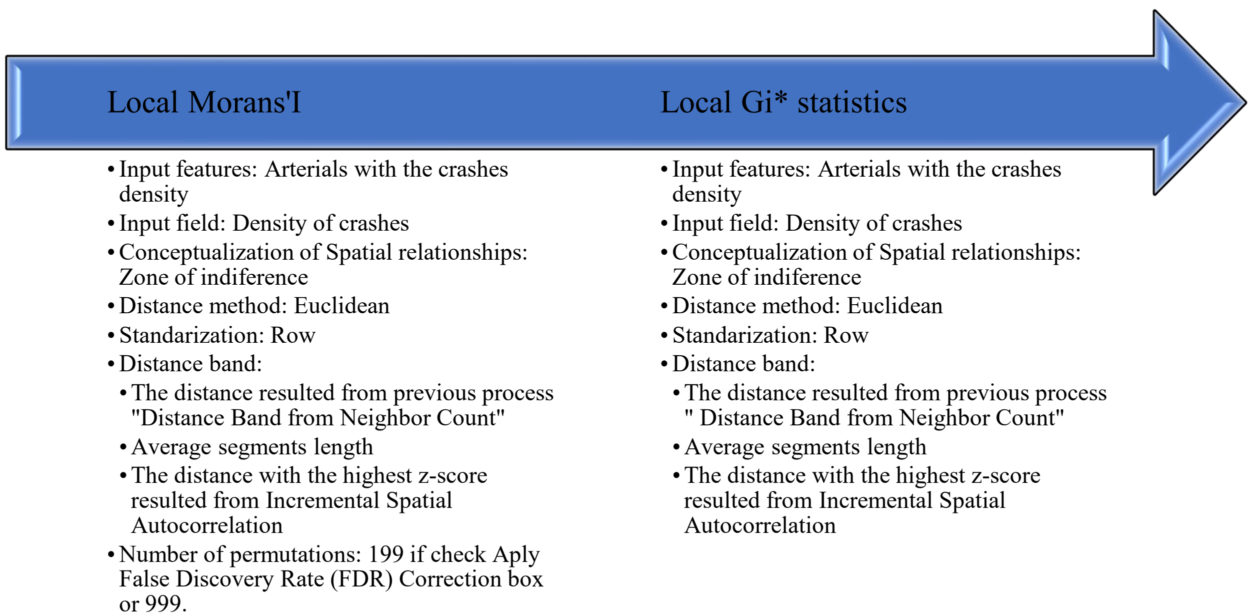


Figure 8. Methodology for Local Moran's I and Gi* statistic in ArcGIS

Results

In the subsequent sections, we will present the results for each question following the application of the methodology outlined before.

Research Question One: Are high-speed, high-access roads more likely to experience crashes than roads with better access management?

After classifying the roads based solely on access management, considering driveways, unsignalized intersections, and signalized intersections, we found that while the presence of medians increases the number of driveways allowed in arterials, they do not significantly impact the classification of roads as well-managed Table 5. We also obtained the road classification based on the speed presented in Table 6.

Table 5. Segment classification only by access management

Class	No. Segments	
	Partial Access	Full Access
Well managed driveways	498/845	431/845
Well managed unsignalized intersections	456/845	456/845
Well managed signalized intersections	129/845	129/845

We used the classification of partial access for each kind of access type as a categorical variable in question 3 to define if access influences VRU crashes.

Table 6. Segment classification only by speed

Speed classification	Arterial Segments
<30 mph	159/845
<35 mph	431/845
<40 mph	655/845

We observed that approximately half of the segments exhibit well-managed driveways and unsignalized intersections. However, around 15% of the segments feature well-managed signalized intersections. This variable serves as a determinant to classify segments as well-managed access, given that only arterials with the three types of accesses identified as well-managed were classified as such.

In Figure 9, an example of a segment classified as well-managed access is depicted. The segment corresponds to 2nd Street between Ranchitos Rd NW and El Pueblo Rd NW with 0.39 miles length and mixed land use. This segment has concentrated accesses to the residential areas controlled by stop signs and one access for a business, and only presents two signalized intersections. This segment also has a traversable median that allows a higher density of driveways.

Figure 9. Example of a segment classified as well-managed access (Source: Google Maps)

On the other hand, we identified a segment classified as high access located on Ventura St NE between Harper Rd NE and San Francisco Rd NE. The length of this segment is 0.64 miles, and it is located in a residential land use. However, this segment includes three signalized intersections, which are the primary factors leading to its classification as high access as they have fewer segments with well-managed signalized intersections. This segment has a non-traversable median with full access, which allows a lower density of driveways.

Figure 10. Example of a segment classified as high access (Source: Google Maps)

After obtaining the classification of the arterial roads for each case (traversable medians with full and partial access) and each speed (30, 35, 40 mph), we linked the total number of crashes in each corridor to apply the ANOVA method.

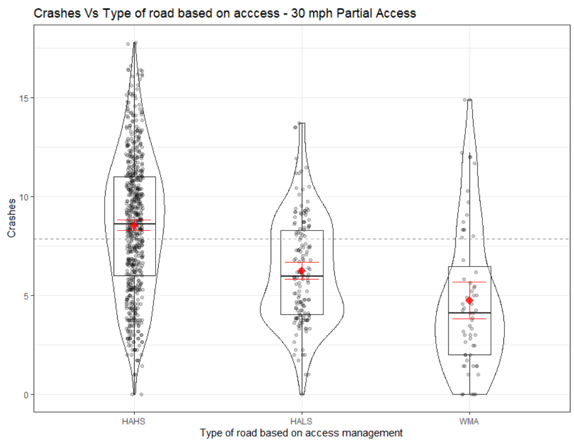


Figure 11. Comparison crashes mean – Partial Access, speed 30 mph.

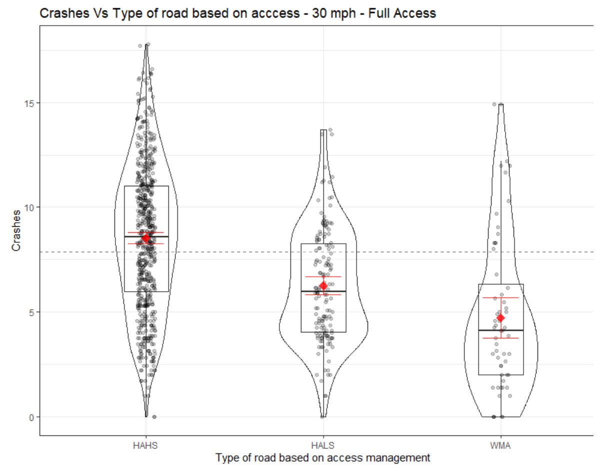


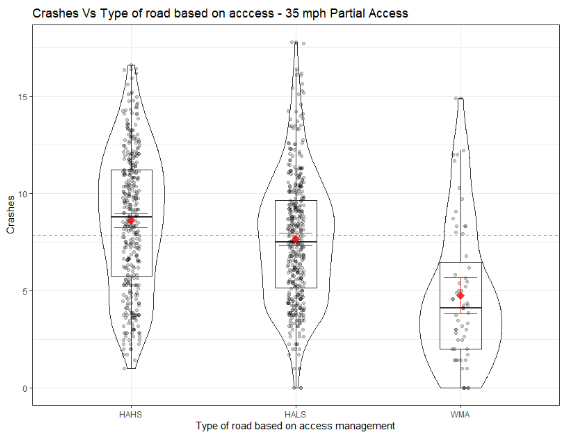
Figure 12. Comparison crashes mean – Full Access, speed 30 mph.

Table 7. Classification arterial roads – Partial Access, speed 30 mph.

Class	Mean Crashes sqrt	Mean Crashes	No. Segments	Miles
HAHS	8.54	73	632	271.64
HALS	6.25	40	154	44.51
WMA	4.76	23	59	52.02

Table 8. Classification arterial roads – Full Access, speed 30 mph.

Class	Mean Crashes sqrt	Mean Crashes	No. Segments	Miles
HAHS	8.53	73	635	273.80
HALS	6.25	40	154	44.52
WMA	4.72	23	56	49.87



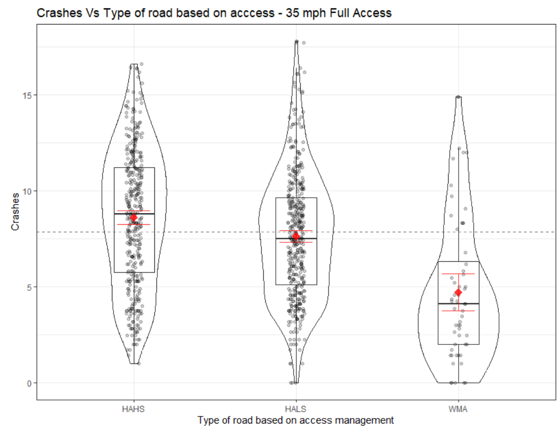


Figure 13. Comparison crashes mean – Partial Access, speed 35 mph.

Figure 14. Comparison crashes mean – Full Access, speed 35 mph.

Table 9. Classification arterial roads – Partial Access, speed 35 mph.

Class	Mean Crashes sqrt	Mean Crashes	No. Segments	Miles
HAHS	8.61	75	371	166.77
HALS	7.63	59	415	149.38
WMA	4.76	23	59	52.02

Table 10. Classification arterial roads – Full Access, speed 35 mph.

Class	Mean Crashes sqrt	Mean Crashes	No. Segments	Miles
HAHS	8.60	74	373	168.20
HALS	7.62	59	416	150.11
WMA	4.72	23	56	49.87

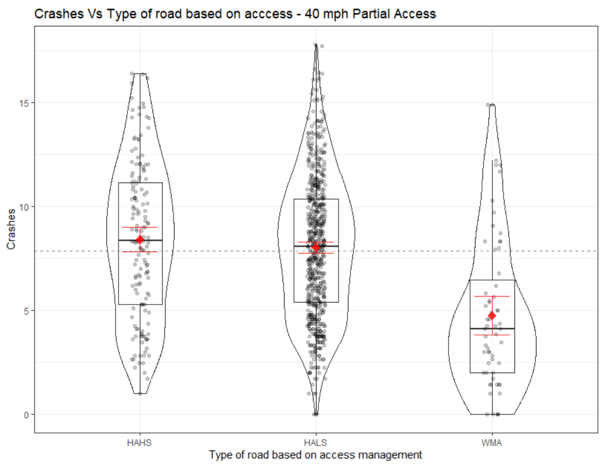


Figure 15. Comparison crashes mean – Partial Access, speed 40 mph.

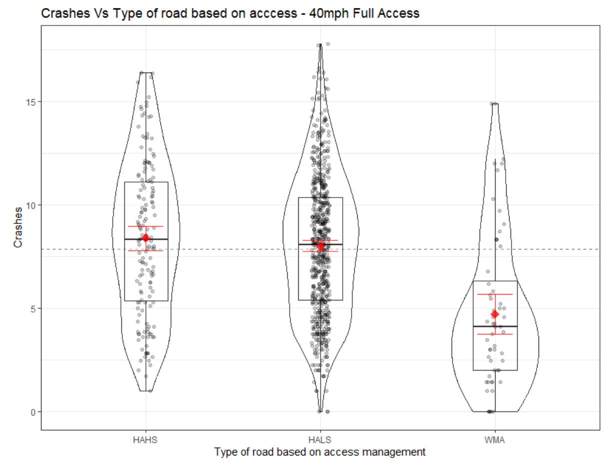


Figure 16. Comparison crashes mean – Full Access, speed 40 mph.

Table 11. Classification arterial roads – Partial Access, speed 40 mph.

Class	Mean Crashes sqrt	Mean Crashes	No. Segments	Miles
HAHS	8.4	71	153	71.18
HALS	8.02	65	633	244.97
WMA	4.76	23	59	52.02

Table 12. Classification arterial roads – Full Access, speed 40 mph.

Class	Mean Crashes sqrt	Mean Crashes	No. Segments	Miles
HAHS	8.38	71	155	72.61
HALS	8.01	65	634	245.70
WMA	4.72	23	56	49.87

In Table 13, Figure 17, and Figure 18, we present the summary of the results from the ANOVA analysis, and the results of the pairwise comparison of the mean of crashes across all road classification is presented in Table 14 and Table 15.

Table 13. Summary of ANOVA results by speed and medians

		Partial Access					Full Access				
Speed	Classification	Sq root (Mean crashes)	Mean crashes	No. Segments	Miles	p-value	Sq root (Mean crashes)	Mean crashes	No. Segments	Miles	p-value
30 mph	HAHS	8.54	73	632	271.64	<2e-16 ***	8.53	73	635	273.80	<2e-16 ***
	HALS	6.25	40	154	44.51		6.25	40	154	44.52	
	WMA	4.76	23	59	52.02		4.72	23	56	49.87	
35 mph	HAHS	8.61	75	371	166.77	5.4e-15 ***	8.6	74	373	168.20	1.1e-14 ***
	HALS	7.63	59	415	149.38		7.62	59	416	150.11	
	WMA	4.76	23	59	52.02		4.72	23	56	49.87	
40 mph	HAHS	8.4	71	153	71.18	6.8e-12 ***	8.38	71	155	72.61	1.5e-11 ***
	HALS	8.02	65	633	244.97		8.01	65	634	245.70	
	WMA	4.76	23	59	52.02		4.72	23	56	49.87	

After applying ANOVA, the results indicate that the means of crashes were significantly different across the three types of classification, regardless of the number of observations in each class, the full or partial access presence of driveways, and the analyzed speed limits.

We complemented this analysis by conducting a pairwise comparison, which examines all pairs of means to elucidate the differences between the three classes of segments. Table 14 indicates the lower and upper limits obtained by applying pairwise comparison with 95% confidence. These ranges vary depending on the number of observations in each class. The range for segments classified as WMA is smaller due to having fewer observations compared to the other two classes of segments.

Table 14. Descriptive statistics of pairwise comparison across access classifications

		Partial Access			Full Access		
		95% Confidence Interval for mean			95% Confidence Interval for mean		
Speed	**Classification**	**Mean crashes**	**Lower bound**	**Upper bound**	**Mean crashes**	**Lower bound**	**Upper bound**
30 mph	HAHS	73	69	78	73	69	78
	HALS	40	33	46	40	33	46
	WMA	23	16	32	23	15	32
35 mph	HAHS	75	69	81	74	69	80
	HALS	59	54	64	59	54	64
	WMA	23	16	32	23	15	32
40 mph	HAHS	71	62	81	71	62	80
	HALS	65	61	69	65	60	69
	WMA	23	16	32	23	15	32

Table 15. Statistical significance of pairwise comparison across access classifications

Speed	**Classification**	**Partial Access**		**Full Access**	
		HALS	WMA	HALS	WMA
30 mph	HAHS	<.0001	<.0001	<.0001	<.0001
	HALS		0.01		0.0094
35 mph	HAHS	0.0002	<.0001	0.0002	<.0001
	HALS		<.0001		<.0001
40 mph	HAHS	0.4289	<.0001	0.4543	<.0001
	HALS		<.0001		<.0001

The statistical significance of the pairwise comparison presented in Table 15 indicates that the mean crashes in segments classified as WMA are consistently statistically different from segments classified as HAHS and HALS, regardless of the presence of full or partial access when the median in non-traversable or the change in the speed cut-off for the analysis. In contrast, segments classified as HAHS and HALS show statistical differences across most comparisons, except at 40 mph, where the mean crashes for HALS segments approach those classified as HAHS regardless of the presence of full or partial access when the median is non-traversable. The following graphics summarize the results from the previous tables, providing a clearer visualization of the differences between the three classifications of segments across different speeds and the presence of full or partial access when the median is non-traversable.

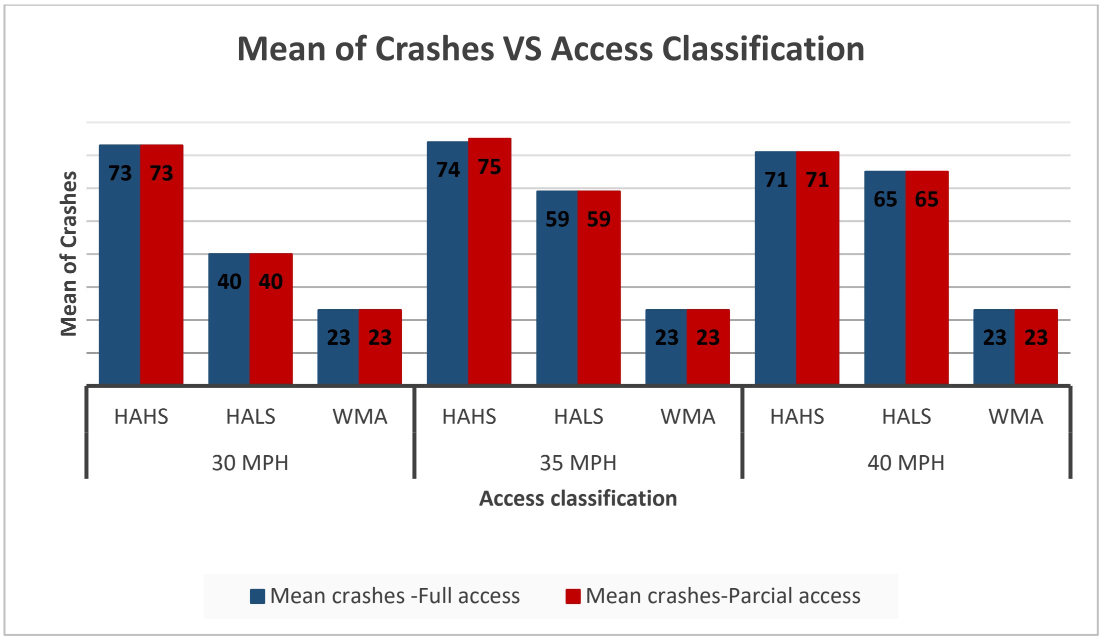


Figure 17. Comparison of results of road classification, speed, and mean of crashes.

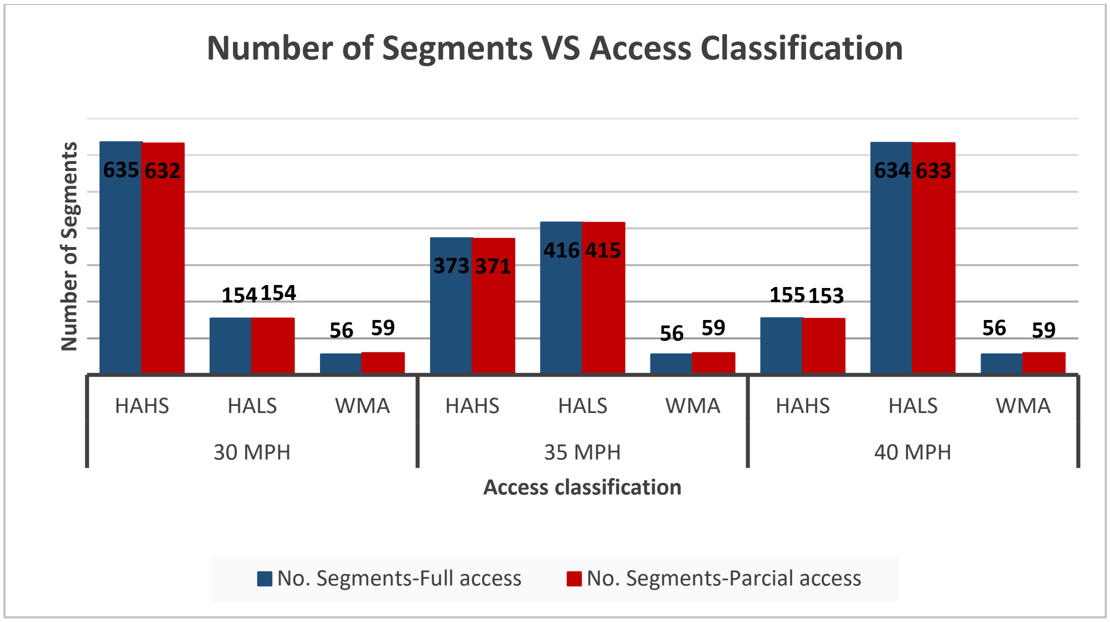


Figure 18. Comparison of results of road classification, speed, and number of segments

These results indicate that the mean number of crashes and the number of segments in each classification do not significantly change for any speed when analyzing the spacing of full or partial access in non-traversable medians. After comparing the three-speed analyses, it is evident that the mean number of crashes remains constant on roads with well-managed access, while roads classified as high access and speed consistently display the highest crash means.

In addition, increasing the cutoff point of the speed affects only the number of segments classified as high access, obtaining a more even distribution with a speed of 35 mph. Thus, we used this classification of access management (35 mph and full access) as a categorical variable for the third question that involves the statistical model. In addition, we generated a map displaying this classification, as depicted in Figure 19, that was shared with MRCOG for their future analyses.

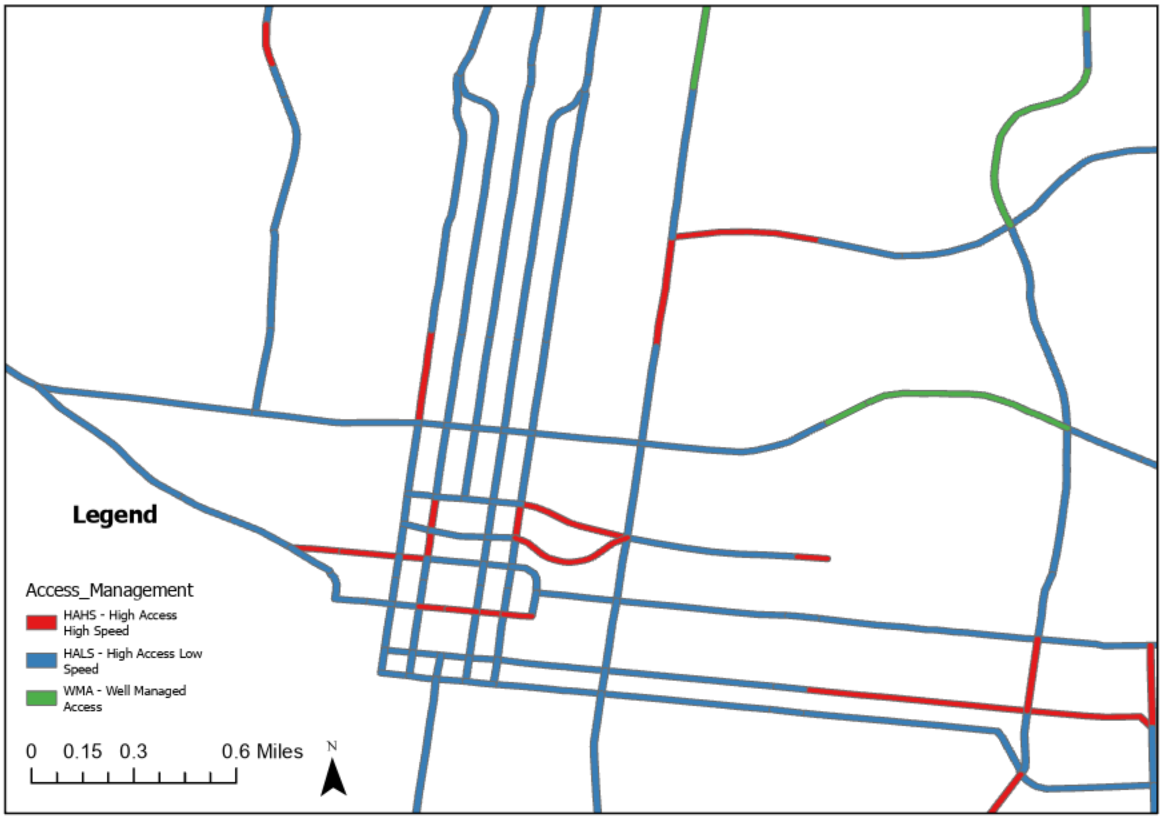


Figure 19. Example of a map with the segment classification by access management speed of 35 mph

Research Question Two: Do more driveway access and intersection per mile correlate to more non-motorized crashes per mile?

To address this question, we first conducted an exploratory analysis with data from smart location database and VRU crashes. Specifically, we evaluated possible patterns or relationships between VRU crashes and the density of three- and four-leg intersections for multimodal-oriented roads designed to accommodate various road users, including vehicles, bicycles, and pedestrians. We employed ArcGIS to analyze the relationships visually and utilized Generalized Linear Regression within this software to ascertain whether a correlation exists between these two variables.

As the Figure 20 and Figure 21 indicate, the majority of the crashes are concentrated around Central Ave, a primary arterial in Albuquerque that accommodates various land uses along its corridor. This area encompasses residential, commercial, educational, and healthcare facilities and unique road infrastructure features, including exclusive bus lanes, bike lanes, and pedestrian facilities. Additionally, this area has the highest population density below the poverty line. The combination of these factors makes this corridor particularly susceptible to crashes, those involving especially VRU crashes.

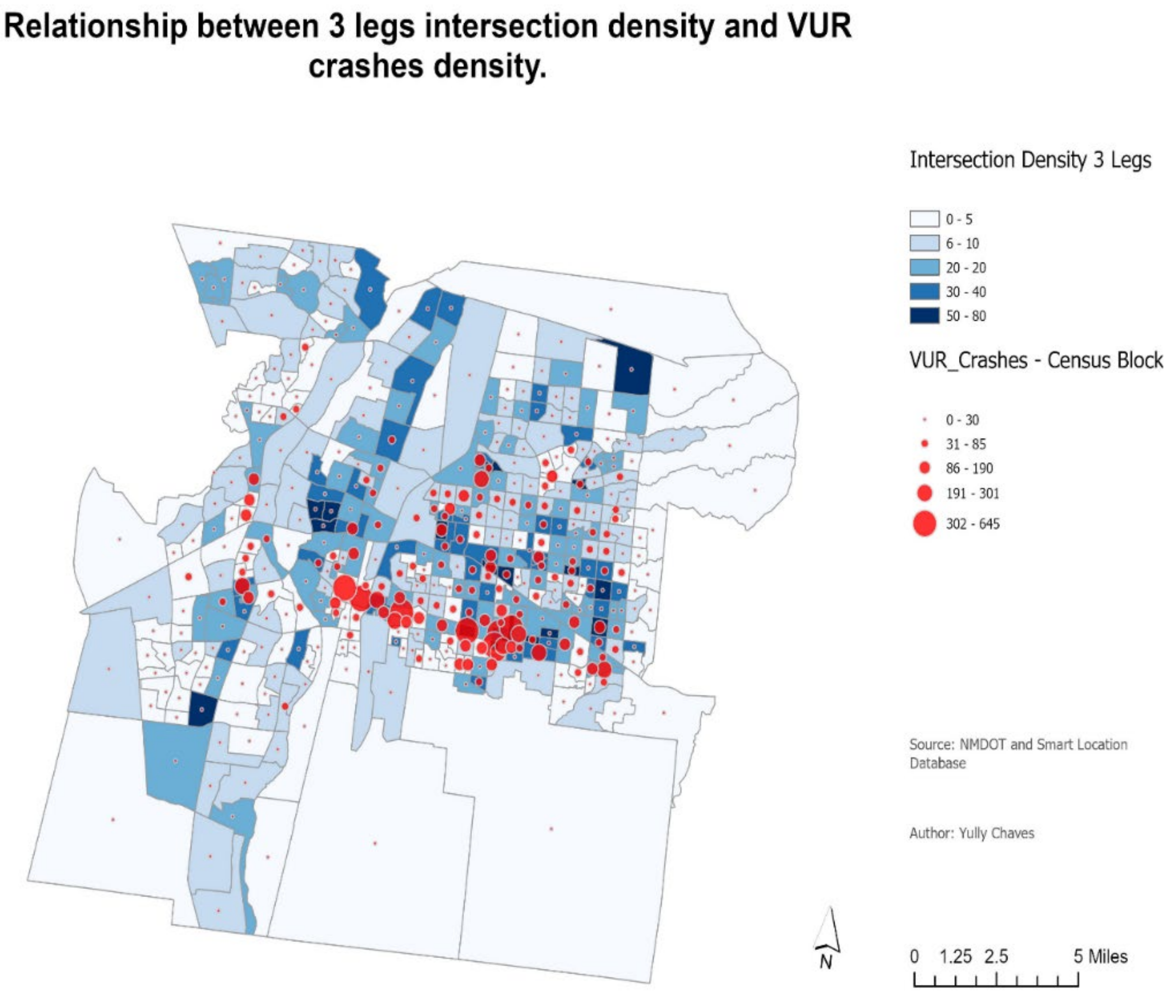


Figure 20. Crashes Density Vs Density of Intersections with three legs.

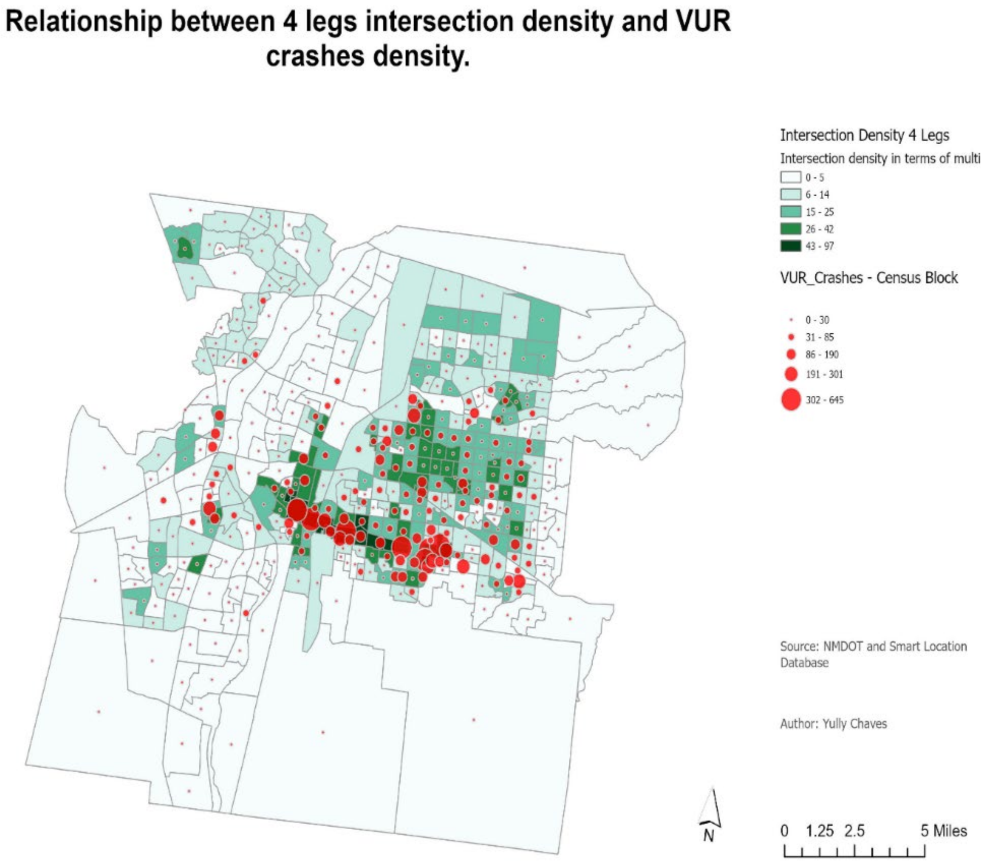


Figure 21. Crashes Density Vs Density of Intersections with four legs.

This data shows that the area with the highest concentration of VRU crashes is centered around Central Avenue. Some of these crashes are situated within census blocks characterized by both high and moderate intersection density for both types of intersections.

Due to the complexity of visualizing this relationship graphically with many census blocks, we employed the statistical tool "Generalized Linear Regression" in ArcGIS. Using a continuous (Gaussian) model, we aimed to understand the potential relationship quantitatively and comprehensively between intersection densities and crash densities. The analysis resulted in the following regression models for each type of intersection:

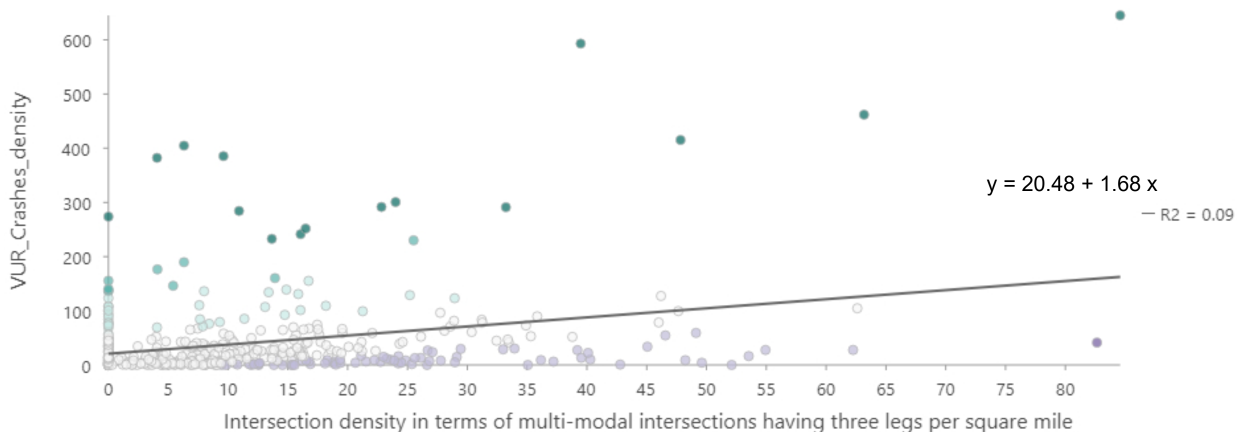


Figure 22. Linear Regression Crashes Density Vs three legs Intersection Density

While the linear regression analysis indicates a positive relationship between crash density and three-leg intersection density, it is important to note that this type of model does not fit the database effectively. This conclusion is supported by the nearly zero R^2 coefficient, suggesting a poor fit and indicating that the model does not explain the variance in the data adequately.

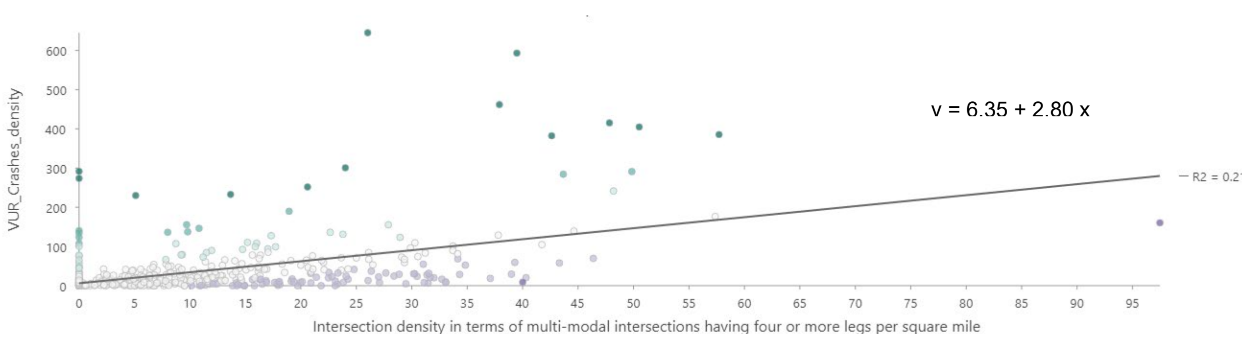


Figure 23. Linear Regression Crashes Density Vs four legs Intersection Density

Conversely, the linear regression moderately fits the relationship between VRU crashes and four-leg intersection density, evidenced by an R^2 value of 0.21. This result indicates a better fit than the three-leg intersection density analysis but still a low value to use this model to explain the relationship between these two variables. However, from the results of this preliminary study, a positive relationship between access density and VRU crashes is discernible.

After obtaining an inadequate fit with a linear regression model, we analyzed the data in R using a negative binomial model with three predictor variables that represent access. This analysis confirmed the positive relationship found. The estimations obtained are presented in Table 16.

Table 16. Negative binomial estimation results of access impacting VRU crashes

Coefficients	Estimate	Std. Error	z Value	pr(>Z)	
Intercept	0.3200	0.074	4.330	1.49e-05	***
Driveway Density	0.0075	0.0022	3.471	0.000519	***
Signalized Intersections	0.0140	0.0028	5.023	5.10e-07	***
Unsignalized Intersections	0.0072	0.005	1.388	0.165140	
Overdispersion = 1.237		AIC = 3265.5			

This statistical model indicates that unsignalized intersection density is not significant in predicting VRU crashes. On the other hand, the number of driveways and signalized intersection density per mile are significant in explaining the frequency of VRU in an arterial segment. A positive relationship between these two variables and VRU crashes is present between crashes and these two variables, indicating that an increase in the density of these variables leads to a corresponding increase in the prediction of VRU crashes in that segment. The prediction of VRU crashes will increase by a factor:

$$VRU\ crashes = e^{0.320009} * e^{0.007513 * driveways\ density} * e^{0.013975\ x\ signalized\ intersections\ density}$$

For instance, if a segment has driveways density = 50 driveways/mile and signalized intersection density = 50 signalized intersections/ mile, the prediction would be:

$$VRU\ crashes = e^{0.320} * e^{0.0075*50} * e^{0.014\ x\ 50}$$

$$VRU\ crashes = 1.377 * 1.45 * 2.02$$

$$VRU\ crashes = 4\ \text{crashes/segment}$$

Although both driveway density and signalized intersection density are significant, based on the estimates obtained and the example provided earlier, we can interpret that signalized intersection density has a more substantial influence in predicting VRU crashes than driveway density, ceteris paribus.

However, it is important to note that the model presents an overdispersion higher than 1, the typical threshold for this statistical value. This overdispersion suggests a potential need to include more variables to improve the prediction of VRU crashes. However, it's worth considering that Payne et al. consider a threshold of 1.5 acceptable for ensuring the performance of the negative binomial model (Payne et al., 2018). Therefore, despite the overdispersion, we can still utilize this model to have preliminary estimations about VRU crashes, identify problematic segments, and incorporate these density metrics into city expansion plans for Albuquerque.

Research Question Three: What other factors related to the built environment correlate with a higher likelihood of pedestrian and bicycle crashes?

With the negative binomial model, we found several explanatory variables significant for predicting VRU crashes in the arterial segments of Albuquerque, presented in Table 17.

Table 17. Negative binomial estimation results of features impacting VRUs safety on arterial segments

Group	Variable	Estimate	P-Value	Significance
Access Management	Intercept	-1.46E+00	8.13E-07	***
	Well managed driveways	-1.55E-01	0.0230	*
Road Features and Facilities	Segment Length	4.14E-01	<0.001	***
	Number of Lanes	7.74E-02	0.007	**
	Presence of left-turns	4.90E-01	<0.001	***
	Schools' density	-1.53E-02	0.0494	*
	Fuel Stations' density	2.20E-02	0.0051	**
	Off-Street Parking' density	9.65E-03	3.09E-05	***
Exposure And Traffic	ADT less than 20K	-2.94E-01	<0.001	***
	VRU exposure boardings	2.43E-03	6.84E-14	***
VRU Facilities	Presence of crosswalks	4.81E-01	0.002	**
	Presence of sidewalk	3.90E-01	<0.001	***
	Presence of bus lanes	5.42E-01	2.19E-08	***
Land Use	Residential area	-2.22E-07	0.034	*
	Jobs density	1.82E-05	<0.001	***
Surrounding Sociodemographic	Density of Population Below Poverty	2.64E-04	6.65E-11	***
	Black or Afro-American population	1.77E-03	0.047	*
	Population over 25 with associate degree	-2.32E-03	0.01	*
Overdispersion	1.028			
Significance	*** 99.9% ** 99% * 95%			

We conducted several iterations of the statistical model to minimize the Akaike Information Criterion (AIC = 2791.8), removing the variables contributing to model inflation, even if they were significant.

Throughout the iterations, the significant road features influencing VRU crashes remained consistent. Some road features, typically associated with crash reduction, such as bike lanes and medians, were not significant in this model. However, their negative estimates confirmed their potential influence in reducing crashes. One notable observation was the variability of sociodemographic variables in the model across iterations. Some of these variables inflated the model, leading us to remove them. Consequently, other sociodemographic variables lost their significance. On the other hand, certain variables remained insignificant across all model iterations, including exposure metrics like the number of people who walk or bike to work, various ethnicities, and levels of education attainment. Therefore, we can interpret these variables as having no discernible impact on crash frequency in Albuquerque city.

As the negative binomial model fits pedestrian crashes well, we tested how the variables found significant in predicting VRU crashes (Table 17) were also significant in predicting only pedestrian crashes. The results are presented in Appendix A.

Research Question Four: What are the spatial patterns of pedestrian and bicyclist crashes and their associated factors (e.g., road characteristics, land use, and sociodemographic)?

After applying the three techniques of spatial analysis described in the methodology section, the results are presented in the following sections.

Kernel Estimation Density (KED)

As prior studies have suggested, cell size and bandwidth play crucial roles in density analysis, as proved by the different bandwidths employed to conduct this analysis. The Figure 25 shows the resulting maps, depicting the locations with the highest density of crashes in Albuquerque. The areas of high crash density in Albuquerque are clearly delineated with both bandwidths, with the same regions highlighted as indicated by the boxes. Depending on the selected bandwidth, the maps may reveal larger areas marked as high density, but the most critical segments remain consistent.

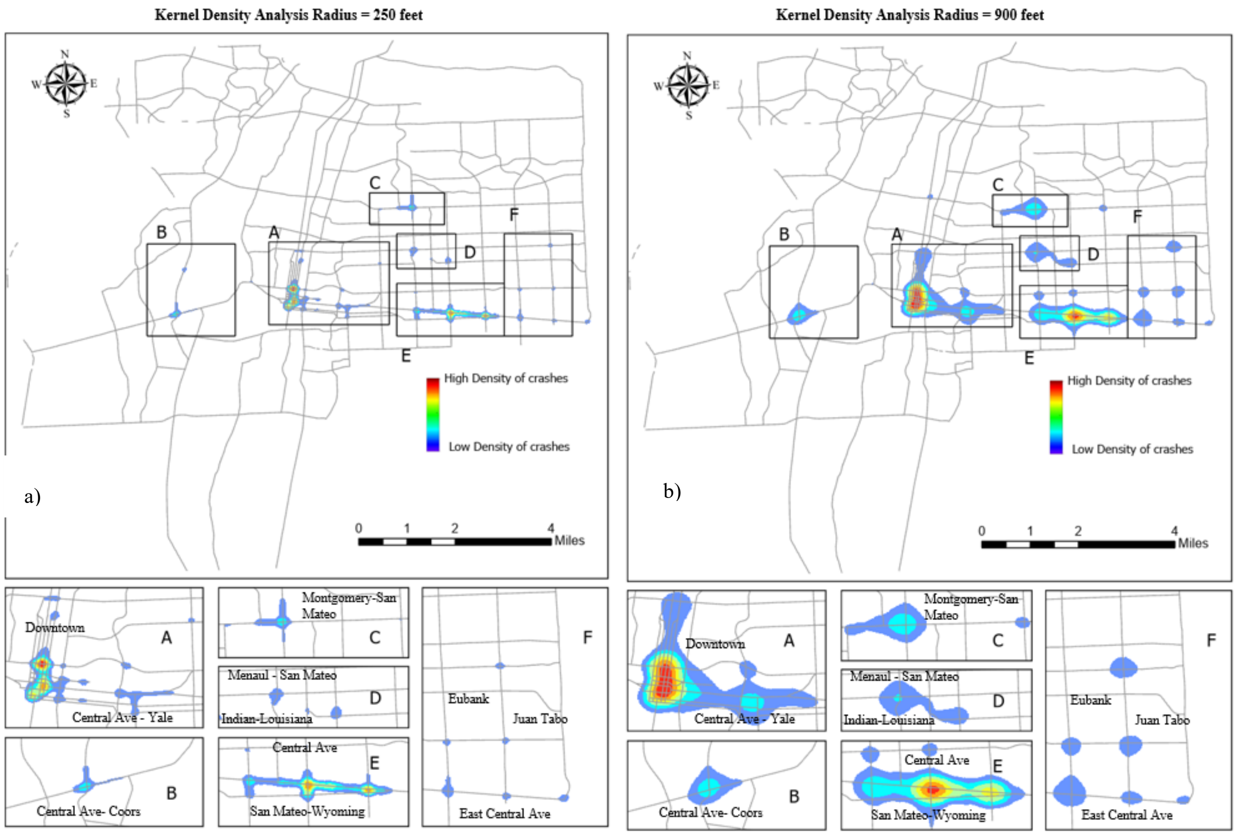
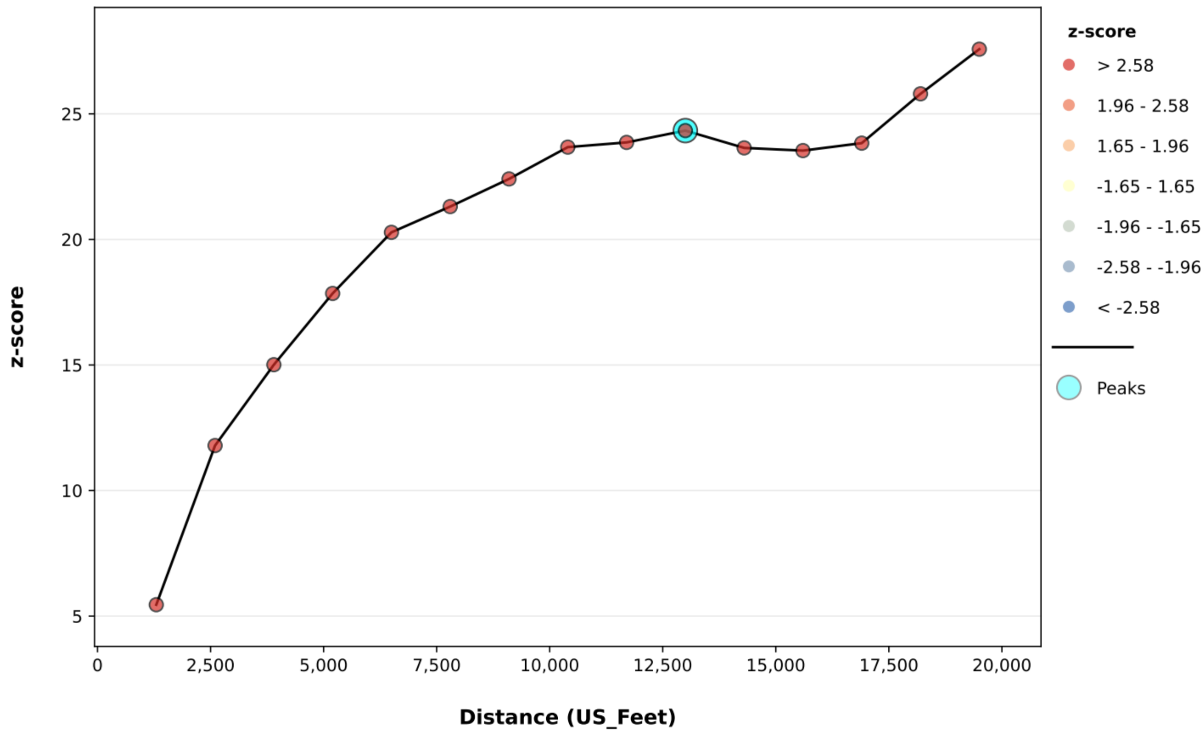


Figure 24. Crashes density a) Radius=900 feet Cell size = 90 feet. b) Radius=2300 feet Cell size = 90 feet

Global Moran's I

The results for obtaining most of the clusters in the data are presented in Figure 26, where a distance band of 13,000 feet gave the highest z-score, indicating the presence of the most clusters.



First Peak (Distance; Value): 13000.00; 24.332812

Max Peak (Distance; Value): 13000.00; 24.332812

Figure 25. Spatial Autocorrelation by Distance

The Global Moran's I result is a figure displaying the p-value, z-score, and Moran's I index. Since we obtained a statistically significant p-value (p-value < 0.05), a positive z-score (24.38), and a positive Moran's Index (0.137), we can infer that segments with a high density of crashes are spatially clustered. However, given that the Moran's Index is not close to one, the autocorrelation is not highly positive.

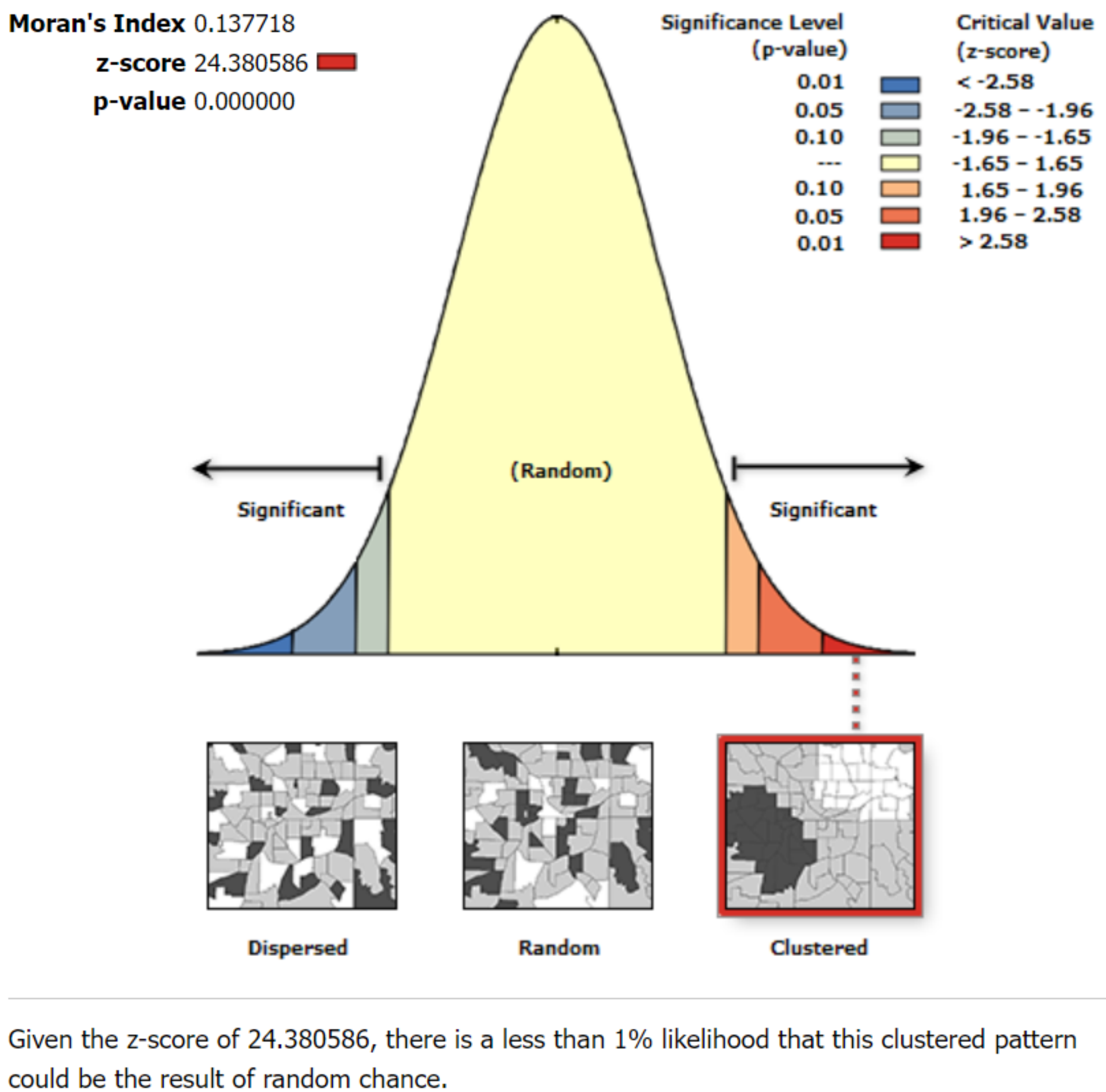


Figure 26. Results spatial autocorrelation.

Local Moran's I and G statistics

After applying these two techniques, we obtained the following maps for each method with the three bandwidths analyzed.

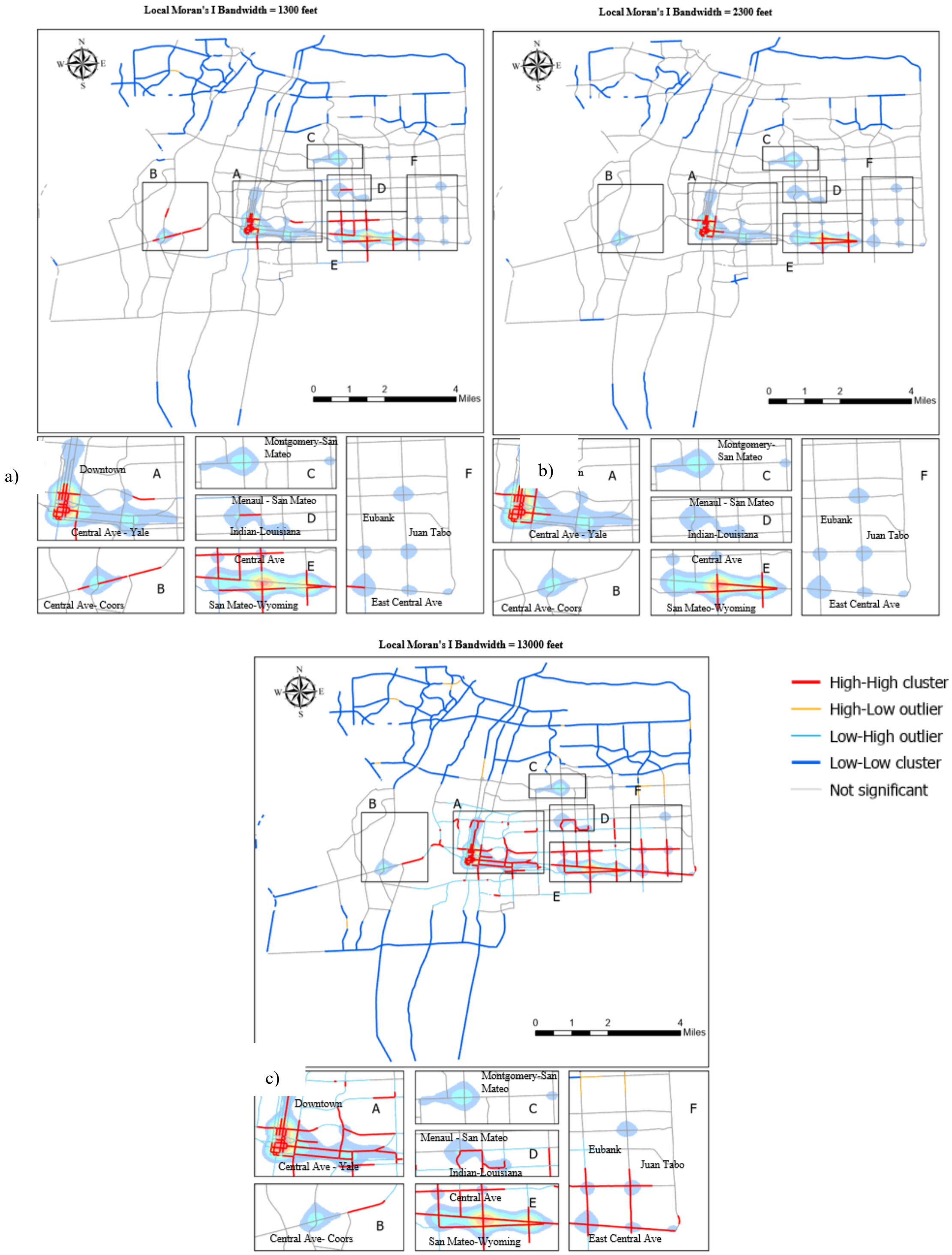


Figure 27. Local Moran's I results a) Bandwidth= 1300 feet. b) Bandwidth= 2300 feet. c) Bandwidth= 13000 feet.

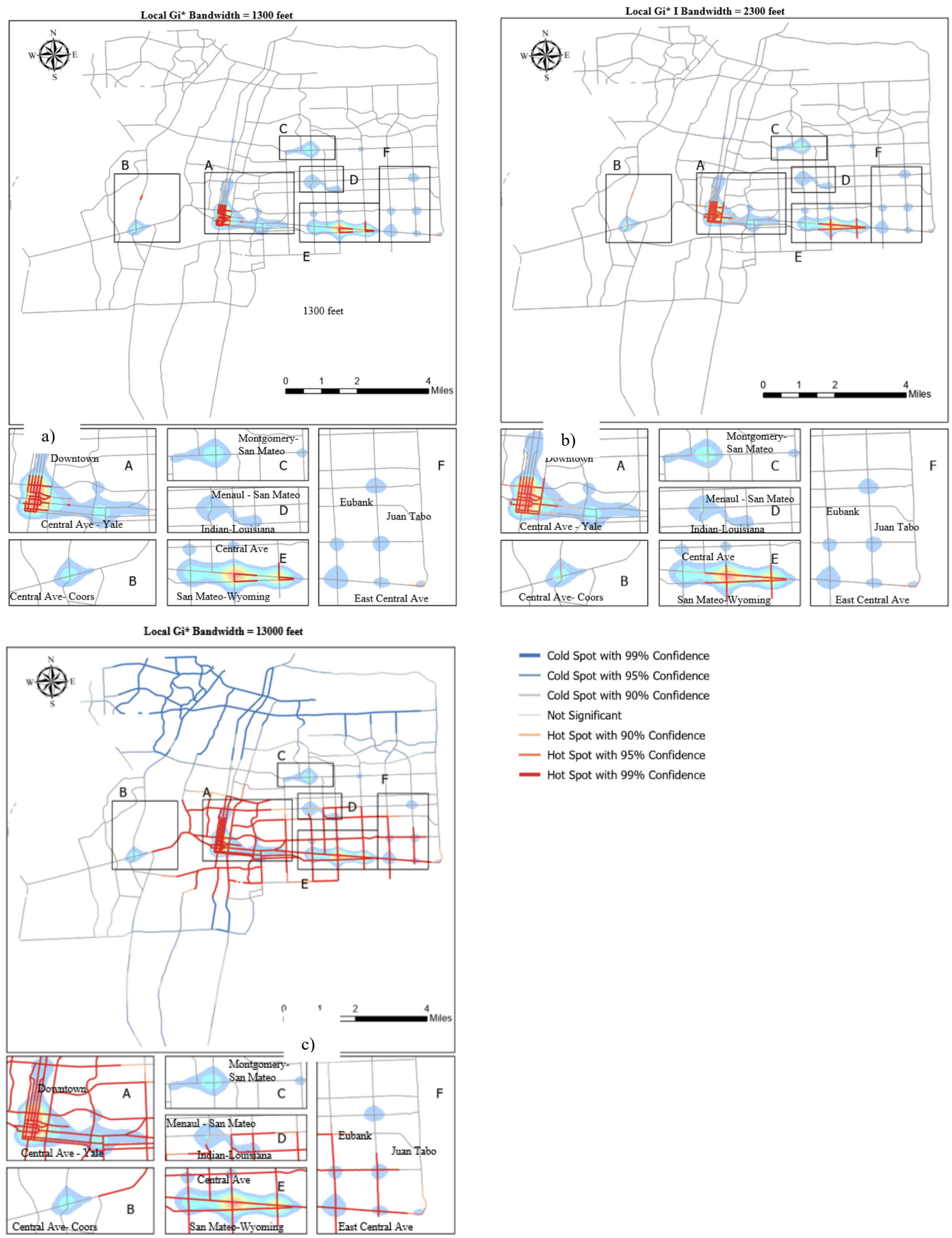


Figure 28. Local Gi statistic results a) Bandwidth= 1300 feet. b) Bandwidth= 2300 feet. c) Bandwidth= 13000 feet.

Both analyses identify hot spots and clusters at the exact locations of high crash density for distances of 1300 and 2300 feet. However, while the bandwidth of 13000 feet produces the most considerable number of hot segments with high crash density, these segments are not concentrated in small areas, making it challenging to identify critical segments to prioritize mitigation measures. The Table 18 displays the number of segments identified as hot segments with each method and bandwidth.

Table 18. Hot segments by bandwidth and method

Bandwidth	Local Moran's' I	Local Gi statistics
1300 feet	77 segments	73 segments
2300 feet	68 segments	94 segments
13000 feet	175 segments	307 segments

We can observe that the number of segments increases with higher bandwidth for the local Gi statistics. However, for the Local Moran's I, the 1300 feet bandwidth has more hot segments than the 2300 feet bandwidth. Nonetheless, with a 13000 feet bandwidth, segments increase even more. Comparing the two methods, Local Moran's I identified fewer segments than the Local Gi statistic for the larger bandwidth. However, for the 1300-foot bandwidth, Local Moran's I results has four more hot segments than Local Gi.

To identify critical crash patterns in Albuquerque's corridors, this study focused on common segments identified by both Local Moran's I and Local Gi* statistics using bandwidths of 1300 and 2300 feet. The bandwidth of 13000 feet yielded significantly different results and was not suitable for pinpointing specific areas for crash mitigation. Therefore, these two bandwidths were chosen as they effectively highlight segments needing interventions to reduce crash frequency, as discussed earlier.

We identified 51 segments in common between the Local Moran's I and Local Gi* statistics for both the 1300- and 2300-feet bandwidths. An additional 14 common segments were present only in the 2300-feet bandwidth. No additional segments were found to be common between the methods for the 1300-feet bandwidth. In total, we identified 65 hot segments, concentrated in 22 main arterial corridors. Some corridors have only one segment, while others have up to seven segments. Clustering the segments by their corresponding corridors facilitates the visualization of the most critical roads. Therefore, we will present only the list of the 22 corridors with the total number of segments contained within each, totaling 65 segments.

Table 19. Hot Corridors per crash frequency

No	Street	Total segments	Location
1	1st St.	1	North of Gold - South of Central
2	2nd Street	6	South of Lomas - North of Lead
3	3rd Street	7	South of Mountain - North of Lead
4 5	4th Street	3	South of Mountain - North Marquette
			North of Coal - South of Lead
6 7	5th Street	5	South of Mountain - North Marquette
			North of Coal - South of Lead
8	6th Street	3	South of Copper - North of Lead
9	Broadway	4	South Martin Luther King Jr - North of Coal
10 11	Central	5	East of 1st - W. of I25W Front RD (Locust)
			East of Louisiana - West of Zuni
12 13	Coal	3	East of 2nd St - west of Broadway
			East of 5th St - West of 3rd St
14	Copper	3	East of 5th St - North of Central
15	Gold	5	East of 6th St - West of 1st St
16	Lead	3	East of 6th St - West of 3rd St
17	Lomas	5	East of 6th St - West of Broadway
18	Louisiana	3	North of Kathryn - South of Copper
19	Marquette	1	East of 3rd St - West of 2nd St
20	Tijeras Ave.	2	East of 5th St - West of 2nd St
21	Wyoming	2	South of Copper - North of Kirtland Gate
22	Zuni	4	Southwest of Central - East of San Pedro
	Total	65	

These results are valuable for local authorities as they enable the geographic identification of corridors with the highest concentration of VRU crashes, facilitating the effective allocation of resources.

We used the results from the Negative Binomial model developed in the third research question presented in this report to identify critical characteristics that potentially impact crash frequency to characterize each corridor, aiming to discern patterns in factors influencing VRU crashes. However, with 65 segments identified across 22 corridors, presenting the features for each segment would result in a lengthy table that may be challenging to interpret. Instead, we clustered the segments in the corridor to which they belong, calculating the average features of the segments for each corridor to facilitate visualization of potential patterns. The results are shown in Table 20.

Table 20. Critical corridors Features based in the results of the negative binomial model

		Exposure And Traffic				Access Management	Road Features and Facilities						VRU Facilities			Land Use		Surrounding Sociodemographic		
		VRU crashes	ADT	ADT <20K	VRU exposure boardings	Access Management Driveways	Segment Length	Number of Lanes	Presence of left-turns	Schools' density	Fuel Stations' density	Off-Street Parking' density	Presence of crosswalks	Presence of sidewalk	Presence of bus lanes	Residential Sqrft.	Jobs density	Density Population Below Poverty	Afro American population	Population over 25 with associate degree
1ST ST.	1	3	2999	Y	770	Y	0.07	2	Y	0	0	14	Y	Y	Y	1383986	34339	1132	85	61
2ND STREET	2	4	8864	Y	16	Y	0.11	3	Y	6	0	39	Y	Y	Y	1403934	31871	1083	94	62
3RD STREET	3	4	4716	Y	5	N	0.27	2	Y	11	0	27	Y	Y	Y	1401212	29362	1030	93	62
4TH STREET	4	6	9906	Y	37	N	0.19	2	Y	13	0	31	Y	Y	Y	1444279	16920	776	114	66
	5	3	3585	Y	2	Y	0.19	2	N	27	0	56	Y	Y	Y	1002993	17597	1088	74	75
5TH STREET	6	3	5402	Y	5	N	0.21	3	Y	9	0	24	Y	Y	Y	1503672	19528	840	137	67
	7	3	4353	Y	0	Y	0.09	2	Y	30	0	26	Y	Y	Y	1288738	30154	1121	82	65
6TH STREET	8	2	4069	Y	2	N	0.09	3	N	24	0	56	Y	Y	Y	1383986	34339	1132	85	61
BROADWAY	9	3	14660	Y	0	Y	0.18	4	Y	4	1	27	Y	Y	Y	1075638	15109	1010	49	54
CENTRAL	10	5	14975	Y	63	Y	0.30	4	Y	0	0	6	Y	Y	Y	1082283	19937	864	42	55
	11	25	25457	N	347	N	0.25	6	Y	0	4	31	Y	Y	Y	509227	2015	3531	154	42
COAL	12	3	8754	Y	0	Y	0.26	4	N	0	0	11	Y	Y	Y	964453	10338	961	48	69
	13	2	8534	Y	0	Y	0.07	2	N	14	0	44	Y	Y	N	1002993	17597	1088	74	75
COPPER	14	3	3632	Y	42	Y	0.11	2	N	10	0	23	Y	Y	Y	1383986	34339	1132	85	61
GOLD	15	2	2972	Y	11	Y	0.07	2	N	23	0	24	Y	Y	Y	1383986	34339	1132	85	61
LEAD	16	3	8319	Y	3	Y	0.07	4	N	39	0	92	Y	Y	Y	1383986	34339	1132	85	61
LOMAS	17	6	18609	Y	10	N	0.11	6	Y	14	1	43	Y	N	Y	1457503	18518	909	130	64
LOUISIANA	18	15	19053	Y	67	N	0.33	6	Y	1	0	32	Y	Y	Y	423983	1404	3276	35	23
MARQUETTE	19	2	3079	Y	0	N	0.07	4	N	0	0	60	Y	Y	Y	1383986	34339	1132	85	61
TIJERAS AVE.	20	2	4506	Y	0	N	0.10	4	Y	7	0	11	Y	Y	N	1383986	34339	1132	85	61
WYOMING	21	7	16070	Y	40	N	0.42	6	Y	0	3	15	Y	Y	Y	580132	2920	3250	126	74
ZUNI	22	7	13178	Y	12	N	0.47	4	Y	0	1	18	Y	Y	Y	525773	1694	4380	108	39

Discussion

This section will discuss the results of the research questions, following the same order as presented in the previous sections.

Access Management

This study places particular attention on access management, as most of the crashes occurred in these locations due to turning movements, traffic volume, and exposure of VRU, leading to a high interaction with other road users and subsequent crashes. The findings across the three questions align with the importance of adequate access management of arterials in reducing crashes. In the negative binomial model developed for the second research question, an increase in VRU crashes is associated with higher densities of driveways and signalized intersections. In the negative binomial model developed for the third research question, we observed that well-managed driveways significantly contribute to reduced VRU crashes. Additionally, in the model developed specifically for pedestrian crashes, presented in Appendix A, well-managed driveways and well-managed signalized intersections are also significant in reducing crashes. This result aligns with the findings of the negative binomial model from the second research question.

Driveway management is an essential variable in reducing VRU as this measure may reduce the conflicts between road users, a finding that resonates with prior research (Brown & Tarko, 1999; Chakraborty & Gates, 2022; X. Wang et al., 2018). Signalized intersections are crucial factors in access management because of their higher concentration along arterial roads and their substantial impact on crash occurrence, particularly VRU crashes, as illustrated by the model in the second research question and the Appendix A. This finding aligns with previous studies linking the density of signalized intersections to crash incidence (J. Lee et al., 2015; Nashad et al., 2016; Wei & Lovegrove, 2013). Although unsignalized intersections do not exhibit significance in predicting VRU crashes based on the model, when analyzing only the access as explanatory variables, they have a positive relationship with VRU crashes. This finding aligns with prior research that established a significant correlation between unsignalized intersection density and VRU crashes (Su et al., 2021b).

The findings of this research demonstrate that access management plays a critical role in crash reduction. The author recognizes that making changes to the current structure of arterials might be a challenging task. Consequently, it is recommended that urban planning entities prioritize adhering to spacing and design requirements for all types of access during city expansions or future developments, avoiding the inclusion of new access points on existing roads that do not meet these standards to enhance road user safety.

Road Features and Facilities

Segment length is positively correlated with VRU crashes, indicating that longer segments are associated with a higher likelihood of VRU crashes This is because longer segments provide more opportunities for road features and their surroundings to interact, increasing the potential for crashes. This finding is consistent with prior studies that found this variable significant in explaining VRU crashes when conducting segment-level safety analysis (Caliendo et al., 2007; Sawalha & Sayed, 2001). Similarly, the number of traffic lanes also demonstrates a positive relationship with VRU crashes. This association can be attributed to higher traffic volume, speed, and wider roads. The combination of these factors creates unsafe conditions for VRU (Vulnerable Road User) crashes. In wider roads, when a pedestrian is crossing and vehicles stop abruptly, vehicles behind them may accelerate to high speeds or change lanes hastily to avoid the conflict without checking properly for VRUs. This behavior leads to a higher incidence of crashes involving pedestrians and other vulnerable road users. This result aligns with previous studies linking the number of lanes to an increased crash risk (Avelar et al., 2013; Sawalha & Sayed, 2001). Even though the speed limit was not significant in our model results, when only modeling pedestrian crashes (Appendix A), this variable was significant, being consistent with prior safety studies (Aarts & van Schagen, 2006; Chakraborty & Gates, 2022; Kröyer, 2015; Long & Ferenchak, 2021).

Although raised medians are not significant in our model and do not enhance the model performance, for which they are not included in our results, its estimate indicates a positive effect in reducing VRU crashes, as the study of Brown & Tarko suggested (Brown & Tarko, 1999). Conversely, left turns are significant variables in the increment of VRU crashes. Although Brown & Tarko found that medians with two-way left turns to alleviate conflicts between turning vehicles and through traffic, their analysis does not focus on VRUs as this study does (Brown & Tarko, 1999). Left turns represent conflict points contributing to VRU crashes due to visibility issues and external distractions because drivers are waiting for a gap between vehicles, prioritizing their safety and creating hazardous conditions for VRUs (U.S. Department of Transportation & NHTSA, 2010)

Schools are negatively associated with the prediction of VRU crashes, which is consistent with prior studies (Chakraborty & Gates, 2022; Zahabi et al., 2011). Several factors can explain this finding. First, speed in school zones is usually lower, with drivers taking more caution when driving in these zones. Besides, school locations are generally situated away from heavily trafficked roads, making these areas safer for VRUs. Additionally, since most parents drop off or pick up their children, fewer students walk or bike on arterial roads, reducing exposure to potential crash risks. On the contrary, facilities such as fuel stations and off-street parking or parking lots located next to arterial roads are positively related to VRU crashes. Previous studies suggest that these facilities increase conflicting movements of vehicles, potentially connecting to more VRU crashes (Kapousizis et al., 2021). Furthermore, vehicles exiting these facilities often enter the road at a lower speed compared to other vehicles, resulting in a speed variance that drivers attempt to mitigate by increasing their speed without consideration for VRUs present on the road. This lack of consideration for VRUs may contribute to an increased risk of crashes involving them.

Road features and facilities have been demonstrated to have positive and negative effects on VRU crash frequency. Thus, local authorities should regulate the number of lanes on arterials to prevent over-dimensioning, which could result in higher speeds, higher traffic, and longer crossing distances, all factors associated with a higher risk of VRU crashes. Road diets may be a solution for reducing the number of lanes on arterials. This measure can yield various positive effects, including mitigating speed and safely allocating space for pedestrians and bicyclists. Measures such as exclusive left-turn lanes, protected left-turns, left arrow lights, and leading pedestrian intervals at intersections should be implemented to mitigate crashes involving left turns on arterials. Besides, authorities should manage the density of facilities such as parking lots and fuel stations, along with the access and exit of the vehicles from these facilities, prioritizing and adopting measures to enhance VRU safety and reduce the likelihood of conflicts and crashes.

Exposure and Traffic-Related Variables

While Annual Daily Traffic (ADT) does not emerge as a significant variable by itself (as a continuous variable), when divided into a range of ADT less than 20,000 vehicles, it is observed as significant in reducing crashes. This distinction may be attributed to the features of roads within these traffic volume ranges, which have lower speeds and fewer lanes, potentially enhancing VRU safety. Thus, arterials with lower traffic volumes experience fewer VRU crashes, aligning with previous studies that indicated that AADT below 30,000 is related to a reduction in bicyclist crashes (Nordback et al., 2017).

On the contrary, VRU exposure correlates with an increased frequency of VRU crashes due to the high activity of pedestrians and bicyclists in those areas (Amoh-Gyimah et al., 2016). Remarkably, the Central Avenue area registers the highest concentration of VRU crashes, as Figure 3 shows. The Pedestrian Composite Index (PCI) from the MRCOG website highlights areas with anticipated high pedestrian activity, coinciding with the Central Avenue region and confirming the model results (MRCOG, 2021). Notably, population density and number of people who walk or bike to work, previously studied as a measure of exposure and used in this study, are not significant in this study. Conversely, the number of boardings per stop as a measure of exposure significantly predicts crashes. This finding contributes to road safety analysis since it evidences the adequateness of this measure as exposure for this kind of analysis, as several guides have suggested (NCHRP, 2015; NYDOT, 2016; L. Thomas et al., 2016; U.S. DOT, 2021b).

Considering these findings, enhancing pedestrian and bicycle facilities along arterials with ADT higher than 20,000 would be a strategic approach. By doing so, even if infrastructure cannot reduce VRU exposure or risky behaviors, which was associated to increase crash rates, it can provide safer corridors for these users, serving as alternative routes for VRU, contributing to overall road safety.

VRU Facilities

The presence of facilities such as crosswalks, sidewalks, and bus lanes are significant variables related to an increase in VRU crashes, a trend consistent with prior research (Chakraborty & Gates, 2022; Merlin et al., 2020; Zhang et al., 2015a). While these facilities are designed to enhance pedestrians' and bicyclists' safety, they also have a counterintuitive effect on VRU safety. This is because they increase VRU exposure and involve behavioral factors inherent to these users, such as using the infrastructure inappropriately. This leads to higher interactions with vehicles and increases the likelihood of VRU crashes. It is important to note that bus stops exhibited similar positive relationships with VRU crashes; however, this variable was excluded from the model due to its collinearity with the presence of bus lanes, which ultimately impacted the model's performance.

Signalization enhancements, such as Rectangular Rapid Flashing Beacons and medians, can be installed to alert drivers to the presence of these users on the road. Moreover, improvements in lighting can be made to enhance visibility for both VRUs and vehicles, particularly at intersections and along corridors encompassing sidewalks and bus stops. All these measures should also be accompanied by education campaigns to inform the population, especially the youngest individuals, as they do not yet have established habits and represent future generations that may generate a real change in the behavior of these users. These proactive measures can help mitigate the risks associated with higher VRU activity in these areas, ultimately enhancing overall safety for road users.

Land Use

The area of residences has a negative relationship with VRU crashes, consistent with findings by Pulugurtha (Pulugurtha et al., 2013). This relationship is attributed to the clustering of residential neighborhoods in Albuquerque, predominantly situated on the city's periphery or along arterials distant from Central Avenue, which is the arterial with more concentration of crashes. Consequently, rather than residential zones directly reducing VRU crashes, the city's configuration negatively correlates this variable with VRU crashes. However, while previous studies found residential land use was positively related to pedestrian crashes, the increase in crashes attributed to this variable is minimal (Amoh-Gyimah et al., 2016).

On the other hand, number of jobs is a significant variable positively correlated with VRU crashes. This finding aligns with Loukaitou-Sideris et al. research, which indicates that areas with more employment increase the likelihood of pedestrian crashes (Loukaitou-Sideris et al., 2005; Siddiqui et al., 2012). This relationship can be explained by the fact that zones with a high number of jobs may generate more transit trips and pedestrian and bicyclist activity, which increases the likelihood of crashes.

These findings highlight the importance for local authorities to adopt and improve safety measures for pedestrians and bicyclists in areas with high employment and population density, typically coinciding with commercial and densely populated areas. In such places, where the likelihood of utilizing alternative modes of transportation is greater, improving infrastructure and implementing safety measures tailored to VRUs can help mitigate crash risks and enhance overall safety for pedestrians and bicyclists.

Surrounding Sociodemographic

Variables such as the density of the population below the poverty line and the Black or Afro-American population are identified as significant and positively correlated with VRU crashes. These variables are highly correlated and present a similar influence on the likelihood of VRU crashes, as they represent part of the most vulnerable population who live in areas with inadequate infrastructure for pedestrians and bicyclists. This finding aligns with previous research (Huang et al., 2010; Wier et al., 2009).

On the other hand, a population over 25 with an associate degree is a significant variable that decreases VRU crashes. This fact could be attributed to individuals with higher education levels being less prone to risks while biking and walking, as they tend to reside in less vulnerable areas compared to populations with lower educational attainment (Su et al., 2021b). In addition, this population is likely to own at least one car, which reduces the likelihood of choosing biking and walking as their primary modes of transportation.

In addition to areas characterized by high densities of commercial activity and population, local authorities should prioritize the implementation of countermeasures that are linked in the reduction of VRU crashes in zones with a high density of population below the poverty line and Black or Afro-American populations. These areas often rely heavily on walking or biking as modes of transportation, making crucial interventions to enhance pedestrian and bicyclist safety in these communities.

Spatial analysis

After identifying the most critical segments regarding VRU crashes and their characteristics, the data shows interesting patterns that align with the findings of the regression model. While certain road features may vary among the corridors, their combination within the same corridor can collectively influence the occurrence of VRU crashes.

The driveway's classification varies across the hot corridors, having well-managed or high driveway classification. However, the corridors with a high density of VRU crashes have a pattern of having high driveway classification and a high volume of traffic. This pattern underscores the significance of access management in ensuring the safety of pedestrians and bicyclists, as high-access corridors tend to increase conflicts between vehicles and these road users. Additionally, the corridors with the highest VRU crash density were classified as high speed (>35mph), while the rest of the segments were designated as low speed (<=35mph). Another typical pattern observed among all the hot corridors is the presence of facilities such as crosswalks, sidewalks, and bus lanes, infrastructure that increase VRU exposure and risky behaviors of pedestrians and bicyclists.

The most critical corridor is Central Avenue, which averages 25 VRU crashes, with one segment recording 41 VRU crashes between East Louisiana and West of Pennsylvania. This corridor exhibits the highest traffic volume, number of lanes, VRU exposure, Afro-American population, and fuel station density. According to the regression model, all these factors contribute to an elevated prediction of VRU crashes. Similarly, corridors such as Louisiana, Wyoming, and Zuni also experienced more VRU crashes, ranging between 7 and 15. Despite having a traffic volume of less than 20,000, these corridors share common features including six lanes (except Zuni with four), high exposure, and similar sociodemographic characteristics such as high gross activity, high population below the poverty line density, high Afro-American population, and low residential area and population with an associate degree. These observations validate the results of the regression models, as all these road features were proven to increase the prediction of VRU crashes.

Conclusions and Recommendations

This study addressed four main questions. Firstly, it examined whether high-speed, high-access arterial roads are more prone to crashes compared to roads with better access management. The study evaluated the relationship between crashes and road access management, using the One-way Analysis of Variance (ANOVA) method to compare the mean of crashes and determine which road had a greater likelihood of crashes. The results confirmed that roads with a high number of accesses and greater speed significantly presented a higher mean number of crashes.

Secondly, it investigated if the density of driveways and intersections on arterials correlates with non-motorized crashes. The study explored the relationship between crashes involving VRU and access, including driveways and signalized and unsignalized intersection density, as predicting variables. A negative binomial model was used to study this relationship. It was confirmed that by analyzing access as the only explanatory variable, driveway and signalized intersection density are significant in predicting VRU crashes. However, the model presented an overdispersion higher than 1, suggesting a potential need to include additional variables to enhance the prediction of VRU crashes, which are included in the following question.

Besides, this research explored other built environment factors associated with higher rates of pedestrian and bicycle crashes on arterial roads. The resulting negative regression model from this study provides evidence that roads with well-managed driveways experienced fewer crashes, validating the conclusion regarding the relationship between VRU crashes and access management. Moreover, lower traffic volumes (less than 20,000) are associated with fewer crashes, while higher VRU exposure is linked to an increase in crashes.

Road features such as larger segment length, greater number of lanes, and higher density of off-street parking and fuel stations are associated with a higher frequency of VRU crashes, as did the presence of left turns. Conversely, the presence of schools positively impacted reducing the frequency of VRU crashes. Additionally, VRU facilities, such as crosswalks, sidewalks, and bus lanes, were connected to increase VRU exposure and risky behaviors by crossing in front of bus stops instead of using the facilities designated for this purpose, subsequently increasing the frequency of crashes. Variables associated with land use and sociodemographic surroundings, such as number of jobs, population below the poverty line, and Black or Afro-American population, were correlated with a higher frequency of crashes. On the other hand, residential areas and populations with associate degrees are likely to experience fewer crashes.

Lastly, this study examined the spatial patterns of VRU crashes in Albuquerque, New Mexico. The findings reveal patterns in numerous arterial corridors across the city supported by the methods employed, including KED, Local Moran's I, and Local Gi statistics. These findings validate the reliability of the regression model, indicating its potential to guide local authorities in implementing targeted measures to improve these identified characteristics to reduce the high frequency of VRU crashes.

While this study's findings exhibit similarities and differences from prior research, it concludes that arterial road features influencing VRU crash frequency vary geographically, with behavioral and cultural factors potentially impacting the occurrence of these incidents. Consequently, safety analyses should be tailored to specific characteristics of the areas under examination.

This study bridges a crucial gap by implementing a novel methodology to evaluate access management and its association with crashes. In addition, this research conducts a thorough assessment of the impact of various factors, including access management, the built environment, land use, and socioeconomic conditions, on VRU crashes, specifically along the arterial roads of Albuquerque, New Mexico. This region exhibits some of the highest VRU safety indices in the United States. Notably, factors such as road width and number of lanes, sociodemographic characteristics, and intersection density contribute significantly to our understanding of VRU crashes, offering a comprehensive perspective when integrated into the same model. Additionally, we introduce a novel metric for assessing VRU exposure in crash analysis—the count of boardings per stop—which has not been explored in this context previously. Finally, the methodology to conduct the spatial analysis can serve as a blueprint for other cities to employ a similar approach, enabling them to allocate resources effectively by identifying their patterns and features that affect road safety.

Overall, this study provides further evidence that arterial characteristics play a significant role in VRU crashes and offers guidance to local authorities on conducting interventions to mitigate crashes on these roads. Firstly, Access management is crucial for reducing crashes despite the challenges of altering arterial structures. Urban planners should prioritize adhering to spacing and design standards during city expansions to enhance road user safety. Addressing road features linked to more VRU crashes requires implementing safety measures like road diets, complete streets, and improved access management to minimize conflicts. Enhancements such as rectangular rapid flashing beacons, medians, and better lighting can improve pedestrian and bicyclist safety, yet infrastructure alone may not reduce VRU exposure or risky behaviors that increase crash rates. Education campaigns, especially for younger individuals, are essential to establish safer habits for future generations. Lastly, targeted interventions and regulations are vital in high-commercial, low-income, and Black or Afro-American populated areas to enhance VRU safety.

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Appendix A

Table 21. Negative binomial estimation results of features impacting only pedestrians' safety on arterial segments

GROUP	VARIABLE	ESTIMATE	P-VALUE	SIGNIFICANCE
ACCESS MANAGEMENT	Intercept	-3.17E+00	3.26E-09	***
	Well managed signalized intersections	-4.71E-01	0.0024	**
	Well managed driveways	-1.96E-01	0.0172	*
ROAD FEATURES AND FACILITIES	Segment Length	5.65E-01	0.001	***
	Speed limit	3.13E-02	0.000643	***
	Presence of left-turns	6.25E-01	9.47E-05	***
	Fuel Stations' density	2.80E-02	0.0010	**
	Off-Street Parking' density	1.14E-02	1.18E-05	***
EXPOSURE AND TRAFFIC	ADT less than 20K	-4.38E-01	6.09E-06	***
	VRU exposure boardings	2.47E-03	1.23E-11	***
VRU FACILITIES	Presence of crosswalks	5.60E-01	0.008	**
	Presence of bike lane	-2.91E-01	0.029	*
	Presence of sidewalk	4.74E-01	0.0001	***
	Presence of bus lanes	7.24E-01	8.11E-09	***
LAND USE	Residential area	-3.50E-07	0.007	**
	Gross activity density	1.88E-05	0.005149	**
SURROUNDING SOCIODEMOGRAPHIC	Density of Population Below Poverty	2.63E-04	2.04E-08	***
	Black or Afro-American population	3.93E-03	<0.001	***
	Population over 25 with associate degree	-2.57E-03	0.022	*
OVERDISPERSION		1.005 AIC = 2232		
SIGNIFICANCE	*** 99.9%	** 99%	* 95%	

The variables found to be significant in predicting pedestrian crashes are quite similar to those that predict VRU crashes. Still there are some additional variables in these results: speed limit instead of the number of lanes, the presence of bike lanes, gross activity density instead of job density, and well-managed signalized intersections.

High speeds are associated with both the frequency and severity of VRU crashes, as highlighted in previous studies (Avelar et al., 2013; Chakraborty & Gates, 2022; Dai & Dadashova, 2021; J. Lee et al., 2015; Long & Ferenchak, 2021; Merlin et al., 2020; Ming Ma et al., 2010). This effect can be attributed to increased stopping distances, reduced driver reaction time, and a narrower field of vision. Combined, these factors make roads less pedestrian-friendly, increasing VRU crashes.

Another additional variable found significant in this model is bike lanes. Although bike lanes are not designed for pedestrians, they may serve as a buffer between pedestrians and traffic, creating a safer environment for these users, which aligns with previous studies (Ming Ma et al., 2010).

Besides, gross activity density is significant instead of job density. Gross activity density results from combining population and job density, which is related to increased pedestrian activity. This finding aligns with the research by Loukaitou-Sideris et al., which indicates that areas with higher population and employment densities increase the likelihood of pedestrian crashes (Loukaitou-Sideris et al., 2005; Siddiqui et al., 2012).

Finally, well-managed signalized intersections, as mentioned in the discussion of access management, have more pedestrian activity and turning movements at these locations, which increases the conflicts between road users.

Although some differences are present in this model, most features that impact VRU crashes remain consistent. This consistency validates the model's performance and highlights the most critical features affecting the safety of these users, which local authorities should address to improve road safety.

Appendix B

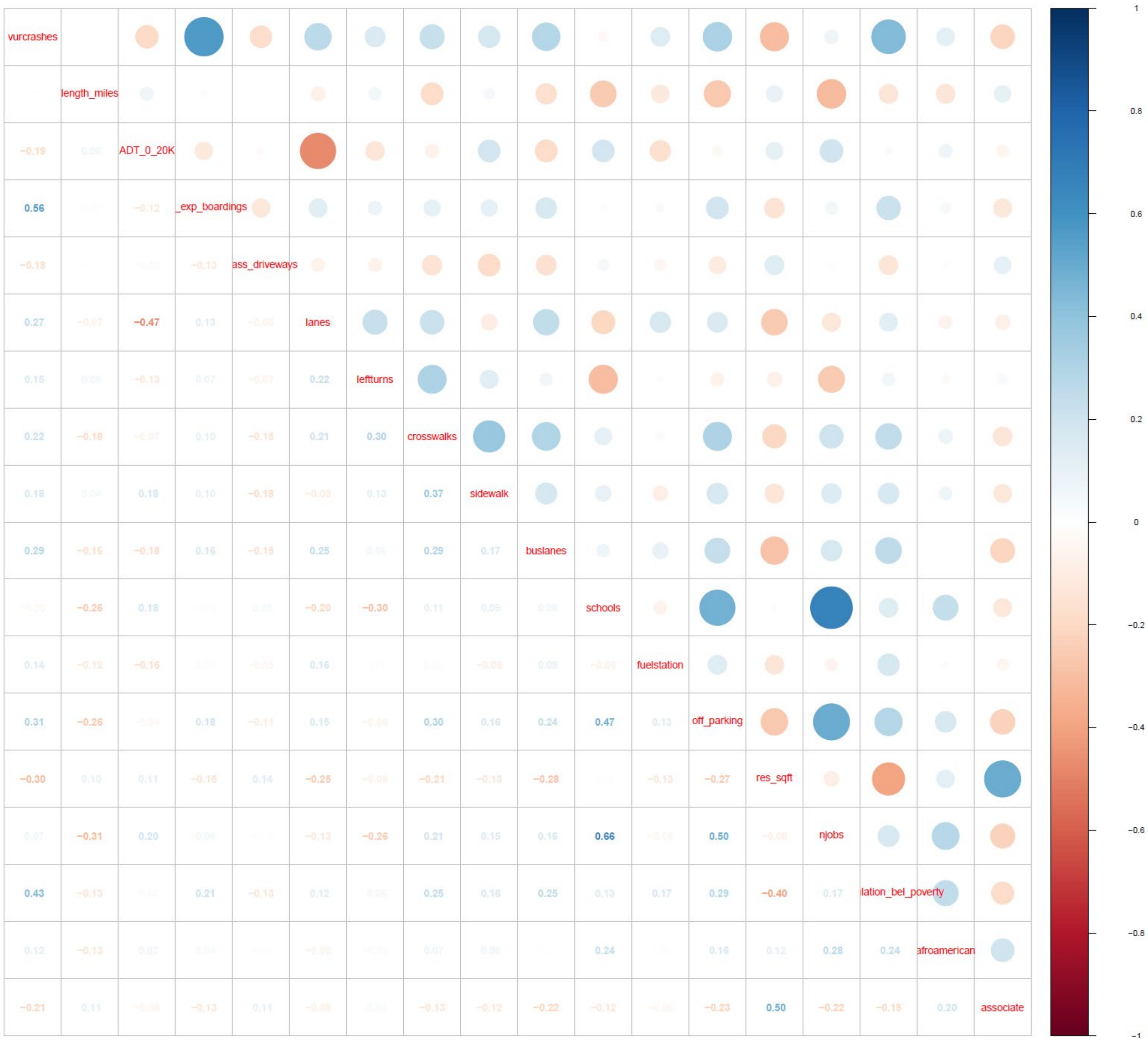

Figure 29. Correlation Matrix significant variables RQ3

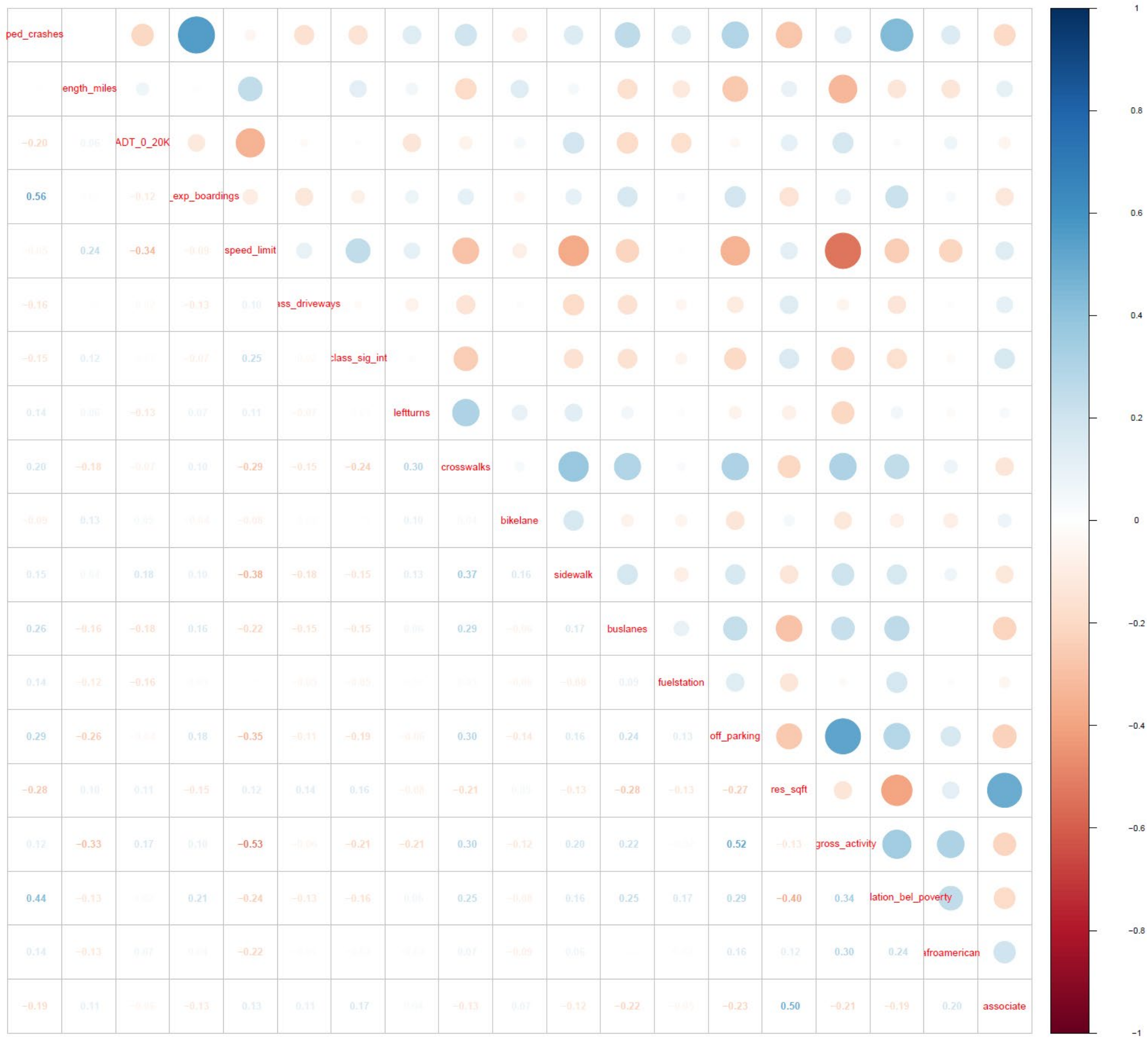

Figure 30. Correlation Matrix significant variables Appendix A