VULNERABLE ROAD USERS

TECHNICAL REPORT

FOUNDATION FOR TRAFFIC SAFETY

Social and Infrastructure Factors Shaping Road Safety: A Multi-Level Analysis of Crashes in Ohio, Texas, and Washington

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Title

Social and Infrastructure Factors Shaping Road Safety: A Multi-Level Analysis of Crashes in Ohio, Texas, and Washington

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Foreword

Traffic crashes are caused by a multitude of factors and oftentimes the burdens associated with crashes are felt unequally across different communities. Understanding the broader context of these crashes and about those involved are important precursors to identifying ways to address safety inequities.

For this study, data from three states, Ohio, Texas, and Washington, were used to examine traffic safety inequities. A multi-level approach was applied to the analysis, considering factors at the individual, neighborhood, and road segment levels. The study highlights disparities and proposes evidence-based recommendations to address traffic safety inequities, aligned with principles of the Safe System Approach (SSA). The findings reported herein should be of interest to researchers and safety advocates working in areas of safe mobility. Additionally, information presented in this document can be a reference for cities and states that are working toward improving road safety in their communities.

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About the Sponsor

AAA Foundation for Traffic Safety
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Founded in 1947, the AAA Foundation for Traffic Safety in Washington, D.C., is a nonprofit, publicly supported charitable research and educational organization dedicated to saving lives by preventing traffic crashes and reducing injuries when crashes occur. Funding for this report was provided by voluntary contributions from AAA/CAA and their affiliated motor clubs, individual members, AAA-affiliated insurance companies, and other organizations or sources.

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List of Abbreviations and Acronyms

AADT	Annual Average Daily Traffic
ACS	American Community Survey
AIAN	American Indian or Alaska Native
BP|CX	Bicycle and Pedestrian Count Exchange
CFA	Confirmatory Factor Analysis
CR	Composite Reliability
CRIS	Crash Records Information System
EAZ	Equity Analysis Zone
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
HDI	Highest Density Interval
HSIP	Highway Safety Improvement Plan
IID	Independent and Identically Distributed
INLA	Integrated Nested Laplace Approximation
IRR	Incidence Rate Ratio
KA	Fatal and Incapacitating Injury (KABCO Injury Classification Scale)
KFF	Kaiser Family Foundation
LATM	Local Area Traffic Management
MVO	Motor Vehicle Occupant
NHPI	Native Hawaiian and Pacific Islander
NOACA	Northeast Ohio Areawide Coordinating Agency
ODOT	Ohio Department of Transportation
OMB	Office of Management and Budget
OR	Odds Ratio
RP	Random Parameter
SED	Socioeconomic Disadvantage
SEM	Structural Equations Modeling
SHSP	Strategic Highway Safety Plan
SLD	Smart Location Database
SS4A	Safe Streets and Roads for All
SSA	Safe System Approach
SVI	Social Vulnerability Index
TIMS	Transportation Information Mapping System
TxDOT	Texas Department of Transportation
TWLTL	Two–Way Left Turn Lanes
USDOT	United States Department of Transportation
VRU	Vulnerable Road User
WSDOT	Washington Department of Transportation

Executive Summary

Underserved populations have experienced disproportionately higher rates of traffic fatalities and injuries in the past decade. The COVID-19 pandemic has worsened these disparities by altering travel patterns and increasing risks in marginalized areas. This research examined traffic crash trends in Ohio, Texas, and Washington, focusing on drivers, passengers, bicyclists, and pedestrians to identify disparities and fatality risks in different communities. This study aimed to uncover demographic and infrastructure factors contributing to these disparities. The goal is to inform evidence-based recommendations aligned with the Safe System Approach (SSA) principles to reduce fatalities and serious injuries in vulnerable populations.

The multi-level analysis captured three perspectives: individual, neighborhood, and roadway segments to provide a comprehensive understanding of the contributing factors to traffic safety-related inequities.

- At the ***individual level***, the study analyzed disparities in personal injury severity among pedestrians, bicyclists, and motor vehicle occupants (MVOs)—including both drivers and passengers—using race/ethnicity data.
- At the ***neighborhood level***, disparities in crash injury rates were evaluated at the census tract level by analyzing sociodemographic and economic factors alongside infrastructure characteristics in an integrated approach to identify interrelated factors contributing to safety disparities.
- At the ***roadway segment level***, the study assessed the safety potential of roadways by applying an SSA framework to roadways in Cleveland, Austin, and Seattle focusing on infrastructure readiness to prevent fatal and serious injury crashes.

Key Findings

Selected findings are highlighted in the tables below, aligned with each of the three levels analysis. Comprehensive findings can be found in the body of the report and the accompanying appendices.

Individual-Level Analysis

Road User	Ohio	Texas	Washington
All Road Users	From 2013 to 2022, *fatalities* increased by 29%. The share of Black *fatalities* increased from 12% to 18%, and Hispanic *fatalities* grew from 2% to 4%, while White *fatalities* declined from 84% to 75%.	From 2017 to 2022, total *fatalities* increased by 18%. Hispanic *fatalities* grew from 30% to 36%, while White *fatalities* dropped from 51% to 45%.	Whites constituted the majority of *fatalities*, but their share declined from 75% in 2013 to 63% in 2022.
Pedestrians	Black pedestrian *fatality rates* increased from 1.4 per 100,000 in 2013 to over 3 per 100,000 in 2022. Black male and female pedestrians were overrepresented in *fatalities*, the degree to which varied by age.	Black pedestrian *fatality* rates were twice the statewide average. Black females were overrepresented in all age groups. AIAN rates nearly doubled by 2022. Hispanic female pedestrians aged 55+ were overrepresented in *fatalities*.	AIAN pedestrian *fatality* rates rose from 6.3 per 100,000 in 2013 to 20 per 100,000 in 2021, which is 12 times the statewide average.
Bicyclists	Black bicyclists had *fatality* rates 2.6 times the statewide average in 2021. White female bicyclists aged 35–54 were overrepresented in *fatalities* by 19.5%.	AIAN bicyclist *incapacitating injury* rates reached four times the state average by 2022.	White female bicyclists in all age groups were overrepresented in *fatalities.* White male bicyclists aged 35–54 years were overrepresented among *fatalities*.
Motor Vehicle Occupants	AIAN and Black individuals consistently exceeded statewide MVO *fatality* averages. By 2022, AIAN *fatalities* were three times the average.	AIAN *fatality* rates were 2.3 times the state average in 2021. Hispanic females were overrepresented by 5.7% relative to their proportion in the population.	AIAN MVO *fatality* rates peaked at 57.7 per 100,000 in 2021, five times the state average.

Neighborhood-Level Analysis

Road User	Ohio	Texas	Washington
Pedestrian	Communities with higher *NHPI* populations and more *mobile homes* exhibited a 99% increase in fatal and incapacitating (KA) injury* rates.	A one-unit increase in the log of *retail jobs* corresponded to an 11% increase in pedestrian fatalities.	Communities with a higher density of *unmarked crosswalks* experienced pedestrian KA injury rates 2.9 times higher.
Bicyclists	*Rural* and *town* communities with higher percentages of *Hispanic* residents experienced 28% and 14% increases in KA injury rates, respectively.	Communities with higher *NHPI* populations and more *retail jobs* were linked to increased KA injuries.	Communities with higher *AIAN* or *Hispanic* populations and greater densities of *unmarked crosswalks* showed higher KA injury rates.
Motor Vehicle Occupants	*Rural* communities experienced higher KA injury rates. Communities with higher percentages of *Black* residents had higher KA injury rates. Communities with higher percentages of *Asian* residents and more multi-lane roads led to a 6% rise in KA injury rates.	*Rural* communities experienced higher KA injury rates.	*Rural* communities experienced higher KA injury rates. Communities with *AIAN* populations combined with roads with *30–40 mph speed limits* led to a 12% increase in KA injuries.

* *KABCO Injury Classification Scale.*

Segment-Level Analysis

This analysis evaluated roadway safety equity at the segment level, focusing on the safety potential of roadway segments. Safety potential was measured using a scoring system aligned with SSA, a concept introduced by the Federal Highway Administration (FHWA) Safe System Roadway Design Hierarchy. Key findings include the following:

- **SSA Alignment**: Socioeconomically disadvantaged areas often exhibit worse SSA Scores, indicating poorer alignment with safety objectives. Cleveland and Seattle demonstrated pronounced disparities in roadway safety potential across socioeconomic and racial groups. In contrast, Austin's proactive safety initiatives helped mitigate some disparities, leading to better SSA alignment in underserved areas.
- **Interactive Tools**: The study developed an equity scoring framework to assess roadway conditions. The resulting scores were integrated into a web-based interactive tool to visualize roadway infrastructure alignment with SSA across segments in Cleveland, Austin, and Seattle. The tool integrates Google Street View, allowing users to inspect roadway features like sidewalks and bike lanes

while assessing segment characteristics for both motor vehicles and vulnerable road users.

Recommendations

The study analysis showed that inequity exists at the individual, neighborhood, and segment levels. To reduce disparities and approach equity, a holistic approach is necessary. Specifically, understanding the complex and dynamic role of many intersecting factors, such as social identities, social roles, and place-based effects, is imperative for safety. Detailed recommendations and associated strategies are provided in the report, along with some state-specific recommendations based on the multi-level analysis.

RECOMMENDATIONS

1. Expand analyses, policies, and practices to address the complexity of human experiences.

2. Conduct place-based analyses to uncover inequities and inform policy.

3. SSA scoring and analysis should consider equity-based strategies and guidance.

Introduction

Achieving equity requires tailored strategies and intentional resource allocation to address the unique challenges and needs faced by different social groups (Powell et al., 2019). Disparities in safety and mobility disproportionately impact certain communities, limiting their access to essential services (Davis, 2023). Beyond the individual level, traffic safety inequities are also a concern at the neighborhood level (Harper et al., 2015) where traffic fatalities and injuries are more prevalent in poorer regions (GHSA, 2021; Harper et al., 2015; Vision Zero Chicago, 2017), representing a significant health disparity and a chronic public health issue for minority communities. Ensuring everyone has safe, reliable, and affordable mobility options requires a commitment to addressing these inequities through inclusive policies, targeted investments, and community-driven solutions.

Unfortunately, individuals belonging to historically underserved social groups (e.g., racial/ethnic minorities, low-income communities, etc.) experience a disproportionate number of traffic fatalities and injuries (Glassbrenner et al., 2022; GHSA, 2021; Harper et al., 2015; Schwartz et al., 2022; Tefft & Wang, 2022; West & Naumann, 2005). Between 2013 and 2022, the number of traffic crash fatalities in the United States (U.S.) increased by 30%, rising from 32,744 to 42,514 (NHTSA, 2024). This national trend was also reflected in Texas, and Ohio whereas in Washington, fatalities experienced a surge of 68%, doubling the national rate.

This sharp increase in fatalities in 2022 compared to 2013 suggests that multiple factors unique to each state, including changes in traffic patterns, changes in enforcement policies, speeding, and reckless driving, may have contributed to a higher risk of crashes, disproportionately affecting marginalized communities. Additionally, these underserved communities experienced worsened traffic safety inequities due to limited access to safe infrastructure for walking and biking and pandemic-related travel disruptions during the COVID-19 pandemic, further compounding the systemic inequities they face.

Traffic safety inequities are prevalent in underserved communities due to various factors. These communities often have a history of disinvestment and disenfranchisement, leading to a lack of resources for infrastructure and transportation improvements (Harper et al., 2015; Schwartz et al., 2022). Minority communities often have lower access to employment opportunities, limiting their ability to purchase and maintain safe vehicles with modern safety features. Besides, underserved communities may also face systemic discrimination and bias in the enforcement of traffic laws, leading to over-policing and disproportionate fines and penalties (Graham et al., 2024). This can result in a strained relationship between law enforcement agencies and the community, leading to a reluctance within the community to report crashes or seek help from law enforcement in the event of a crash. In addition, these communities often have limited access to healthcare resources and trauma centers, which can exacerbate the severity of injuries sustained in crashes and contribute to higher rates of fatalities (GHSA, 2021; Harper et al., 2015; Schwartz et al., 2022).

The rising fatalities underscore the urgent need to examine the structural factors that place underserved communities at greater risk, including historical disinvestment, economic constraints, and disparities in infrastructure and enforcement. Addressing these disparities requires comprehensive, equity-focused policies and investments that prioritize the safety and well-being of vulnerable road users in historically marginalized communities.

Research Goal and Objectives

The primary goal of this research was to examine inequities in traffic safety and recommend evidence-based solutions to address them.

Main Research Objectives

1. Conduct a comprehensive review of equity in traffic safety.
2. Investigate and review how traffic safety countermeasures and other policies and programs, including non-transportation-specific factors like being disadvantaged socially and economically, contribute to inequities in traffic safety.
3. Provide equity in traffic safety and decrease differences where they exist by following Safe System Approach principles.

In the following sections, the outcomes from a literature review are presented and summarized. Next, an in-depth analysis of traffic safety inequities is presented using three states as case examples (Texas, Ohio, and Washington). For each, different levels of analysis were conducted to shed insights related to individuals, neighborhoods, and road segments. Finally, policy implications and recommendations are provided.

Literature Review

The literature review synthesized findings from peer-reviewed journals, reports, and policy documents across disciplines, including traffic safety, transportation planning, equity, social justice, and public health. This section is structured following the research questions in the sidebar. First, it discusses transportation and non-transportation-related factors associated with traffic safety inequities. Next, current policies and programs are examined that tackle safety inequities in the three case study states of Ohio, Texas, and Washington. Lastly, existing gaps pertaining to equity in traffic safety are identified in the three states and key findings from the literature review are summarized.

Guiding Research Questions

1. What are the underlying causes of traffic safety inequities, including both transportation- and non-transportation-related factors?

2. What policies and programs have been implemented to address inequities in traffic safety, and what evidence exists regarding their effectiveness?

The research team performed a comprehensive search using various keyword combinations for publications from the past decade. The team's access to databases such as Transportation Research International Documentation (TRID) allowed the retrieval of scientific publications from peer-reviewed journals. Supplementary data sources, including Google, Google Scholar, Web of Science, Scopus, and organizational websites were used to find projects, white papers, toolkits, and unpublished papers centered on equity in traffic safety. The research team utilized a combination of 42 search terms and Boolean logic, including key terms such as crash, minority, inequality, safety, poverty, unemployment, safe system approach, pedestrian, and bike. A total of 83 peer-reviewed papers, including project reports and documents produced by state agencies and associations, were identified from the larger initial pool of documents.

Underlying Causes of Traffic Safety Inequities

Transportation-related Factors

Roadway infrastructure inequities are a significant concern, particularly in underserved communities, where the availability and quality of pedestrian and bicycle facilities often lag behind those in more resourced areas. Prior research has identified racial disparities in pedestrian (FHWA, 2024; Roll & McNeil, 2022), bicyclist (Behnood & Mannering, 2017; FWHA, 2024), and motor vehicle occupant (MVO) injuries (Haskins et al., 2013; Kposowa & Adams, 1998; Pirdavani et al., 2017). Others have highlighted the critical need for improvements to sidewalks, crosswalks, and bicycle lanes, which are disproportionately absent or inadequate in low-income neighborhoods (Roll & McNeil, 2022). This inequity is compounded by the lack of clear pedestrian and bicycle signage, further exacerbating safety risks. Research by Liu et al. (2024) emphasizes that targeted investments in infrastructure, such as enhanced pedestrian pathways and public transit facilities, can yield substantial benefits in these neighborhoods. Moreover, disparities in crash risk and severity are closely tied to the built environment. Prior research indicates that factors such as driver behavior and crash location may impact injury severity differently across racial/ethnic groups (Haskins et al., 2013; Kposowa & Adams, 1998; Roll & McNeil, 2022; Sanders & Schneider, 2022). Inequalities may arise from differences in roadway design, investment, and infrastructure between disadvantaged and affluent neighborhoods, raising environmental justice concerns (Zhu et al., 2024). Various racial/ethnic groups may experience varying levels of risk due to differences in access to resources, healthcare, vehicle safety features, and neighborhood infrastructure (Zhu et al., 2024). Areas with a prevalence of major arterial roads and higher travel speeds are associated with increased injury severity and fatality risk (Merlin et al., 2020; Stoker et al., 2015). Addressing these disparities through equitable roadway infrastructure and safety interventions is critical to reducing injury risks and improving accessibility and safety for all road users.

The roadway environment and exposure significantly contribute to traffic safety inequities. Research highlights that two-thirds of fatal pedestrian crashes occur at night or in low-light conditions, underscoring the need for improved lighting and visibility (Stoker et al., 2015). Additionally, income and racial disparities in pedestrian injuries are evident in areas with high poverty rates and predominantly people-of-color populations (Yu et al., 2022). Low-income neighborhoods also face higher safety risks due to the design of the built environment. For example, blocks with higher densities of traffic signals and bus stops per mile experience increased pedestrian crash frequencies, pointing to the need for better-designed pedestrian infrastructure (Lin et al., 2019). Furthermore, urban areas with non-access-controlled principal and minor arterials experience more frequent pedestrian crashes due to high traffic volumes (Mansfield et al., 2018). These findings emphasize the urgent need for targeted interventions, such as enhanced lighting conditions, safer roadways, and a well-designed built environment, to address traffic safety inequities and protect vulnerable populations.

Non-Transportation Factors

Socioeconomic Disparities. Socioeconomic factors significantly contribute to traffic safety inequities, with poverty and income disparities playing a critical role. Guerra et al. (2019) found that a 1% increase in poverty within a census tract was associated with a 0.22% rise in pedestrian crashes, a 0.24% increase in injuries, and a 0.17% rise in fatalities in Philadelphia, Pennsylvania. Mansfield et al. (2018) reported that a $1,000 decrease in a census tract's median income is associated with a 1% increase in pedestrian fatal injuries nationally. These findings highlight the disproportionate burden of traffic injuries and fatalities sustained by individuals from low-income communities, calling for targeted safety interventions and infrastructure investments in these communities.

Demographic Disparities. Demographic factors such as race, ethnicity, and age also play a significant role in traffic safety inequities, with certain groups facing higher risks of injury and fatality. Sanders and Schneider (2022) found that Black and Native American pedestrians experience higher fatality rates in darkness compared to White pedestrians (79%, 83%, and 72%, respectively). In contrast, Asian pedestrians aged 65 years or older are 1.7 times more likely to be killed than their White counterparts. Furthermore, driver behavior reflects racial and gender biases that exacerbate these disparities. Coughenour et al. (2020) observed that driver-yielding rates are higher for women and White pedestrians compared to men or Black pedestrians in Las Vegas, Nevada. Similarly, Goddard et al. (2015) reported that Black male pedestrians at a marked midblock crosswalk in Portland, Oregon, experience 32% longer wait times and are passed by twice as many cars compared to White pedestrians. These patterns illustrate the urgent need for interventions that address demographic inequities in traffic safety through education, enforcement, and equitable policy changes.

Health Disparities. Health equity is a topic that garners substantial interest in traffic safety. It emphasizes the need for fair opportunities for all to maintain health while addressing safety disparities. Braveman et al. (2018) state that health equity is about ensuring everyone has a fair chance to be healthy. Healthy People 2030 defines health equity as “the attainment of the highest level of health for all people”, and health disparity as “a particular type of health difference that is closely linked with social, economic, and/or environmental disadvantage (Office of Disease Prevention and Health Promotion, 2024). Henning-Smith et al. (2018) found that residents of micropolitan areas (rural areas of 2,500 to 50,000 people) with health-limiting conditions face unique transportation challenges, such as reluctance to travel, reduced reliance on specialized transportation, and having travel restricted to daylight hours.

The COVID-19 pandemic also exacerbated traffic safety inequities, amplifying socioeconomic and racial disparities in crash outcomes (Neuroth et al., 2024; Tefft & Wang, 2022). For example, motor vehicle collision–related health outcomes in North Carolina returned to or exceeded pre-pandemic levels by the end of 2021, worsening racial and ethnic disparities. Lower-educated individuals experienced higher traffic mortality as they drove more during the pandemic, while college graduates who traveled less due to remote work faced reduced road dangers (Tefft & Wang, 2022). Public health initiatives must address these disparities to ensure equitable impact across communities.

Active transportation offers public health benefits through physical activity but exposes certain populations to higher safety risks. People in low-income areas are more likely to walk or bike due to limited vehicle access, increasing their exposure to unsafe traffic and crash risks (Guo et al., 2020). While active transportation interventions can promote health equity, Hansmann et al. (2022) identified significant knowledge gaps in their impacts. For instance, limited research has explored the health equity impacts of active transportation interventions, and the available findings provide only weak evidence of positive outcomes. Integrating health equity considerations into traffic safety efforts, especially for vulnerable road users like pedestrians and bicyclists, is essential for creating safer and more equitable transportation systems.

Policies and Programs that Address Traffic Safety Inequities.[1] Traffic fatalities and injuries are disproportionately high in low-income regions, yet remain inadequately addressed (Dumbaugh et al., 2022). This has resulted in fragmented systems that hinder equitable access to resources and public health. Tailoring national and state strategies to align with traffic safety culture and justice is essential in closing the inequity gaps. In recent years, policies and programs have improved to address transportation inequities at the national level.

Equity-based policies address disparities by promoting multimodal planning, improving safety in underserved areas, and prioritizing accessibility. In sections below, summaries of state-level equity approaches are provided for Ohio, Texas, and Washington. Many of the existing policies are comprehensive and data driven; the goal of this research is not to rewrite these policies but to provide additional evidence and new ways of gathering and analyzing data to guide future recommendations for policy revision and growth toward equity.

Safety initiatives have been implemented through different approaches, such as Complete Streets and Vision Zero, and more recently, emphasis has been placed on the Safe System approach (SSA). Complete Streets are policies and initiatives to create safe roads for all road users, including pedestrians, bicyclists, motorists, and transit riders of all ages and abilities (Smart Growth America, 2024). On the other hand, Vision Zero is a road safety initiative that originated in Sweden in the 1990s and started to gain formal recognition with policy adoption in the early 2000s in the U.S. It is founded on the belief that everyone has the right to safe mobility and that planners, engineers, and policymakers are responsible for ensuring safe travel options for all road users and achieving a transportation system with zero fatalities or serious injuries.

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[1] This section was originally drafted prior to January, 2025. Policies and programs may have changed subsequently.

SSA is a comprehensive road safety strategy that aims to eliminate fatalities and serious injuries on roadways (United States Department of Transportation [USDOT], 2022b). The key principle of the SSA is recognizing that people will make mistakes, and the road system should be designed to account for these errors without resulting in severe injuries or fatalities. SSA is a core concept for the current analysis. State DOTs vary in the extent to which they utilize this approach and to the extent to which they incorporate equity into SSA, with Washington explicitly mentioning equity as an essential factor for SSA. All states are implementing some elements of SSA (e.g., in Strategic Highway Safety Plans (SHSPs)), but the key is to adopt more of those elements.

National Equity Strategies

A noteworthy program, the Rebuilding American Infrastructure with Sustainability and Equity (RAISE), presents a distinctive opportunity for transportation agencies' investments in road, rail, transit, and port projects aimed at achieving national objectives (USDOT, 2023a). It prioritizes regions facing persistent poverty and historically disadvantaged communities.

Another national equity strategy is the USDOT's Justice40 Initiative (USDOT, 2022a), a government-wide effort under President Joe Biden that seeks to ensure that at least 40% of the benefits from specific federal investments reach disadvantaged communities. This initiative is designed to counteract decades of systemic inequities and

National Equity Strategies

Rebuilding American Infrastructure with Sustainability and Equity (RAISE)

One of the five projects in Ohio, includes the *State to Central: Building Better Neighborhoods* and *Connecting Toledo to Opportunity*.

In Texas, the program supports nine projects, including the *Texas Active Transportation Network*

In Washington, eight awards have been granted, including projects such as the *West Side Transformation: Multimodal Connections to Shoreline South Regional Transit Hub*

Safe Streets and Roads for All (SS4A)

Ohio received nineteen awards for projects, including the *Cleveland Zero Supplemental Planning and the Clair Avenue Demonstration Project*.

Texas received twenty-seven awards and is implementing initiatives such *as Place-Based Planning and Demonstration Projects for Vulnerable Road User Safety* in McLennan County.

Washington, recipient of twenty-eight awards, allocated one to the *Safe Streets for Spokane* project.

historical underinvestment in these areas. For the USDOT, Justice40 represents a critical opportunity to close gaps in transportation infrastructure and public services, ultimately enhancing mobility, accessibility, and economic opportunities for marginalized populations. Justice40 aims to create more inclusive and sustainable communities by prioritizing equity in transportation investments.

Other programs that contribute to advancing equity in transportation include the Safe Streets and Roads for All (SS4A) initiative, which aligns with the USDOT's National Roadway Safety Strategy, aiming for zero fatalities using SSA (USDOT, 2023b).

State-Level Strategic Highway Safety Plans

Federal Highway Administration (FHWA) mandates each state's Strategic Highway Safety Plan (SHSP) and currently lacks clear equity considerations, an "equity" safety priority, or a direct connection with SSA. SHSPs are data-driven (i.e., based on crash statistics), long-term plans designed to pinpoint safety priorities. They also entail establishing goals and cultivating a shared understanding of these safety priorities among state agencies.

The state SHSP presents a unique opportunity for highway safety programs and partners in each state to collaborate, synchronize goals, pool resources, and collectively address the safety challenges specific to the state. As such, the SHSP offers a distinctive initial chance for states to incorporate SSA principles and core elements into their existing SHSP frameworks (FWHA, 2022). Furthermore, it provides an avenue to redefine the SHSP by realigning countermeasures and strategies to better align with SSA goals. This is particularly significant given that such alignment is lacking in the SHSPs of numerous states, including the three case study states, i.e., Ohio, Texas, and Washington.

Safety priorities and programs for the three states are summarized in the sections below. In general, the safety priorities are similar, with some differences in the rank ordering (Ohio Department of Transportation [ODOT], 2020; Texas Department of Transportation [TxDOT], 2021; Washington Traffic Safety Commission, 2021). These priorities include roadway departure, intersections, young drivers, speeding, impaired driving, older drivers, seat belts, motorcycles, commercial motor vehicles, distracted driving, pedestrians and bicycles, and highway-railroad crossings.

Equity-Based Policies and Safety Programs in Ohio

In 2023, Ohio released a Vulnerable Road User Guide that is part of its "*Toward Zero Deaths*" strategic plan (ODOT, 2023). This guide included a six-part action plan, including equity. To work towards reducing disproportionately severe crashes among historically marginalized communities, two strategies were proposed: (a) coordinate with local governments on project delivery challenges (e.g., "*engage representatives from* *disadvantaged communities to further inform assistance and priorities*", p. 24) and (b) produce tools and resources that enable and ensure equity within planning, funding, scoping, design, and construction (e.g., "*create specialized outreach and engagement materials for traditionally underserved communities", "utilize equity tools as part of project prioritization, development, and selection*", and "*develop projects that improve safety for all users and do not unintentionally exacerbate racial, economic, or geographical disparities*," p. 25).

The Ohio Department of Transportation (ODOT) developed equity metrics for its funded safety-related projects. The developed metrics have been used for the Safe Routes to School program (ODOT, 2024) and the *Walk.Bike.Ohio* program (DeWine & Marchbanks, 2021). The objectives of these programs were to ensure the transportation system accommodates users of all ages, abilities, and incomes and provides opportunities for all Ohioans in urban, suburban, and rural areas to access connected walkways and bikeways. One major finding from these programs was that 35% of Ohio residents lived in high-need areas with "*high rates of poverty, high mortality rates, limited English proficiency, limited access to motor vehicles and beyond*" (Toward Zero Deaths, 2024).

> *ODOT has established performance targets to prioritize funding in high-need, high-demand areas and has actively pursued collaborations with organizations capable of supporting its equity objectives.*

ODOT modified its Highway Safety Improvement Program (HSIP) process in the Fall of 2021 by incorporating equity components into the scoring system (Toward Zero Deaths, 2024). The revised HSIP process now combines crash data with corresponding U.S. Census data. ODOT's research revealed that fatal and serious injury crashes are disproportionately prevalent by 9.8% within census block groups where the poverty rate (population with income below the poverty line) is at or exceeds 10%. Their findings indicated a direct correlation between economic distress (poverty) and the occurrence of severe crashes.

However, the Ohio SHSP lacks explicit mentions of equity or related terms, and may need to incorporate more equity considerations in the coming years (ODOT, 2020). The priority areas identified in Ohio's SHSP are outlined in Table 1, along with the connections to SSA elements (apart from post-crash care) and principles.

Table 1. Linking Ohio's SHSP Priority Areas to SSA.

SHSP priority	Main SSA element	Two main SSA principles
1. Roadway departure	Safe roads	• Humans make mistakes • Redundancy is crucial
2. Intersections	Safe roads	• Redundancy is crucial • Safety is proactive
3. Young drivers (15–25 years old)	Safe road users	• Humans are vulnerable • Responsibility is shared
4. Speeding	Safe speeds	• Safety is proactive • Responsibility is shared
5. Impaired	Safe road users	• Responsibility is shared • Humans are vulnerable
6. Older drivers (65+ years old)	Safe road users	• Humans are vulnerable • Responsibility is shared
7. Seat belts	Safe road users	• Responsibility is shared • Redundancy is crucial
8. Connected automated vehicles	Safe vehicles	• Redundancy is crucial • Safety is proactive
9. Motorcycles	Safe road users	• Humans are vulnerable • Safety is proactive
10. Commercial motor vehicles	Safe vehicles	• Redundancy is crucial • Safety is proactive
11. Distracted driving	Safe road users	• Humans make mistakes • Safety is proactive
12. Impaired driving	Safe road users	• Humans make mistakes • Safety is proactive
13. Pedestrians and bicycles	Safe road users	• Humans are vulnerable • Safety is proactive
14. Highway railroad crossings	Safe roads	• Redundancy is crucial • Safety is proactive
15. Data	Safe road users	• Humans are vulnerable • Safety is proactive

Note. A safety priority area can be associated with multiple SSA elements and principles.

Equity-Based Policies and Safety Programs in Texas

Texas has a plan to end daily traffic fatalities (Vison Zero Texas, 2024). However, unlike the other two states, equity is not centralized in policy plans (e.g., see TxDOT, 2023). TxDOT does, however, utilize the Rebuilding American Infrastructure with Sustainability and Equity (RAISE) Discretionary Grant program to invest in transit projects that advance equity in safety. For example, the Capital Area Metropolitan

Planning Organization (CAMPO) 2040 Regional Transportation Plan "*strongly encourages all recipients of federal, state, and/or local funds to continue making safety a major priority as it develops and implements transportation projects throughout the region*" (CAMPO, 2015, p. 24). The one safety objective in the action plan is to make "*three miles of improvements to high crash corridors,*" which is listed under the Social Equity section.

Table 2 presents the safety priority areas in Texas (TxDOT, 2021). Texas operates a Statewide Transportation Enhancement Program (TxDOT, 2022). The federal Transportation Equity Act for the 21st Century (1997) identified twelve project categories eligible for funding as transportation enhancement activities. Of these twelve projects, two are specifically dedicated to traffic safety. These include the provision of facilities for pedestrians and bicycles and the provision of safety and education activities for pedestrians and bicyclists. The first project focuses on constructing or reconstructing sidewalks, walkways, curb ramps, off-road multi-use trails with logical connections, and non-vehicular bridges and underpasses. The second project is geared toward providing education through training programs and distributing educational materials dedicated to pedestrian and bicycle safety.

Table 2. Linking Texas's SHSP Priority Areas to SSA.

SHSP priority	Main SSA element	Two main SSA principles
1. Roadway and lane departure	Safe roads	• Humans make mistakes • Redundancy is crucial
2. Speed related	Safe speeds	• Safety is proactive • Responsibility is shared
3. Intersection safety	Safe roads	• Redundancy is crucial • Safety is proactive
4. Occupant protection	Safe road users	• Responsibility is shared • Redundancy is crucial
5. Impaired driving	Safe road users	• Responsibility is shared • Humans are vulnerable
6. Distracted driving	Safe road users	• Humans make mistakes • Safety is proactive
7. Vulnerable road user: Pedestrian	Safe road users	• Humans are vulnerable • Safety is proactive
8. Vulnerable road user: Pedalcyclist	Safe road users	• Humans are vulnerable • Safety is proactive
9. Post-crash care	Safe road users	• Humans are vulnerable • Responsibility is shared
10. Younger drivers	Safe road users	• Humans are vulnerable • Responsibility is shared
11. Older drivers	Safe road users	• Humans are vulnerable • Responsibility is shared

***Note**: A safety priority area can be associated with multiple SSA elements and principles.*

The Urban Institute found that racial gaps in wealth and access to opportunity contribute to increasing transportation inequities in many cities in the U.S., particularly in Dallas and South Dallas (Stacy et al., 2022). Case studies in these parts of Dallas, Texas, showed the necessity of addressing structural inequities in transportation by emphasizing that local governments and transit agencies should move beyond individual programs and initiatives and focus on comprehensively transforming decision-making processes. This transformation involves integrating historically excluded voices and prioritizing equity in all decision-making processes.

As part of its housing and neighborhood revitalization program, the City of Dallas considers infrastructure as one of the pillars (City of Dallas, 2024). The objective is to prioritize infrastructure investments in equity strategy target areas. Recognizing the significance of functional infrastructure in developing and preserving affordable housing, the city emphasizes targeting areas facing challenges such as low homeownership rates, low median home values, and high housing-cost burdens. Specifically, the city aims to identify key infrastructure priorities, addressing needs such as transportation enhancements. Additionally, it aims to leverage planned private investments in mixed-income housing developments, while aligning with infrastructure development guidelines outlined in adopted city plans related to equity and housing affordability.

Equity-Based Policies and Safety Programs in Washington

Washington has a long history of equity and social justice policy, and perhaps is the most comprehensive in equity policy of the three states. Recently, in 2019, the Washington legislature created the Environmental Justice Task Force to address issues of race, equity, diversity, and inclusion, including reports recommending policy and community engagement (Washington State Department of Transportation [WSDOT], 2021a). In 2021, the Healthy Environment for All (HEAL) Act was passed, which focuses on environmental and health disparities among communities of color, low-income households, and other marginalized groups. This was the first law in Washington to coordinate a state agency approach to environmental justice, including a focus on transportation safety. For example, key elements include the creation of an environmental justice council, providing a voice to disproportionately affected communities, and requiring agencies to track, measure, and report on environmental justice implementation, while also assessing benefits and burdens for vulnerable populations in investment decision-making.

In 2022, the Move Ahead Washington transportation package mandated a Complete Streets approach (which uses an SSA framework) in all transportation projects by the WSDOT on state highways exceeding $500,000 (Revised Code of Washington, 2022). The goal of Complete Streets is to accommodate *all* road users and modes of transportation (walking, biking, driving, riding transit, or any combination of modes).

Then, in 2023, the legislature adopted revisions to the Growth Management Act focusing on equity in transportation safety. These changes aim to reduce crash exposure, including supporting "*transportation-efficient land use planning*" and reducing single-occupant vehicle travel.

Washington's SHSP (WSDOT, 2024) acknowledges that disparities in access, resources, and safety exist due to many compounded decisions made over time across multiple systems. For example, less street lighting, fewer sidewalks, and higher speed arterials in some communities vs. others exist because of a ripple effect of many disparities in funding, design practices, improvements, maintenance, and developments over time. Below are the key items outlined for an equitable approach to transportation safety (WSDOT, 2024):

Washington's SHSP directly outlines an equity framework with the goal of "zero deaths and zero serious injuries by 2030" using a "systems thinking."

- Disaggregate data by population demographics (such as race/ethnicity, income, housing, disability, English proficiency, other equity-related factors) and travel mode use to gauge potential negative impacts within traditionally underserved populations.
- Understand how limited transportation options within different road design and operational contexts might affect transportation safety behaviors and how to consider these factors in safety projects and programs.
- Address differences in land-use policy and prosecution of traffic safety laws by these same demographics.
- Address improvements in all relevant systems (e.g., land-use policy, infrastructure projects, transit access) with a focus on historically underinvested communities.
- Include these affected communities in transportation safety decision-making.

The Washington's SHSP is also referred to as Target Zero, with the goal of reducing traffic deaths and serious injuries to zero by 2030 (Washington Traffic Safety Commission, 2021). A comparative analysis documented in this SHSP report reveals a concerning trend, with a 23% increase in traffic fatalities and a 7% rise in serious injuries in 2019 compared to the period of 2012–2014. These findings are particularly significant because each identified safety priority area involved at least 25% of the traffic fatalities or serious injuries during the three-year analysis period. Table 3 outlines the safety priority areas.

Table 3. Linking Washington's SHSP Priority Areas to SSA.

SHSP priority	Main SSA element	Two main SSA principles
1. Impairment involved (driver/non-motorist)	Safe road users	• Responsibility is shared • Humans are vulnerable
2. Lane departure	Safe roads	• Humans make mistakes • Redundancy is crucial
3. Speeding involved	Safe speeds	• Safety is proactive • Responsibility is shared
4. Young drivers aged 16-25	Safe road users	• Humans are vulnerable • Responsibility is shared
5. Distraction involved (driver/non-motorist)	Safe road users	• Humans make mistakes • Safety is proactive
6. Intersection-related	Safe roads	• Redundancy is crucial • Safety is proactive
7. Traffic data systems	Safe road users	• Redundancy is crucial • Safety is proactive
8. Emergency Medical Services (EMS)	Safe road users	• Humans are vulnerable • Safety is proactive
9. Evaluation, analysis, and diagnosis	Safe road users	• Redundancy is crucial • Safety is proactive
10. Cooperative automated transportation	Safe vehicles	• Redundancy is crucial • Safety is proactive
11. Unrestrained vehicle occupants	Safe road users	• Responsibility is shared • Redundancy is crucial
12. Motorcyclists	Safe road users	• Humans are vulnerable • Safety is proactive
13. Pedestrians and bicyclists	Safe road users	• Humans are vulnerable • Safety is proactive
14. Older drivers aged 70+	Safe road users	• Humans are vulnerable • Responsibility is shared
15. Heavy truck involved	Safe vehicles	• Redundancy is crucial • Safety is proactive

Note*: A safety priority area can be associated with multiple SSA elements and principles.*

A report produced by Toole Design, the Joint Transportation Committee (JTC), and the Association of Washington Cities (AWC) revealed the impacts of transportation investment patterns on designated populations in Washington's cities (Toole Design, 2023). Some of the plans, policies, and efforts aimed at creating an equitable transportation system included are as follows:

- The **AWC Equity Resource Guide** (AWC, 2021) is a valuable tool for any city in Washington. It provides a starting point to guide communities toward stronger, more equitable, and more inclusive spaces. This comprehensive guide introduces key concepts such as "Diversity," "Equity," and "Inclusion," offering clear definitions and elucidating the application of an equity lens in the assessment of potential policies and programs.

- The **JTC Statewide Transportation Needs Assessment** (BERK Consulting, 2020) evaluated long-range statewide transportation needs and priorities. This evaluation also identified existing and potential funding mechanisms to address these needs. A key finding from the study is the inadequacy of funding to meet the identified needs adequately. This limitation underscores the challenge of balancing competing needs and highlights the need to incorporate equity considerations into resource distribution decisions for effective prioritization.
- The **WSDOT Equity Study** (Barber et al., 2021) employed academic methodologies to address inquiries in four equity-related areas concerning the agency and its operations. These areas include equitable compensation in property acquisition, equity of highway construction program investments, workforce representation, and distribution of benefits for transportation investments. A significant portion of the study report concentrated on analyzing equity within the WSDOT workforce.
- **WSDOT's Anti-Racism Policy and Diversity, Equity, and Inclusion Planning** (WSDOT, 2021b) describes their renewed commitment and intentions regarding "diversity, equity, and inclusion planning" with the goal of better serving all users. This policy reaffirms a commitment to equal opportunity, while ensuring compliance with applicable laws. Notably, it recognizes the potential harm that state projects and decisions can impose on communities of color.
- Other plans include WSDOT's Strategic Planning Listening Sessions & Organizational Equity Readiness Baseline Assessment (WSDOT, 2021d), Washington Transportation Plan 2040 and Beyond (Washington State Transportation Commission, 2018), Washington State Active Transportation Plan (WSDOT, 2021c), and Puget Sound Regional Council Regional Transportation Plan (Puget Sound Regional Council, 2022). These initiatives typically commence at the state level and extend to regional and local levels. Noteworthy studies, such as the Seattle Transportation Equity Framework and Seattle Equity Analysis, further contribute to a comprehensive approach to equity considerations in transportation.

Summary

One of the current gaps in knowledge regarding equity in traffic safety is the limited understanding of how social, economic, and demographic factors intersect with crash risks and outcomes for different road users from an equity and an SSA perspective. Disparities in pedestrian, bicyclist, and MVO safety across different communities remain underexplored, particularly in relation to SSA. The current project aims to provide a guiding framework to help inform strategies to enhance equity in traffic safety in Ohio, Texas, and Washington, specifically for pedestrians, bicyclists, and MVOs.

The insights derived from the literature review were in turn multidisciplinary, data-driven, and grounded in a comprehensive framework of strategies aiming to address traffic safety equity challenges. These insights underscored the interconnectivity between transportation and non-transportation factors which collectively enhance the understanding of traffic safety equity.

Interconnected Factors Influencing Traffic Safety Equity

- Inadequate infrastructure and poor design can serve as indicators for identifying and addressing the disparities that perpetuate unequal traffic safety outcomes.
- Non-transportation factors provide multidimensional equity considerations, incorporating social and economic factors.
- Understanding both transportation and non-transportation factors are essential for devising comprehensive strategies to promote equity in traffic safety.

Several factors contributing to traffic safety inequities begin with transportation-related issues. Infrastructure disparities and shortcomings in transportation design, such as the lack of pedestrian and bicycle facilities and inadequate signage in underserved communities—predominantly home to Black and Hispanic populations—are significant contributors. The role of inadequate infrastructure and design is recognized in perpetuating disparities in traffic safety outcomes, providing a foundation for addressing these issues in the pursuit of equity in transportation systems.

In addition to transportation-related factors, evidence from the literature points to the critical role of non-transportation-related contributors. Socio-demographic and economic factors, such as lower income levels and systemic disadvantages experienced by people of color in underserved areas, are key drivers of inequities.

The non-transportation factors provide a multidimensional nature of equity considerations, incorporating social and economic factors beyond the realm of transportation infrastructure and design. These non-transportation–related factors consider a human perspective that further enriches the understanding of traffic safety inequities. This perspective includes social justice considerations and implications for public health and recognizes the broader societal context and human dynamics influencing traffic safety outcomes. Effective policies and programs targeting transportation inequities, particularly in traffic safety, should carefully consider these factors.

Through a comprehensive review of SHSPs of Ohio, Texas, and Washington, it was found that priority areas require attention to address inequities. The use of SSA was identified as a strategic approach to target and mitigate disparities in these priority areas, emphasizing a proactive and targeted intervention to enhance safety and equity in the transportation systems of these states. Additionally, there are often deficiencies in explicit acknowledgement of equity considerations within the SHSPs. No clear connections between the safety priority areas, equity, and SSA are made. This recognition underscores the need for a more deliberate and integrated approach to address equity issues within the context of SHSPs and to establish stronger connections with SSA for more comprehensive and inclusive SHSPs in Ohio, Texas, and Washington.

It is worth noting that while the safety priority areas remain consistent across the three states, their order varies, as illustrated in Table 4. This variation highlights the nuanced emphasis placed on specific safety concerns in each state, reinforcing the importance of tailoring strategies to address unique regional and equity considerations within the broader context of safety priorities.

Table 4. Variation of the Order of Safety Priority Areas across the Three States.

Ohio	Texas	Washington
1. Roadway departure	1. Roadway and lane departure	1. Impairment involved (driver/ non-motorist)
2. Intersections	2. Speed related	2. Lane departure
3. Young drivers (aged 15–25)	3. Intersection safety	3. Speeding involved
4. Speeding	4. Occupant protection	4. Young drivers (aged 16–25)
5. Impaired	5. Impaired driving	5. Distraction involved (driver/ non-motorist)
6. Older drivers (65+ years old)	6. Distracted driving	6. Intersection-related
7. Seat belts	7. Pedestrians	7. Traffic data systems
8. Connected automated vehicles	8. Pedalcyclists	8. EMS
9. Motorcycles	9. Post-crash care	9. Evaluation, analysis, and diagnosis
10. Commercial motor vehicles	10. Younger drivers	10. Cooperative automated transportation
11. Distracted driving	11. Older drivers	11. Unrestrained vehicle occupants
12. Impaired driving	-	12. Motorcyclists
13. Pedestrians and bicycles	-	13. Pedestrians and bicyclists
14. Highway railroad crossings	-	14. Older drivers aged 70+
15. Data	-	15. Heavy truck involved

Method

A variety of data sources and analytic approaches were used to assess traffic safety inequities across various racial and ethnic groups in Ohio, Washington, and Texas. Given this diverse set of data sources, the analysis is organized into three levels: individual, neighborhood, and roadway segment.

Individual Level

At the *individual level*, the analysis examined racial and ethnic disparities in crash injury severity over time, using injury rates per 100,000 population and comparisons to White populations. Disaggregating by road user type and applying an intersectional lens by age and gender, the study identified overrepresented groups in severe outcomes.

Data Sources

The Fatality Analysis Reporting System (FARS), managed by the National Highway Safety Administration (NHTSA), is a national database containing information of all known traffic fatalities in the U.S. involving at least one motor vehicle (NHTSA, 2022). The individual analysis used ten years (2013–2022) of FARS data to examine fatality trends in Ohio and Washington through time series analysis. Race and ethnicity categories for Ohio and Washington were defined based on the 1997 Office of Management and Budget (OMB) guidelines (OMB, 1997). Over 95% of traffic fatalities in both states included race/ethnicity data.

In addition to analyzing injury counts over time, crash rates per 100,000 population were calculated. These rates were based on race/ethnicity estimates from the Kaiser Family Foundation (KFF) survey, which draws on American Community Survey (ACS) data (KFF, 2023).

In Texas, inconsistencies in FARS race/ethnicity coding—especially in distinguishing between Hispanic and White individuals involved in fatal crashes—raised concerns about the reliability of trend analyses using this national database. To overcome these limitations, the individual-level analysis for Texas used six years of data (2017–2022) from the Texas Department of Transportation's Crash Records Information System (CRIS) (TxDOT, 2024). This state-specific dataset enabled a more accurate and detailed examination of regional trends and across varying levels of injury severity. Race and ethnicity classifications were based directly on definitions used in the CRIS database.

Individual-Level Analysis Framework

The individual-level analysis aimed to uncover disparities in traffic crashes over time in the following ways:

1. Examining trends in traffic fatality risks over time across racial and ethnic groups to highlight historical inequities in transportation systems.
2. Breaking down injury severity outcomes (i.e., fatalities, incapacitating injuries, and non-incapacitating injuries) by road user types such as pedestrians, bicyclists, and MVOs to account for their unique vulnerabilities related to crash speed, vehicle design, conspicuity issues, and the lack of adequate infrastructure that disproportionately impacts their safety.
3. Estimating injury severity rates per 100,000 population and calculating ratios relative to the White population to emphasize the systemic disparities that have affected minority groups (Glassbrenner et al., 2022).

4. Conducting an intersectional analysis of injury outcomes by gender and age within each racial and ethnic group, standardized by population share, to identify disproportionate impacts. This analysis is further described below.
5. Applying advanced modeling techniques to individual-level CRIS data from Texas to examine injury severity disparities across racial and ethnic groups for pedestrians, bicyclists, and MVOs, enabling a deeper understanding of inequities in crash outcomes (see section below).

Intersectional Analysis. An intersectional analysis of race/ethnicity, gender, and age was conducted to examine disparities in traffic injury outcomes among pedestrians, bicyclists, and MVOs. The analysis included: (a) calculating the percentage of injury outcomes by gender and age within each racial-ethnic group, and (b) computing counts and percentages per 1,000 based on the median population for each gender–age group within each racial-ethnic category. This approach highlights whether a group's injury involvement is above or below its population share, offering insights into relative impacts across demographics. Crash data were sourced from FARS for Ohio and Washington and CRIS for Texas. Population estimates by age, gender, and race/ethnicity were obtained from the ACS (United States Census Bureau, 2024). More details regarding this analysis can be found in Appendix A.2.

Statistical Analysis of Texas Using Random Parameter (RP) Binary Logit Model. Because the Texas crash database, i.e., CRIS, includes race and ethnicity data, it was possible to perform an advanced statistical analysis revealing a deeper understanding of inequities across varying levels of injury severity. FARS, by contrast, captured only fatalities as a severity level. In the CRIS database, crash outcomes are categorized into five levels of injury severity using the KABCO scale: killed (K), incapacitating injury (A), non-incapacitating injury (B), possible injury (C), and not injured (O) (National Safety Council, 1990). This analysis focused on the most severe outcomes (K and A), aligning with SSA and Vision Zero goals, which promote equitable, shared responsibility in safety planning to reduce serious injuries and fatalities. Changes in travel patterns necessitate dividing the analysis into pre-COVID (2018–2019) and post-COVID (2021–2022) periods (Vingilis et al., 2020).

A wide range of crash-related variables from the CRIS database—including road-user demographics, infrastructure features, environmental conditions, vehicle characteristics, and contributing behaviors—were incorporated into the RP binary logit model. These variables were selected based on prior research and their relevance to injury outcomes. More details regarding this analysis can be found in Appendix A.4.

Neighborhood Level

In the *neighborhood-level* analysis, disparities in crash injury rates were assessed by aggregating counts of MVOs, pedestrians, and bicyclists with killed or incapacitating injuries (KA injuries) at the census tract level across Ohio, Washington, and Texas. Building on the individual-level findings, this analysis connects personal injury outcomes to broader geographic patterns by incorporating sociodemographic, economic, and population characteristics, along with factors influencing access to safe transportation. By examining these patterns, the analysis highlights the need for targeted interventions to reduce injury and fatality rates in underserved areas.

Neighborhood Data Sources

Table 5 presents the data sources utilized for the neighborhood analysis covering the pre-COVID (2018–2019) and post-COVID (2021–2022) periods. The analysis incorporated five key data categories: crash data, road geometry and inventory, sociodemographic and economic data, area type, and other data, such as school and transit stop locations.

All data were aggregated at the census tract level (Table 5). For point data such as crashes, schools, and transit stops, 50-foot buffers were created around each point. A 50-foot distance was selected to capture immediate proximity effects, ensuring that points were associated with the most relevant surrounding census tracts without overextending their influence. These points were then assigned to all census tracts intersecting the buffers.

Roadway features were segmented to include only the portions falling within each census tract. Most equity-related data were sourced from the 2022 Social Vulnerability Index (SVI) database (Centers for Disease Control and Prevention [CDC], 2022), while job-related variables were derived from the 2021 Smart Location Database (SLD) database (U.S. Environmental Protection Agency & U.S. Department of Transportation, 2020). Four area types were considered: city, suburban, town, and rural. The area type with the largest proportion in a tract was used to classify the entire tract, with most census tracts having over 80% of their area classified under a single type. School data included public and post-secondary schools, with data provided by National Center for Education and Statistics (NCES) for the 2022–2023 school year.

Table 5. Neighborhood Analysis Data Sources.

Data	Ohio	Texas	Washington
Crash data	Ohio Department of Public Safety (ODPS)	Crash Records Information System (CRIS)	WSDOT Public Disclosure Request Center
Roadway geometry/ inventory and traffic data	Transportation Information Mapping System (TIMS)	Texas Roadway Inventory	WSDOT Geospatial Open Data Portal
Equity-related/ sociodemographic and economic data	SVI and SLD	SVI and SLD	SVI and SLD
Area type	NCES	NCES	NCES
Schools (locations)	NCES	NCES	NCES
Transit stops (locations)	TIMS	Transit stop locations are provided only for some major cities	WSDOT Geospatial Open Data Portal

Neighborhood-Level Analysis Framework

The neighborhood-level analysis aimed to identify area-based factors contributing to disparities in KA injuries across Ohio, Washington, and Texas in the following ways:

1. Aggregating counts of MVO, pedestrian, and bicyclist KA injuries at the census tract level to align with individual-level insights.
2. Using non-parametric tests to assess if significant differences exist in KA injury counts across census tracts between pre-COVID (2018–2019) and post-COVID (2021–2022) periods, determining whether separate models are required for each period.
3. Developing advanced statistical count models for pedestrians, bicyclists, and MVOs based on the findings from the non-parametric test, to evaluate how sociodemographic, economic, and environmental factors influence injury risks, with population used as an offset to represent individuals at risk. The population at the census tract level was used as an offset in the modeling process to identify factors contributing to disparities in crash rates across neighborhoods in the three states. For more information about the neighborhood methodology, see Appendix B.3.

Road Segment Level

Finally, in the *roadway segment-level* analysis, roadway safety potential was evaluated—rather than historical crash outcomes—by measuring infrastructure readiness to prevent serious injury crashes. This approach aligns with the SSA, which emphasizes preventing fatal and serious injuries. It offers a proactive, human-centered assessment that identifies underserved areas where infrastructure improvements could mitigate future traffic injuries and fatalities. The analysis also explored how disparities in safety potential are patterned by neighborhood-level socioeconomic and demographic characteristics, providing insights into the systemic factors contributing to roadway safety inequities.

Road Segment Data Sources

The SSA Scoring method required detailed roadway inventory data. As such, the scope of analysis was narrowed down to the city level rather than the state level. The selection of the case study cities was driven by the availability of comprehensive and in-depth data. One case study city was selected for each of the three study states: Cleveland (Ohio), Seattle (Washington), and Austin (Texas). Several cities, such as Columbus and Cincinnati in Ohio, Tacoma and Olympia in Washington, and Houston, Dallas, San Antonio, and El Paso in Texas, were considered for selection, but were not selected due to limitations in data availability.

The data sources for implementing the scoring framework and examining systemic factors in roadway safety inequities included the following:

- Geodatabases of respective cities[2,3,4]—the source of roadway shapefiles, including geometry, roadway features, traffic volume, and posted speed limit
- Open Street Map (OpenStreetsMap Foundation, n.d.)[5]—an additional source of roadway geometric characteristics, i.e., number of lanes, lane width, etc.
- Crash Data—a surrogate source of information at roadway segments with missing data, i.e., lighting condition, roadway features, etc.
- ACS (U.S. Census Bureau, 2024)[6]—source of demographic information

[2] https://data.austintexas.gov/browse?limitTo=maps&sortBy=relevance&page=1&pageSize=20
[3] https://data.clevelandohio.gov/search?collection=App%2CMap
[4] https://data-seattlecitygis.opendata.arcgis.com/
[5] https://openstreetdata.org/
[6] https://www.census.gov/programs-surveys/acs/data.html

- SVI Data (CDC, 2022)—a comprehensive tool used to identify communities that are more vulnerable to various risks due to socioeconomic factors

Data preparation and processing for scoring roadway segment safety potential involved segmenting, merging, and conducting quality checks. Roadway segments with uniform characteristics—such as the number of lanes, lane width, median width, Annual Average Daily Traffic (AADT), and posted speed limit—were identified. At the same time, interstate facilities were excluded to focus on roadways accessible to vulnerable users. Merging and quality checks ensured consistency by integrating multiple data sources and aggregating them at the segment level. Scoring was applied to non-intersection segments only, as intersections require additional detailed data for accurate evaluation.

After scoring, socioeconomic, and demographic data from the SVI database (CDC, 2022) were spatially merged with the roadway segments. This step enabled the examination of systemic factors contributing to roadway safety inequities.

Road Segment-Level Analysis Framework

The road segment-level analysis evaluates roadway safety potential—rather than crash history—through a proactive, equity-focused framework that does the following:

1. Scores roadway segments using the FHWA SSA project-based alignment framework (FHWA, n.d.).
2. Links contextual data by merging census tract-level socioeconomic and demographic indicators from the CDC's SVI with the scored roadway segments.
3. Applied Structural Equations Modeling (SEM) to examine the relationships among demographic and socioeconomic factors and SSA Scores. See Appendix C.1 for more information regarding the segment analysis framework.

Results

Following from the method section, the analysis is organized into three levels: individual, neighborhood, and roadway segment. At the *individual level*, the study examined injury severity disparities among pedestrians, bicyclists, and MVOs. By modeling injury severity outcomes and utilizing race and ethnicity data, it highlighted inequities in exposure to varying levels of injury severity, offering critical insights into traffic safety disparities across racial/ethnic groups.

The *neighborhood-level* analysis investigated crash injury rates at the census tract level across the three states. By integrating sociodemographic, economic, and road-related factors, the evaluation identified neighborhood characteristics contributing to disparities in crash rates. The findings aim to inform targeted interventions to reduce injury and fatality rates in underserved communities.

Finally, the *roadway segment-level* analysis evaluated the safety potential of roadways based on their alignment with SSA goals, which emphasize preventing fatal and serious injuries. This proactive analysis assessed infrastructure readiness to mitigate high-risk crash scenarios and identified areas where improvements could reduce future injuries and fatalities.

Together, these analyses provided a multi-faceted understanding of traffic safety inequities and laid the groundwork for targeted strategies to promote equity and reduce disparities in traffic injury outcomes.

In the subsections that follow, only selected or illustrative tables and figures are included alongside the text. To increase readability, comprehensive information is relegated to an associated appendix. Specific details are noted by section and key results or highlights can be hyperlinked to the relevant table or figure. After hyperlinking to a figure, table, or Appendix, readers can return to their previous location by pressing Alt+Left Arrow.

Individual Level Analysis

The *Individual Analysis* section presents a comprehensive analysis of traffic fatalities and injuries across Ohio, Washington, and Texas, highlighting disparities among pedestrians, bicyclists, and MVOs by race and ethnicity (see Appendix A for complete details). For Ohio and Washington, a decade-long (2013–2022) analysis using FARS data identifies critical disparities in traffic fatalities across racial and ethnic groups. In Texas, a six-year (2017–2022) analysis using CRIS data reveals significant disparities in fatal, incapacitating, and non-incapacitating injuries among these groups. These findings provide a foundation for developing targeted interventions to address traffic safety inequities in the three states. Beyond exploratory analysis, this study leverages CRIS data's detailed inclusion of race and ethnicity to examine factors influencing injury severity among pedestrians, bicyclists, and MVOs. Using a RP binary logit model, the analysis evaluates disparities in crash risks before and after the COVID-19 pandemic, identifying consistent and emerging risk factors for each group. The following sections summarize key findings by race and ethnicity and road user type, offering insights to guide equitable and effective traffic safety strategies.

Trends in Traffic Fatalities and Injury Rates by Race and Ethnicity

Ohio. Table A.1 presents the annual count of traffic fatalities in Ohio from 2013 to 2022. It is evident that there is an overall increasing trend in the number of fatalities in Ohio. Over 90% of the observed fatalities were distributed among Whites and Blacks, with Whites constituting a significantly larger portion. While the total fatalities increased from 989 in 2013 to 1,275 in 2022 (28.9% increase), the proportion of Whites in fatal crashes decreased from 84.3% in 2013 to 74.6% (9.7% decrease) in 2022. However, the proportion of traffic fatalities for Blacks increased from 11.5% to 18.4% and from 1.8% to 4.3% for Hispanics.

Traffic fatality trends among different races and ethnic groups were investigated during the same decade, this time by calculating fatalities per 100,000 population. As shown in Figure 1, in Ohio, Blacks and American Indian or Alaska Native (AIAN) groups had the highest fatality rate, which has been increasing over the years. The fatality rate for AIAN rapidly increased in 2022 at around 2.7 times the statewide average rate. The rates for Blacks increased significantly from 2019 through 2021, peaking at 1.7 times the statewide average rate, then decreased in 2022. In Ohio, Whites and Hispanics had generally lower fatality rates compared to Blacks and AIAN. Nonetheless, the fatality rates of Hispanics doubled, increasing from 5 fatalities per 100,000 population in 2013 to over 10 traffic fatality rates per 100,000 population in 2022. Asians had the lowest observed rates throughout the 10-year study period and Native Hawaiian and Pacific Islander (NHPI) had very low recorded involvement in crashes, although their rate per 100,000 population fluctuated.

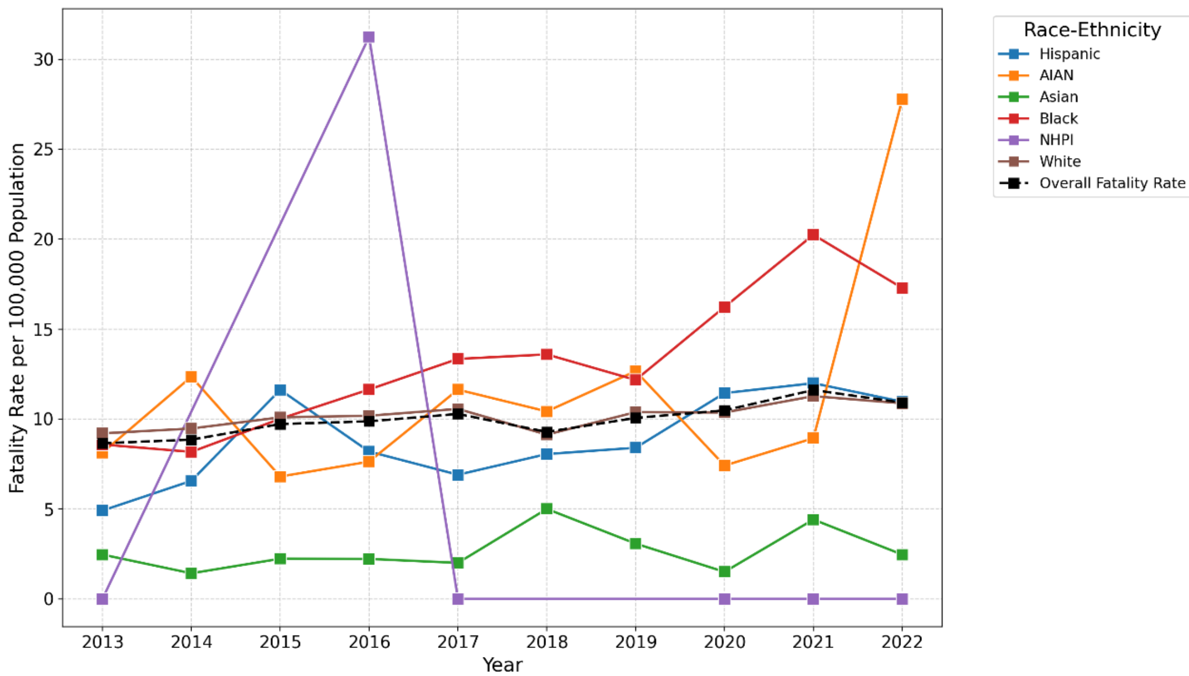


Figure 1. Fatality Rate in Traffic Crashes Per 100,000 Population in Ohio, by Race/Ethnicity, 2013–2022

To assess changes in disparities over time, the injury rate per population relative to White people was determined for each race/ethnicity group, as shown in Table A.2 . In Ohio, the relative fatality rate per population for Blacks increased from 0.93 in 2013 to 1.59 in 2022. This means that the fatality rate for Blacks was 7% lower than Whites in 2013, and the rate increased to 59% higher than Whites by 2022. Hispanics also had a fatality rate 47% less than Whites in 2013, which increased to 1% higher by 2022. More noticeably, the AIAN fatality rate changed from 12% less than Whites in 2013 to 156% higher than Whites in 2022. Asian fatality rates remained low relative to Whites throughout the 10-year study period.

Motor Vehicle Occupants. MVO fatalities in Ohio increased by 24.6% from 2013 to 2022 (Table A.3), with growing racial and ethnic disparities over time.

- Asian MVOs were the only group (along with NHPI) whose fatality rates did not increase over the 10-year period (Figure A.3).
- Black MVOs experienced a notable increase in both their fatality rate and their share of total fatalities, rising from 10.6% in 2013 to 17.2% in 2022 (Table A.3). Their fatality rate shifted from 15% lower than Whites in 2013 to 46% higher in 2022 (Table A.4), consistently exceeding the statewide average in several years.

- AIAN MVOs had some of the highest fatality rates throughout the period. Their rate rose from just below that of Whites in 2013 to nearly three times the statewide average in 2022, 193% higher than the White rate (Table A.4).
- Hispanic MVOs saw steady increases, shifting from 50% lower fatality rates than Whites in 2013 to 7% higher by 2022 (Table A.4).

Pedestrians. Over the 10-year study window (2013–2022), pedestrian fatalities increased sharply in Ohio—an 88.2% increase overall—yet the magnitude and trajectory of that rise varied markedly by race and ethnicity. These results are summarized in Table A.3.

- White pedestrians accounted for 67% of all pedestrian fatalities and, while their absolute numbers grew, their per capita fatality rate stayed below the statewide average throughout the study period (Figure A.1).
- Black pedestrians comprised a quarter of fatalities but experienced the highest risk: their fatality rate increased from approximately 1.5 per 100,000 in 2013 to over 3.0 per 100,000 in 2022, more than double the statewide average by the end of the period (Figure A.1). The relative pedestrian fatality rate for Black pedestrians increased from 2.04 in 2013 (104% higher than Whites) to 2.73 in 2022 (173% higher) (Table A.4).
- Hispanic pedestrians made up 5.2% of pedestrian fatalities (Table A.3) and their per capita fatality rate peaked at 2.5 per 100,000 in 2018, nearly twice the statewide average that year (Figure A.1).
- Asian pedestrians maintained the lowest per capita rates each year, with only minor fluctuations that stayed below the statewide mean (Figure A.1).

Bicyclists. Bicycle fatalities in Ohio generally declined from 2013 to 2022 (Table A.3), and fatality rates remained low (below 1 per 100,000 population) across all racial and ethnic groups. However, racial disparities in bicyclist safety persisted and, in some cases, worsened. Key findings based on Figure A.2 and Table A.4 include the following:

- White bicyclists maintained relatively stable and consistently low fatality rates over the decade (Figure A.2).
- Black bicyclists experienced the highest fatality rates in several years, peaking in 2021 at approximately 2.6 times the statewide average (Figure A.2). Their rate shifted from being 29% lower than that of Whites in 2013 to 36% higher in 2022 (Table A.4).
- Asian bicyclists saw the steepest relative increase. Their fatality rate was 100% lower than Whites from 2013–2016 but rose sharply, reaching 100% higher in 2017 and 217% higher in 2022 (Figure A.2).

Texas. Table A.5 shows annual counts of traffic *fatality*, *incapacitating*, and *non-incapacitating injuries* in Texas from 2017 to 2022. Fatalities increased by 18%, from 3,743 in 2017 to 4,426 in 2022. Whites and Hispanics accounted for most fatalities, with Whites' share declining from 51.1% in 2017 to 44.9% in 2022, while Hispanics' proportion rose from 30% to 36.4%. Incapacitating injuries mirrored fatality trends, with Whites having the largest share but declining from 48.5% to 43% over the same period. Hispanics saw a steady increase in their share of injuries, rising from 30.5% in 2017 to 35.1% in 2022. Non-incapacitating injuries showed even higher counts, with Hispanics comprising 38.1% in 2022, the highest proportion among all race/ethnicity groups. These data highlight persistent racial and ethnic disparities in Texas traffic injuries, with increasing Hispanic and Black representation and a decreasing share for Whites.

Figure 2 shows the fatality rates by race/ethnicity group in Texas from 2017 to 2022 (Figures A.4 and A.5 show similar information for incapacitating and non-incapacitating injuries*)*. As illustrated in Figure 4, the AIAN and Black populations had the highest fatality rates during this period. The AIAN rate increased significantly, peaking in 2021 at 30 fatalities per 100,000 population, with a slight drop in 2022, but remaining the highest. At their peak in 2021, AIAN individuals experienced fatality rates twice as high as the overall average rate. Black populations also faced an increased risk. Black fatality rates rose, peaking over 20 per 100,000 population in 2021 before decreasing in 2022, with the rate 1.5 times higher than the overall average in 2021. Furthermore, White individuals also had fatality rates 1.2 times above the statewide overall rate in 2021. Asians consistently had the lowest fatality rates.

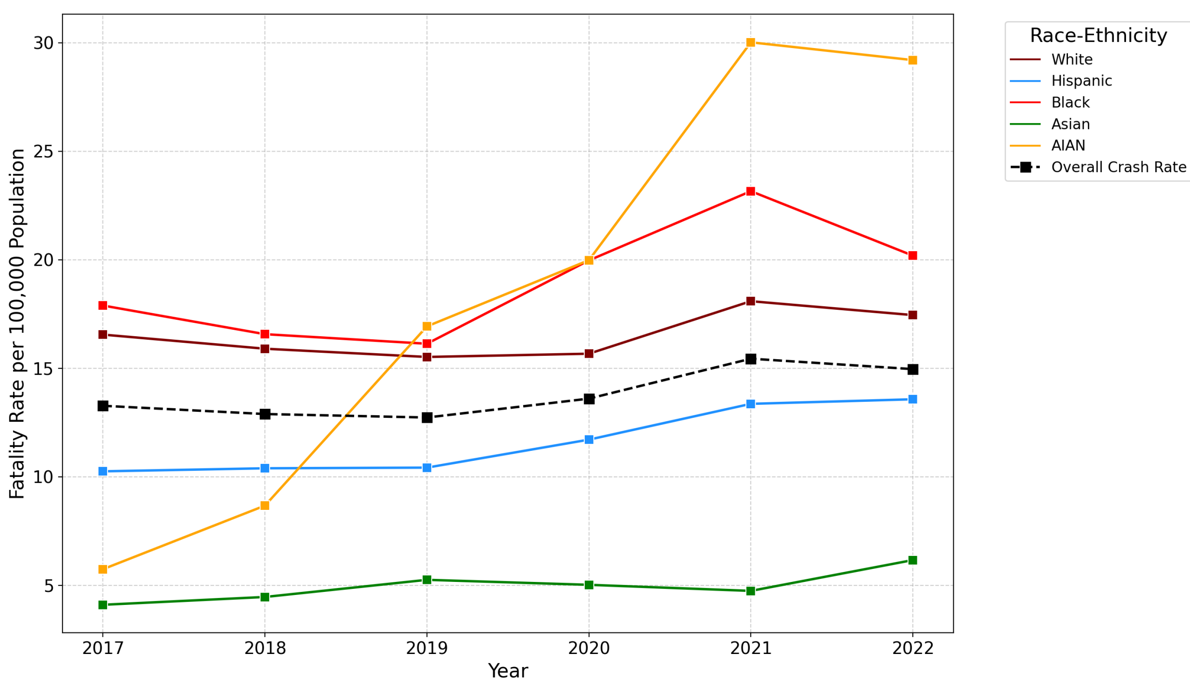


Figure 2. Fatality Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

Figure A.4 shows that AIAN populations experienced consistently rising incapacitating injury rates from 2017, sharply rising after 2020 to nearly 200 per 100,000 population, three times higher than the overall rate. The Black population also experienced high rates, starting at nearly 85 per 100,000 population in 2017, peaking at over 100 per 100,000 in 2021, and slightly declining in 2022, reaching about 1.3 times higher than the overall rate in 2021 and remaining above pre-COVID levels even after a slight decline by 2022. White individuals had a risk slightly above the overall rate, peaking at 1.1 times higher than the overall rate in 2021. Asians had consistently low rates throughout the study period.

Figure A.5 shows that Black populations consistently had the highest non-incapacitating injury rates, often around 1.6 to 1.7 times higher than the overall rate throughout the study period. Initially below the overall rate, AIAN populations underwent a striking surge after 2020, reaching 2.7 times higher than the state average by 2022. In contrast, the White population injury rate generally hovered near the state average rate. These disparities underscore the fact that, even as the overall rate shifted over time, Black and AIAN communities bore a disproportionate share of non-incapacitating injuries.

As shown in Table A.6, in Texas, AIAN fatality rates were initially 65% lower than those of Whites in 2017 but rose steadily to 67% higher by 2022. Similarly, Black population fatality rates, which were 8% higher than those of Whites in 2017, climbed to 16% higher by 2022. Disparities were especially pronounced in 2020 and 2021, likely reflecting broader COVID-related road safety impacts.

For incapacitating injuries, in Texas, AIAN rates were 52% lower than Whites in 2017, and sharply increased to 172% higher by 2022. The Black injury rate rose from 24% higher than that of Whites in 2017 to 43% higher by 2022. Hispanic individuals, initially 34% lower than Whites, saw their disparity narrow to 21% by 2022. Among AIAN individuals in Texas, non-incapacitating injury rates, which were 50% lower than those of Whites in 2017, rose to over three times that of Whites by 2022. Black individuals' injury rates steadily increased, with rates 51% higher than those of Whites in 2017, widening to 78% by 2022.

Motor Vehicle Occupants. Among MVO fatalities, Hispanic fatalities steadily increased, while White fatalities, though highest in number, declined proportionally.

- White MVOs had the largest absolute numbers of fatalities and injuries but a declining share over time (Table A.7 through Table A.9).
- Asian individuals consistently had the lowest and most stable rates.
- AIAN fatality rates rose from 48% lower than Whites in 2017 to 78% higher in 2022 (Table A.11). Their incapacitating injury rates exceeded three times the

statewide average by 2022 (Figure A.13), and non-incapacitating injuries peaked above 500 per 100,000—2.7 times the state average (Figure A.14).

- Black individuals had elevated fatality rates, peaking at 31% higher than Whites in 2020. Their non-incapacitating injury rates increased from 89% to 111% higher than Whites (Table A.11).
- Hispanic rates increased across all categories, with fatalities shifting from 32% lower than Whites in 2017 to 10% lower in 2022. Non-incapacitating injury rates also rose from 2% lower to 13% higher than Whites (Table A.11).

Pedestrians. Pedestrian safety outcomes in Texas from 2017 to 2022 revealed persistent racial and ethnic disparities in both fatalities and injuries.

- White pedestrians accounted for the largest share of fatalities throughout the period but experienced a proportional decline. Fatalities decreased from 43.1% in 2017 to 38.9% in 2022 (Table A.7).
- Hispanic pedestrians saw a steady increase in fatalities, which rose from 31.3% to 36.6% (Table A.7).
- As indicated in Figure A.6, Black pedestrians consistently had fatality rates nearly twice the statewide average.
- Although the absolute numbers were small (Table A.7), AIAN pedestrians experienced exponential increases, with fatality rates peaking in 2020 and reaching nearly double the state average by 2022 (Figure A.6).
- Asian pedestrians consistently had the lowest fatality rates across all years.

Bicyclists. Similar to pedestrians, bicyclist injury outcomes in Texas revealed racial and ethnic disparities in both fatalities and injuries.

- White bicyclists consistently had the highest number of fatalities and injuries, though their share of fatalities declined slightly from 58.6% in 2017 to 53.3% in 2022 (Table A.7).
- Hispanic bicyclist fatalities rose sharply, from 20.7% in 2017 to 35.6% in 2021 (Table A.7).
- Black bicyclists generally experienced higher fatality rates than Whites, peaking at 1.75 times the White rate in 2019 before declining (Table A.11). They also had the highest incapacitating injury rates, exceeding White rates by up to 35% in 2020, and led in non-incapacitating injury rates until 2020.
- The incapacitating injury rate of AIAN relative to Whites surged by 149% in 2022 (Table A.11), and their non-incapacitating injury rates fluctuated, peaking at twice the average in 2021 (Figure A.11).
- Asian bicyclists consistently had low rates across all injury categories.

Washington. In the case of Washington (Table A.13), Whites constituted most of the observed fatalities but saw a decrease in their proportion from 75.2% in 2013 to 63.4% in 2022. Hispanics constituted the second highest proportion, which remained relatively constant over the ten years. As indicated in Figure 3, throughout the study period, AIAN individuals in Washington consistently had the highest fatality rates. At the same time, NHPI also exhibited significantly higher rates than those observed in Ohio. Fatality rate trends for Hispanics, Blacks, and Whites remained relatively stable. Similar to Ohio, Asian fatality rates in Washington were consistently low.

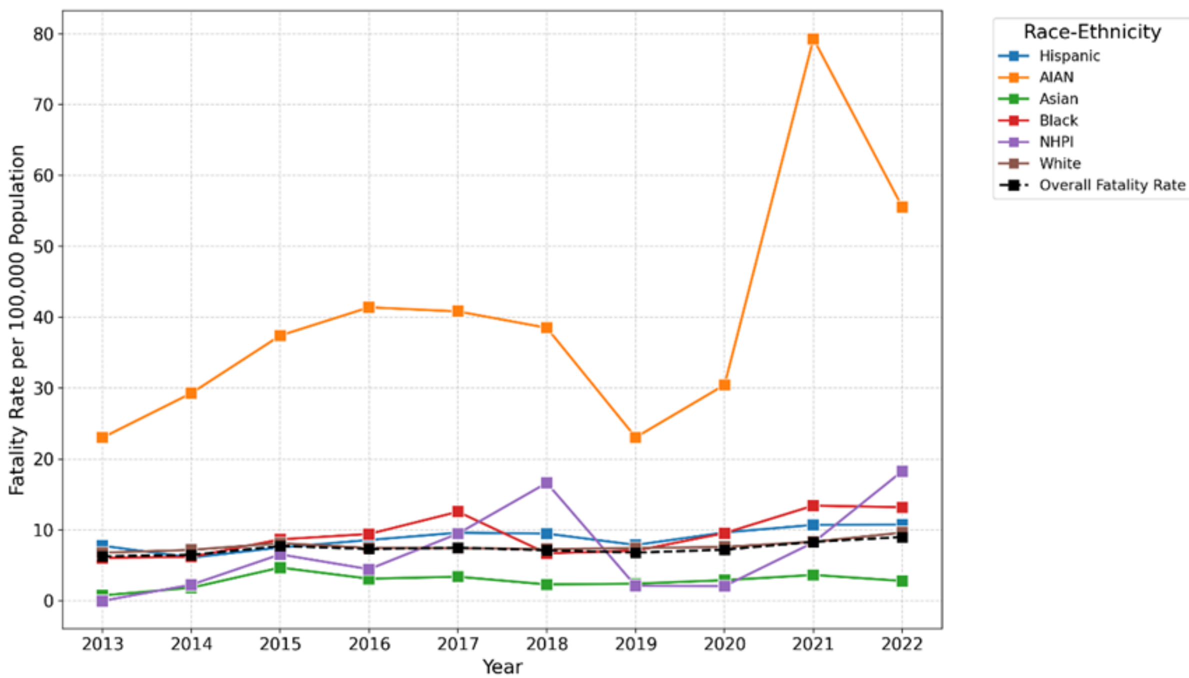


Figure 3. Fatality Rate in Traffic Crashes Per 100,000 Population in Washington, by Race/Ethnicity, 2013–2022

In Washington (Table A.14), AIAN, Blacks, and NHPI all experienced increased fatality rates relative to Whites from 2013 to 2022. NHPI experienced a change from 62% lower fatality rates than Whites in 2014 to 90% higher fatality rates in 2022.

Motor Vehicle Occupants. Washington also experienced an upward trend in MVO fatalities. The number of fatalities increased by 57.9%, rising from 375 in 2013 to 592 in 2022 (Table A.15). Other key findings include the following:

- White MVOs consistently accounted for the majority of fatalities, though their share declined from 77.1% in 2013 to 62.7% in 2022 (Table A.15).
- Hispanics had the second highest share of fatalities, with steady increases throughout the period.
- AIAN individuals had the highest fatality rates per 100,000 population, often 4 to 5 times the statewide average, peaking at 57.7 in 2021 compared to under 10

statewide (Figure A.17). Their rate rose from 135% higher than Whites in 2013 to 468% higher in 2022 (Table A.16).

- Black MVOs showed rising rates, shifting from 20% lower than Whites in 2013 to 40% higher by 2022 (Table A.16).
- NHPI MVOs experienced sharp increases, with rates peaking at 2.5 times the statewide average (Figure A.17); their rates shifted from 3% lower than Whites in 2015 to 139% higher in 2022 (Table A.16).
- Asians consistently had the lowest and most stable fatality rates, similar to trends observed in Ohio.

Pedestrians. As indicated in Table A.15, in Washington, pedestrian fatalities increased by 157.1% from 2013 to 2022. Hispanics, AIAN, and Black individuals consistently had higher relative pedestrian fatality rates compared to Whites (Table A.16). Other groups maintained consistently low rates with minor fluctuations. Figure A.15 shows clear disparities in pedestrian fatality rates across racial and ethnic groups in Washington over time. Key findings include the following:

- AIAN pedestrians had the highest pedestrian fatality rates, rising from 6.3 per 100,000 population in 2013 to 20 in 2021—approximately 12 times the statewide average.
- Black pedestrian fatality rates increased notably from 2018, peaking in 2021 at 2.3 times the statewide average.

Bicyclists. Similar to Ohio, bicyclist fatalities in Washington remained relatively steady over the 10-year period (Table A.15), with overall fatality rates low across all racial and ethnic groups (Figure A.16). However, significant disparities persisted for certain populations:

- AIAN bicyclists experienced the highest fatality rates overall, with peaks in 2016, 2018, and 2021, exceeding twice the statewide average (Figure A.16).
- Black bicyclists had the highest single-year fatality rate in 2020, reaching 3.4 times the statewide average (Figure A.16).
- Other groups, including Whites, generally maintained low and stable rates throughout the period (Figure A.16).
- By 2022, all minoritized racial and ethnic groups had lower fatality rates than Whites (Table A.16).

Intersectional Analysis by Race/Ethnicity, Gender, and Age

An intersectional analysis by race/ethnicity, gender, and age was conducted by comparing injury outcomes to the median population, highlighting over- or under-representation across demographic groups. Figure 4, for instance, shows that in Texas, Black (21% crashes vs. 9% population) and Hispanic (35% crashes vs. 22% population) female pedestrians aged 55+ are overrepresented in fatal crashes. In comparison, White females pedestrians aged 55+ (41% crashes vs. 61% population) are underrepresented. Findings significant at the 95% confidence interval for different groups are highlighted below.

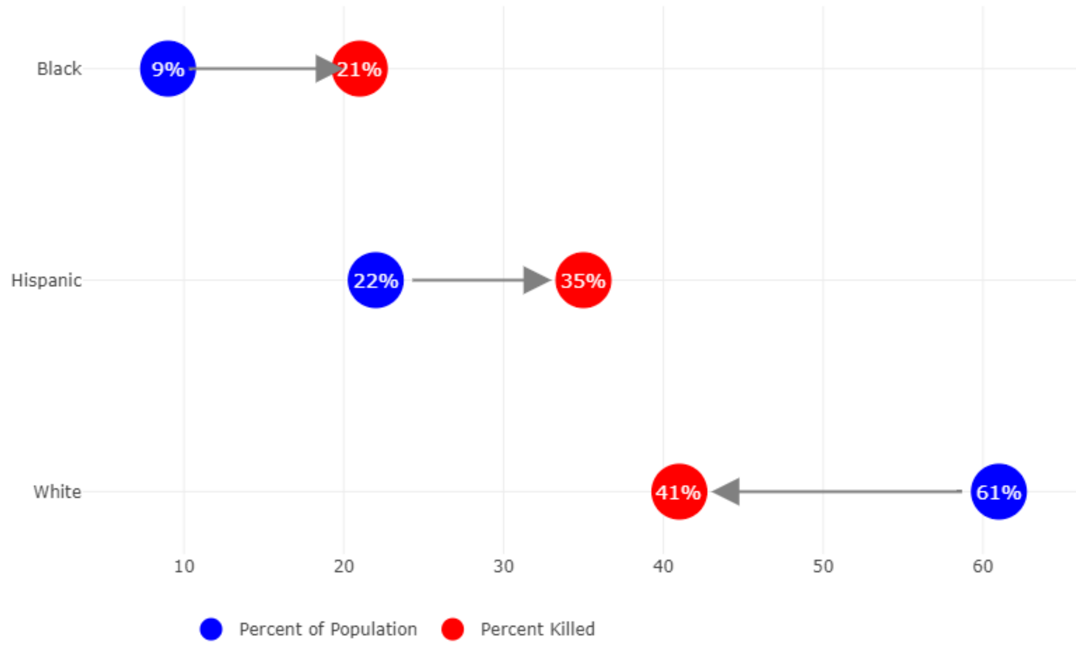


Figure 4. Intersectional Analysis Results for Female Pedestrians 55 Years and Older in Texas

Ohio.

- Black male pedestrians aged 18 or younger and those aged 35–54 years were the most overrepresented male groups in fatal pedestrian crashes, exceeding their median population proportions by 28.8% and 12.5%, respectively (Table A.17).
- Black female pedestrians aged 18–34 years were significantly overrepresented, with their fatality proportion (34.3%) exceeding their median population proportion by 20% (Table A.17).
- Among bicyclists, White females aged 35–54 years were significantly overrepresented in fatal crashes, with fatalities 19.5% higher than their median population proportion (Table A.18).
- Black female bicyclists aged 55 and older faced significant overrepresentation, with their fatality proportion (22.2%) exceeding their median population proportion by 12.7% (Table A.18).

Texas.

- Black female pedestrians were significantly overrepresented across all age groups in fatalities (except those under 18), as well as in incapacitating and non-incapacitating injuries, with overrepresentation ranging from 8.9% to 14.5% (Table A.20; Table A.21; Table A.22).
- Black male pedestrians showed similar patterns across all injury severities, except for fatalities in the 35–54 years and 55+ years age groups.
- White male pedestrians aged 35–54 years were overrepresented in fatalities by 13.1% (Table A.20).
- Hispanic female pedestrians aged 55+ were significantly overrepresented in fatalities and non-incapacitating injuries, with a similar trend observed for Hispanic males 55+ (Table A.20; Table A.21).
- White male and female bicyclists were significantly overrepresented across most age groups in incapacitating and non-incapacitating injuries (Table A.23; Table A.24; Table A.25).
- Black male bicyclists aged 18 years and younger were overrepresented in non-incapacitating injuries by 8.2% (Table A.25).
- White male MVO occupants were overrepresented in fatality across all age groups except those aged 55+. The overrepresentation ranged from 7.1% to 12.9% (Table A.26).
- Hispanic female MVO occupants were overrepresented in fatality by 5.7% in the 18–34 age group (Table A.26).
- Black male MVO occupants were significantly overrepresented across all age groups in non-incapacitating injuries (Table A.28).
- Black female MVOs were overrepresented in non-incapacitating injuries in all groups except those aged 55+ (Table A.28).

Washington.

- White female bicyclists were significantly overrepresented in fatalities, particularly in the under-18, 35–54, and 55+ age groups.
    - Among bicyclists under 18, White females accounted for 100% of fatalities, exceeding their population proportion of 61.1% by 38.9% (Table A.30).
    - White female bicyclists aged 35–54 surpass their median population proportion of 71.3% by 28.7% (Table A.30).
    - White female bicyclists aged 55+ accounted for 100% of fatalities in their category, exceeding their base proportion of 86% by 14% (Table A.30).

- These findings highlight critical vulnerabilities among White female bicyclists across various age groups.
- White male bicyclists aged 35–54 (86.1%) were also notably overrepresented in fatal crashes, surpassing their base population proportion of 71.9% by 14.3% (Table A.30).

Analysis of Texas Individual Data Using the State Crash System

Table A.32 through Table A.34 in Appendix A.4.1 summarizes injury trends in Texas for the three road user types. The results for six random parameter models presented in this section include the three road user types, i.e., pedestrians, bicyclists, and MVOs, examined during pre- and post-COVID periods; however, only post-COVID results are described in the text. Appendix A.4.2 provides additional details regarding the analysis. Table A.35 through Table A.40 in Appendix A.4.3 present the fixed effect estimates of each factor across all racial/ethnic groups and the group-specific random coefficients for the pre- and post-COVID models. The inclusion of random variables was justified using likelihood ratio tests and comparisons of log-likelihood values (Cousineau & Allan, 2015).

The effect of the variables was assessed using odds ratio (OR) interpretation, where the overall effect of a variable in increasing the likelihood of KA injury crash for a given category of the variable compared to the reference category is given as OR = $e^{(FE)}$, where FE is the fixed effect coefficient. In addition, the effect for a specific racial group in terms of OR is obtained as $e^{(FE + RE)}$ (Baayen et al., 2008), where RE is the random coefficient for that group. The discussion focuses on statistically significant variables identified at a 95% confidence level where p-values are less than 0.05.

The findings highlight the importance of considering both fixed and random effects in crash modeling to understand and address systemic disparities. The results underscore the need for targeted interventions, such as enhanced enforcement and education on impaired driving, improved lighting and infrastructure in areas with high minority populations, and speed management programs tailored to address the groups most affected by speeding-related crashes. By addressing these disparities, efforts to improve roadway safety can be made more equitable and effective across all demographic groups.

Pedestrian Injury Severity based on Roadway Environment. The final pedestrian RP models included nine variables, with two fixed effects and seven varying by race/ethnicity based on findings from prior studies (Roll & McNeil, 2022; Sanders &

Schneider, 2022). In the post-COVID (2021–2022) model (see Table A.36), several fixed effects were linked to increased fatal and serious injury risks for pedestrians:

- Roads with 30–40 mph posted speed limits were 3.68 times riskier, and those with 45+ mph limits had a 7.07 times risker than roads under 25 mph.
- Poor lighting also increased risks, with dark–not-lighted (OR = 3.55) and dark–lighted conditions (OR = 2.31) increasing risk.
- AIAN pedestrians had heightened risks in older age groups (35–54 and 55+) compared to the young age group (under 18).
- Heightened risks for AIAN were observed under higher posted speed limits (30–40 mph and 45+ mph) compared to lower posted speed limits (under 25 mph).

Race/ethnicity disparities were evident in the effects of lighting conditions. Figure 5 presents the effect of lighting conditions on different racial/ethnic groups, showing the OR for KA injury outcomes during the post-COVID period.

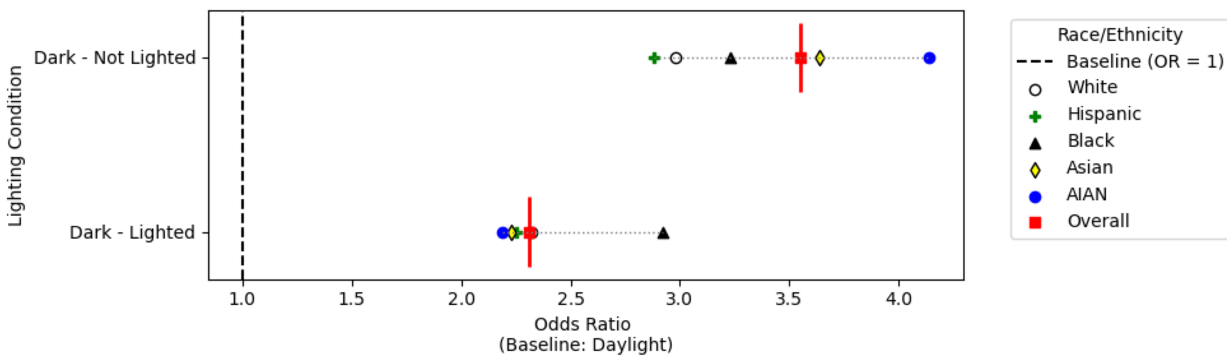


Figure 5. Effect of Lighting Condition on Pedestrian Injury Severity by Race/Ethnicity Groups (Post-COVID)

Bicyclist Injury Severity based on Roadway Environment. Prior studies (Behnood & Mannering, 2017; Kim et al., 2007) suggest that several variables may influence bicyclist injury outcomes differently across racial and ethnic groups. The final RP models for bicyclists included nine variables, with one treated as having only a fixed effect and eight having both fixed and varying effects across racial/ethnic groups. RPs were estimated accordingly. The pre- and post-COVID model results are provided in Table A.37 and Table A.38, respectively.

Bicyclist injury severity in the post-COVID period was significantly influenced by age, intersection location, and vehicle body type. Older bicyclists (55+) were at notably higher risk, with odds of KA injury 2.78 times higher compared to those under 18. RP estimates revealed notable disparities; in particular, Asians (OR = 5.68) and AIAN (OR = 3.15) in the 55+ age group had much higher risks.

Motor Vehicle Occupant Injury Severity. Several variables influence MVO injury outcomes based on racial/ethnic groups (Roll & McNeil, 2022). For MVOs, thirteen variables were specified in the final RP models, of which seven were considered to have only fixed effects, and six were considered to have fixed and random effects. The pre- and post-COVID RP model results, presented in Table A.39 and Table A.40, provide insights into the factors influencing fatal and serious injury crashes and how these factors vary across racial/ethnic groups.

For the post-COVID model, fatal and serious injury crashes were associated with male drivers, older drivers, higher posted speed limits, substance involvement, weekends, low-visibility conditions, and non-urban locations.

The random coefficient estimates provide deeper insights into the disparities across racial/ethnic groups.

Alcohol/Drug Impairment. Figure 6 presents the effect of alcohol/drugs across different racial/ethnic groups in terms of OR of KA injury for the post-COVID period. Crashes involving Black MVOs and substance impairment had a 2.22 times higher risk of KA injury, exceeding the overall risk, and above the overall OR of 1.76. There were also elevated risks for Hispanic MVOs (OR = 1.91) and White MVOs (OR = 1.81) in substance-involved crashes.

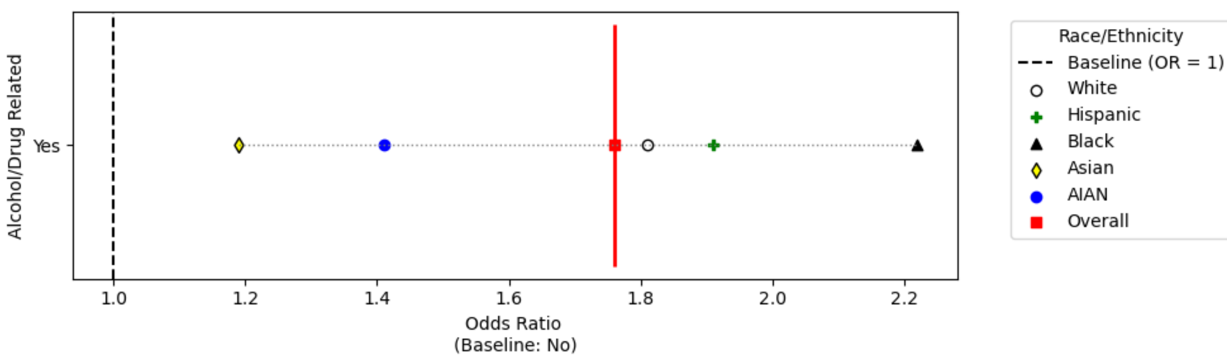


Figure 6. Impact of Alcohol/Drug Impairment on MVO Injury Severity by Race/Ethnicity Group (Post-COVID)

Lighting Condition. Racial/ethnic disparities were also evident under reduced visibility conditions, with Hispanic, Black, Asian, and AIAN MVOs experiencing heightened risks.

- Hispanic MVOs experienced above-average risks in both dark–lighted and dark–not-lighted conditions.
- Black MVOs faced higher risk in dark–not-lighted conditions.
- Asian MVOs had elevated risk in dark–lighted settings.

- Hispanic, Black, Asian, and AIAN MVOs all showed increased risk during dawn/dusk conditions.

Area Type. The RP analysis revealed that differences by area type, as shown in Figure 7, were associated with distinct racial/ethnic disparities in the risk of MVOs sustaining fatal or serious injuries.

- Asian MVOs faced the highest risk in rural areas, with odds of sustaining fatal or serious injuries 3.33 times higher than in cities.
- White and AIAN MVOs also showed elevated risks in rural settings.
- Black MVOs had comparatively lower rural and town crash risk.

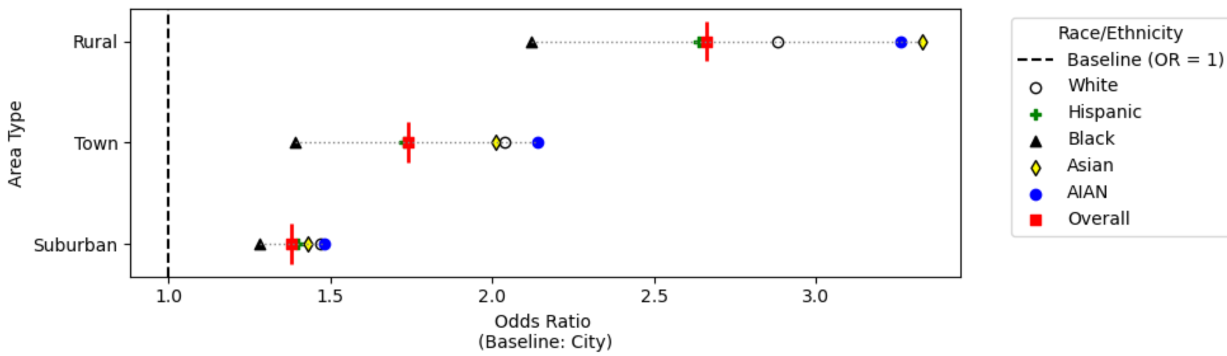


Figure 7. Effect of Area Type on MVO Injury Severity by Race/Ethnicity Groups (Post-COVID)

Posted Speed Limit. Disparities in high-posted speed limit effects were evident post-COVID, with White (OR = 1.90), Hispanic (OR = 1.54), and AIAN (OR = 1.50) MVOs facing the highest risks on roads over 45 mph, exceeding the overall risk (OR = 1.47). These variations may reflect differences in high-speed zone exposure or enforcement practices.

Motor Vehicle Occupant Age. Older MVO occupants, especially White and Hispanic, faced disproportionate risks, highlighting the intersection of age and ethnicity in crash outcomes.

Summary of Individual Level Analysis by State

Ohio.

AIAN. In Ohio, the AIAN fatality rate shifted dramatically from 12% lower than that of Whites in 2013 to 156% higher in 2022. Similarly, AIAN MVO fatality rates in Ohio rose from 2% below Whites in 2013 to 193% higher by 2022.

Black. In Ohio, as total fatalities rose from 989 in 2013 to 1,275 in 2022 (a 29% increase), the proportion of Black fatalities increased from 11.5% to 18.4%. The fatality rate per 100,000 population for Black individuals grew from 0.9 in 2013 to 1.6 in 2022, shifting from 7% lower to 59% higher than Whites.

In Ohio, pedestrian fatalities among Black individuals surged from 1.4 per 100,000 in 2013 to over 3 per 100,000 in 2022, the highest among all racial/ethnic groups. Black bicyclists in Ohio consistently had the highest fatality rates. Black MVOs in Ohio experienced a significant rise in fatality rates, shifting from 15% lower to 46% higher than Whites.

Hispanic. In Ohio, Hispanic traffic fatality rates doubled from 5 per 100,000 population in 2013 to over 10 per 100,000 population in 2022, with Hispanics having the second-highest pedestrian fatality rates after Blacks. Relative to Whites, Hispanic fatality rates increased from 50% lower in 2013 to 7% higher in 2022.

White. In Ohio, over 70% of traffic fatalities involved White individuals, despite their proportion decreasing from 84.3% in 2013 to 74.6% in 2022 as total fatalities rose by 28.9% (from 989 to 1,275).

Texas.

AIAN. In Texas, AIAN individuals faced alarming trends across all injury severities. Fatality rates surged from 65% below Whites in 2017 to 67% above Whites in 2022. Incapacitating injuries increased even more dramatically, shifting from 52% below Whites in 2017 to 172% above Whites in 2022. Non-incapacitating injuries followed a similar trajectory, tripling over the same period.

AIAN pedestrians in Texas consistently experienced higher fatality and injury rates, with incapacitating injuries spiking notably in 2021. The RP model results revealed that AIAN individuals faced the highest risks in poorly lit areas, particularly post-COVID.

Asian. In Texas, the RP model results revealed that post-COVID, Asian pedestrians faced elevated risks in poorly lit areas.

Black. In Texas, pre-COVID, Black pedestrians faced the highest risks in poorly lit areas. Black MVOs in Texas were disproportionately involved in collisions related to alcohol or drug impairment.

By 2022, incapacitating injury rates for Black individuals in Texas were 43% higher than for Whites, with non-incapacitating injury rates also remaining elevated. Intersectional analysis revealed that Black female pedestrians were significantly overrepresented in fatalities and injuries across most age groups, while Black male pedestrians were disproportionately affected in non-incapacitating injuries.

Hispanic. While Hispanic fatality rates in Texas remained below those of Whites, they steadily rose, narrowing the gap from 38% lower in 2017 to 22% lower in 2022.

White. In Texas, Whites consistently had the highest proportion of fatalities and injuries across all road user categories; however, their representation declined over time as that of minoritized groups increased. White males, particularly those aged 35–54, were significantly overrepresented in bicyclist fatalities and injuries. According to the RP model, White bicyclists in Texas faced higher risks in high-speed zones.

Pedestrians were more vulnerable in dark–not-lighted areas compared to lighted areas, differing from MVOs who faced higher risks in dark–lighted conditions.

Washington.

AIAN. In Washington, AIAN MVO fatality rates increased even more steeply, from 135% higher than Whites in 2013 to 468% higher in 2022. AIAN groups exhibited the highest traffic injury rates, with the most severe rates observed in Washington.

Washington also recorded the highest pedestrian fatality rates among the three states, with AIAN groups disproportionately affected. AIAN pedestrian fatality rates increased from 6.3 per 100,000 population in 2013 to 20 per 100,000 in 2021, consistently exceeding those of Whites.

Black. In Washington, Black fatality rates also increased relative to Whites, with Blacks experiencing the second-highest pedestrian and MVO fatality rates after AIAN groups. Blacks accounted for the second-highest number of traffic fatalities after Whites across Washington.

Hispanic. In Washington, Hispanic pedestrian fatality rates exceeded those of Whites, with Hispanic male pedestrians aged 18–54 being overrepresented after Whites.

NHPI. In Washington, NHPI individuals experienced significantly higher traffic fatality rates compared to those in Ohio and Texas. Over time, NHPI fatality rates in Washington underwent a dramatic shift, increasing from 62% lower than Whites in 2014 to 90% higher by 2022.

White. In Washington, Whites constituted the majority of fatalities, but their share declined from 75.2% in 2013 to 63.4% in 2022.

Neighborhood-Level Analysis

Neighborhood sociodemographic and economic characteristics, transportation infrastructure, and traffic exposure influence safety inequities (Mőller et al., 2021; Roll & McNeil, 2022; Zhu et al., 2024). This section outlines the evaluation of traffic safety disparities at the neighborhood (census tract) level in Ohio, Texas, and Washington. The overall objective is to develop recommendations that promote greater equity in traffic safety outcomes across the three states. This evaluation connects to the individual-level analysis by focusing on the count of MVOs, pedestrians, and bicyclists who sustained KA injuries within each census tract.

Exploratory Analysis

This section focuses on exploring KA injuries sustained by MVOs, pedestrians, and bicyclists across census tracts in Ohio, Texas, and Washington. KA injury rates (calculated as the number of KA injuries per 1,000 population within a tract) were analyzed using the median rate as a threshold to distinguish tracts with higher rates from those with lower rates. Additionally, patterns in the percentages of race/ethnicity groups across these tracts were computed.

Table 6 presents the race/ethnicity composition of census tracts in Ohio, Texas, and Washington, with KA injury rates below and above the median for each road user type. The median percentage of each race/ethnicity group was calculated for both categories of tracts, and the difference between the two categories was then determined to identify where each race/ethnicity group had a higher percentage than the median. The spatial distribution of KA injury rates by road user type across census tracts in the three states during the combined pre- and post-COVID period is illustrated in Figure B.1 through Figure B.9 in Appendix B.1. These rates were calculated as the number of KA injuries per 1,000 population within each tract. The analysis included 3,155 census tracts in Ohio, 6,830 in Texas, and 1,770 in Washington, with reported population and race/ethnicity data.

Table 6. Race/Ethnicity Composition (Median Percentage) in OH, TX, and WA Census Tracts below and above the Median KA Injury Rate by Road User Type.

	Ohio			Texas			Washington		
Race/Ethnicity (median %)	**Below median**	**Above median**	**Above vs. Below***	**Below median**	**Above median**	**Above vs. Below***	**Below median**	**Above median**	**Above vs. Below***
Pedestrians									
Pct_White	87.4	79.2	**↓−8.2**	49.7	31.7	**↓−18.0**	75.4	66.3	**↓−9.1**
Pct_Hispanic	2.3	2.9	↑0.6	25.6	38.7	↑+13.1	7.7	10.2	↑+2.5
Pct_Black	2.6	6.7	**↑4.1**	5	6.9	↑+1.9	0.9	2.2	↑+1.3
Pct_Asian	0.5	0.7	↑0.15	1.6	1.0	**↓−0.6**	3.3	5.6	↑+2.3
Pct_AIAN	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.3	↑+0.1
Pct_NHPI	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pct_MultiRace	2.7	3.2	↑0.5	2.1	1.5	**↓−0.6**	5.2	8.8	**↑+3.6**
Pct_OtherRace	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Bicyclists									
Pct_White	85.1	83.4	**↓−1.7**	43.3	34.4	**↓−9.0**	72.4	68.6	**↓−3.8**
Pct_Hispanic	2.5	2.9	↑0.4	29.6	36.4	**↑+6.8**	8.8	9	↑+0.2
Pct_Black	3.6	4.7	**↑1.1**	5.5	7.1	↑+1.6	1.2	1.8	↑+0.6
Pct_Asian	0.5	0.6	↑0.1	1.2	1.5	↑+0.3	3.6	6.4	**↑+2.9**
Pct_AIAN	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.3	↑+0.1
Pct_NHPI	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pct_MultiRace	2.8	3.1	↑0.3	1.9	1.8	↓−0.1	5.4	5.6	↑+0.2
Pct_OtherRace	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Motor Vehicle Occupants									
Pct_White	82.6	87.9	**↑5.3**	38.6	44	**↑+5.4**	71.2	70.5	↓−0.7
Pct_Hispanic	2.9	2.1	↓−0.8	31.7	31	↓−0.7	7.9	9.9	↑+2.0
Pct_Black	5.1	2.4	**↓−2.7**	5.8	6	↑+0.2	1.4	1.3	↓−0.1
Pct_Asian	1.1	0.2	↑0.9	2.4	0.6	**↓−1.8**	5.9	3	**↓−2.9**
Pct_AIAN	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.3	↑+0.1
Pct_NHPI	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Pct_MultiRace	3.1	2.6	↓−0.5	1.9	1.8	↓−0.1	5.6	5.3	↓−0.3
Pct_OtherRace	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Note: ** Values in bold indicate the largest increase or decrease for each road user type; Pct = Percentage.*

Ohio.

Pedestrians (median rate = 0%): Compared to tracts with injury rates below the median, tracts with above-median KA injury rates have a lower median White population (−8.2%), but higher median population of Black (+4.1%), Hispanic (+0.6%), multiracial (+0.5%), and Asian (+0.15%) populations.

Bicyclists (median rate = 0%): A similar pattern is observed for bicyclist KA injury rates, with higher median percentages of Black (+1.1%), Hispanic (+0.4%), multiracial (+0.3%), and Asian (+0.1%) populations in tracts with injury rates above the median.

MVOs (median rate = 2.2%): Tracts with MVO KA injury rates above the median have a higher median percentage of Whites (+5.3%) and Asians (+0.9%), but lower median percentages of Black (−2.7%), Hispanic (−0.8%), and multiracial (−0.5%) populations.

Texas.

Pedestrians (median rate = 0.3%): Compared to tracts with pedestrian KA injury rates below the median, those with injury rates above the median have a lower median percentages of White (−18.0%), Asian (−0.6%), and multiracial (−0.6%) populations, but higher median percentages of Hispanics (+13.1%) and Blacks (+1.9)

Bicyclists (median rate = 0%): Tracts with bicyclist KA injury rates above the median have a higher median percentages of Hispanics (+6.8%), Blacks (+1.6%), and Asians (+0.3%), but lower median percentages of White (−9.0%) and multiracial (−0.1%) populations.

MVOs (median rate = 3.0%): Tracts with MVO KA injury rates above the median have a higher median percentage of Whites (+5.4%) and Blacks (+0.2%), but lower median percentages of Asian (−1.8%), Hispanic (−0.7%), and multiracial (−0.1%) populations.

Washington.

Pedestrians (median rate = 0.2%): Compared to tracts with pedestrian KA injury rates below the median, those with injury rates above the median have a lower median percentage of Whites (−9.1%), but higher median percentages of multiracial (+3.6%), Hispanic (+2.5%), Asian (+2.3%), Black (+1.3%), and AIAN (+0.1%) populations.

Bicyclists (median rate = 0): Tracts with bicyclist KA injury rates above the median have higher median percentages of Asian (+2.9%), Black (+0.6%), Hispanic (+0.2%), multiracial (+0.2%), and AIAN (+0.1%) populations and a lower median percentage of Whites (−9.0%).

MVOs (median rate = 6.9): Tracts with MVO KA injury rates above the median have higher median percentages of Hispanic (+2.0%) and AIAN (+0.1%) populations, but lower median percentages of Asian (−2.9%), White (−0.6%), multiracial (−0.3%), and Black (−0.1%) populations.

Table B.1 through Table B.3 provide an overview of variables related to area/population metrics, race/ethnicity composition, socio-demographics and economics, roadway characteristics, exposure factors, and KA injury counts by road user type for Ohio, Texas, and Washington, respectively. Area type and population measures highlight the diversity in tract size and population density, with a wide range of tract areas and population sizes. Socio-demographics and economics include indicators such as poverty rate, disability prevalence, and housing characteristics. Roadway-related variables capture the density and characteristics of road infrastructure, such as bicycle lanes and more. The exposure factors, like annual average daily traffic (AADT), are also included in the tables in Appendix B.2.

Bayesian Estimates of Fatal and Incapacitating Injury Rates by Road User Type

This section presents the results of neighborhood statistical models categorized by road user type for the three states. These models used the total population at the census tract level as an offset, with the total count of KA injury outcomes as the response variable.

The Bayesian model results were interpreted using Incidence Rate Ratios (IRRs), which assess the rates of KA injury outcomes of exposed populations in census tracts relative to their exposure to specific variables of interest (area type, race/ethnicity, socio-demographic and economic factors, and roadway-related traffic exposure, such as AADT). IRRs provide insights into how these exposures influence the rate of KA injury outcomes when combined.

- IRR = 1: the exposure does not affect the relative count (rate) of KA injuries
- IRR>1: the exposure is associated with higher rates of KA injury outcomes
- IRR<1: the exposure is associated with lower rates of KA injury outcomes

Two types of Bayesian models were developed. The first consists of standard models, which include no interaction effects. The second incorporated all the variables from the standard models, along with an interaction term between a race/ethnicity group and variables related to area type, sociodemographic and economic factors, roadway characteristics, or traffic exposure. Two-way interactions were considered, and each interaction was included one at a time to avoid model overfitting.

In Bayesian models, variables are considered significant if their 95% Highest Density Intervals (HDIs) do not include zero among the credible values. Unless otherwise specified, the results discussed in this section primarily focus on significant variables and interaction terms derived from post-COVID analyses.

Ohio. Table B.4 and Figure B.11 present the pre- and post-COVID pedestrian KA injury model results for Ohio. The Ohio bicyclist KA injury models—detailed in Table B.5 and interaction effects in Figure B.12—demonstrate how demographic, socioeconomic, and roadway factors influence KA injury rates. Lastly, Table B.6 and Figure B.13 highlight the role of area type, roadway features, and key demographic interactions on KA injury rates for MVOs. Except where noted, results are from the post-COVID models. The key takeaways are summarized in Table 7 below.

Table 7. Summary of Key Model Outcomes by Road User Type in Ohio.

Pedestrians (Table B.4)	**Bicyclists**[a] (Table B.5)	**MVOs (**Table B.6)
Area type • *Suburban* tracts experienced a 44% reduction in pedestrian KA injury rates compared to urban tracts • *Town* tracts saw a 70% reduction	**Race/ethnicity and area type** • Each 1% increase in the *Asian* population corresponded to a 7% rise in KA bicyclist injuries	**Area type** • *Rural* tracts experienced the most substantial increase in KA injury rates, with rates 2.66 times higher than urban areas
Demographics and socioeconomics • A 1% increase in *Asian* residents led to an 8% decrease in KA injury rates • A 1% increase in *uninsured residents* led to a 7% increase in injury rates	**Demographic effects** • A 1% increase in *uninsured residents* was linked to a 4% increase in injuries • A 1% increase in *residents with disabilities* corresponded to a 6% increase in KA injury rates	**Roadway exposure** • Tracts with a greater density of *45–55 mph roads* saw a 7% increase in KA injury rates, while those with 60+ mph roads saw a 19% increase. • A unit increase in the log of Mean *AADT* was associated with a 48% rise in KA injury rates
Roadway exposure • A higher share of roads posted at *45–55 mph* was linked to an 18% increase in pedestrian KA injuries	**Roadway exposure** • Tracts with higher densities of *multi-lane roads* saw a 4.29-fold increase in KA bicyclist injuries	**Interaction effects** (Figure B.13) • Tracts with both a high *Asian* population and a high density of *multi-lane roads* had a 6% increase in KA injuries • Tracts with higher NHPI and elderly populations saw a 4% increase • KA injury rates decreased in town tracts with higher Hispanic populations (−9%), potentially reflecting the moderating role of lower density
Interaction effects (Figure B.11) • Tracts with both a higher *NHPI* population and more *mobile homes* experienced a 99% increase in injury rates • Tracts with a higher *AIAN* population combined with more *office jobs* saw a 38% increase in pedestrian KA injuries	**Interaction effects** (Figure B.12) • *Town* tracts with more *Hispanic* residents experienced a 28% increase in injury rates • *Rural* tracts with more *Hispanic* residents experienced a 14% increase • Tracts featuring both higher *school density* and a greater *multiracial* population had a 5% increase in injury rates	

Note. [a] *Combined pre- and post-COVID models.*

Texas. Table B.7 and Figure B.14 summarize the pre- and post-COVID pedestrian KA injury model results for Texas, highlighting consistent effects of land use, roadway exposure, and demographic interactions. The Texas bicyclist injury models are detailed in Table B.8 and illustrated via interaction effects in Figure B.15. Lastly the key findings from the Texas MVO model results, presented in Table B.9 and visualized through interaction effects in Figure B.16, highlight how area type, employment composition, and roadway characteristics were associated with variations in KA injury rates for MVOs across pre- and post-COVID periods. The key takeaways are summarized in Table 3 below.

Table 8. Summary of Key Post-Pandemic Model Outcomes by Road User Type in Texas.

Pedestrians (Table B.7)	**Bicyclists** (Table B.8)	**MVOs** (Table B.9)
Area type • *Town* tracts experienced 34% lower pedestrian KA injury rates than urban tracts	**Demographic effects** • Each 1% increase in residents identifying as *multiple* races or *other* races was linked to a 17% and 41% decrease in KA bicyclist injuries, respectively • Each 1% increase in the *youth* (≤ 17 years) and *elderly* (≥ 65 years) populations corresponded to 7% and 8% increases in injury rates	**Area type** • *Rural* tracts consistently had significantly higher KA injury rates than urban tracts in both periods, with post-COVID rates 1.72 times higher • *Town* tracts exhibited lower KA injury rates, with a 35% reduction post-COVID compared to urban areas
Employment land use • A one-unit increase in the log of *service jobs* was associated with a 4% increase in pedestrian KA injury rates • A one-unit increase in the log of *industrial jobs* corresponded to a 6% increase • A one-unit increase in the log of *retail jobs* corresponded to an 11% increase	**Socioeconomic factors** • A 1% rise in the *below poverty* rate was associated with a 5% increase in KA injuries • A 1% increase in the share of *industrial jobs* led to a 28% increase in injury rates • A 1% increase in *residents with disabilities* was linked to a 5% increase in injury rates	**Employment and land use** • Tracts with a higher share of *industrial* jobs experienced 14% increases in KA injury rates

Pedestrians (Table B.7)	**Bicyclists** (Table B.8)	**MVOs** (Table B.9)
Roadway exposure • A one-unit increase in the density of roads with *30–40 mph speed limits* was linked to a 16% rise in pedestrian injury rates • A similar increase in the density of *45–55 mph* roads was linked to a 7% rise • A one-unit increase in the log of *AADT* led to a 44% increase post-COVID (compared to 39% pre-COVID)	**Interaction effects** (Figure B.15) • Tracts with higher *NHPI* populations and more *retail jobs* saw a 2.89-fold increase in KA injury rates • *NHPI* populations combined with more *office jobs* corresponded to a 2.57-fold increase in KA injury rates • Tracts with more *other*-race residents and *office jobs* experienced a 17% rise in KA injury rates • In *rural* tracts, a higher *Black* population was associated with a 4% increase in bicyclist injuries (Barajas, 2018) • *Rural* areas with more *multiple*-race residents saw a 39% decrease in injury rates versus urban tracts	**Roadway characteristics** • High *multi-lane road* density was associated with a 14% increase in KA injury rates. • A 1% increase in the density of roads with *45–55 mph speed limits* corresponded to a 5% rise in KA injury rates • *AADT* had a strong effect with a one-unit increase in the log of AADT leading to a 47% increase in KA injury rates

Washington. The results of the pedestrian model for both pre- and post-COVID periods combined are presented in Table B.10. Figure B.17 shows the IRRs of the significant interaction terms for the pedestrian model in Washington. Table B.11 presents the results of the bicyclist model for Washington across both pre- and post-COVID periods, while interaction effects are summarized in Figure B.18. Detailed results for the MVO model for Washington are reported in Table B.12, with interaction effects illustrated in Figure B.19. The key takeaways are summarized in Table 9 below.

Table 9. Summary of Key Model Outcomes by Road User Type in Washington.

Pedestrians[a] (Table B.10)	**Bicyclists**[a] (Table B.11)	**MVOs** (Table B.12)
Area type • *Suburban* tracts had a 22% lower KA injury rate than urban tracts • *Town* tracts had a 37% lower KA injury rate than urban tracts	**Employment** • A 1% increase in *service jobs* corresponded to a 39% increase in bicyclist KA injuries	**Area type** • *Rural* tracts had 76% higher KA injury rates compared to urban tracts • *Town* tracts experienced a 44% decrease in KA injury rates
Socioeconomic and land-use factors • A one-unit increase in the log of *retail jobs* was associated with a 15% increase in pedestrian KA injury rates • Tracts with a higher density of *unmarked crosswalks* experienced pedestrian KA injury rates 2.87 times higher	**Interaction effects** (Figure B.18) • Tracts with a higher *AIAN* population and greater *unmarked crosswalk* density saw a 2.11-fold increase in bicyclist KA injuries • Higher *Hispanic* population and *unmarked crosswalk* density led to a 13% increase in injury rates • In *rural* tracts, however, a higher *Hispanic* population was associated with a 5% decrease in bicyclist KA injuries compared to urban tracts	**Race/ethnicity** • Each 1% increase in *Black* population was associated with a 3% increase in the KA injury rate • Each 1% increase in *NHPI* population was associated with a 5% increase in the KA injury rate • Each 1% increase in *other race* population was associated with a 9% increase in the KA injury rate
Traffic volume • A one-unit increase in the log of *AADT* corresponded to a 28% increase in pedestrian KA injury rates		**Employment and land use** • Each 1% increase in *retail employment* was associated with a 10% increase in the KA injury rate • Each 1% increase in *industrial employment* was associated with a +18% increase in the KA injury rate

Pedestrians[a] (Table B.10)	**Bicyclists**[a] (Table B.11)	**MVOs** (Table B.12)
Interaction effects • Tracts with a higher percentage of *other* ***race*** residents and more *30–40 mph roads* saw a 20% increase in KA injury rates.		**Roadway exposure** • Tracts with a higher density of roads *45–55 mph* was associated with a 17% increase in the KA injury rate • Tracts with a higher density of roads *60+ mph* was associated with a 24% increase in the KA injury rate **Interaction effects** (Figure B.19) • *Town* tracts with a higher percentage of *multiracial* residents were associated with a 15% increase in KA injury rates • Tracts with a higher *AIAN* population and a greater density of roads with *30–40 mph speed limits* experienced a 12% increase in KA injury rates • *Town* tracts with a higher percentage of *NHPI* residents showed a 42% decrease in KA injury rates.

Note. [a] *Combined pre- and post-COVID models.*

Summary of Neighborhood Analysis

The neighborhood analysis highlights significant disparities in KA injuries across census tracts in Ohio, Texas, and Washington. Spatial patterns revealed that tracts with higher KA injury rates are often associated with specific demographic characteristics. For example, in Texas, MVO injury rates were higher (above the median rate) in tracts with higher percentages (above the median percentage) of Whites and Blacks, while in Washington, tracts with high MVO injuries were associated with greater Hispanic and AIAN populations. For pedestrians and bicyclists, tracts with above-median KA injury rates frequently had larger shares of minority populations, underscoring inequities in KA injuries in some neighborhoods compared to others.

The type of area (i.e., urban, suburban, rural, or town) significantly influences the likelihood of KA injury risks, underscoring the need for closer examination and safer planning strategies for roadway design in these locations to better accommodate all road users. Rural tracts consistently exhibited higher injury rates for MVOs across all three states. Conversely, suburban and town tracts experienced lower pedestrian KA injuries compared to urban tracts. For bicyclists, the patterns are more complex. In Ohio, rural and town tracts with higher Hispanic populations face amplified bicyclist KA injury risks. In Texas, bicyclist injury risks were linked to a combination of a higher NHPI or Hispanic population and an increased density of retail or office jobs. Hispanic and AIAN populations in tracts with higher densities of unmarked crosswalks were at a higher risk of bicyclist injuries in Washington.

These findings emphasize the urgent need for targeted safety interventions to address higher rates of fatalities and incapacitating injuries in underserved communities or tracts. Prioritizing resource distribution effectively, improving roadway infrastructure, and implementing inclusive traffic safety programs are critical steps to mitigate disparities. By focusing on the underlying factors contributing to KA injury risks, this analysis underscores the importance of creating safer and more equitable mobility outcomes for all road user types in Ohio, Texas, and Washington.

Segment Analysis

The segment analysis presents an evaluation of roadway segment safety based on a proactive approach that evaluates the safety potential rather than solely on crash outcomes. This means that the segment evaluations focus on how well roadways align with the SSA goals, aiming to prevent fatal and serious injury crashes by creating road systems tolerant of human errors.

The segment analysis includes a segment-level SSA Scoring system that combines exposure, likelihood, and severity metrics to assess road safety potential across sociodemographic contexts. It incorporates roadway data, like AADT and road geometry, and integrates socioeconomic and demographic indicators based on the SVI database. The SSA Score, which is used as an indicator of roadway alignment with Safe System principles, identifies segments that are less safe with higher scores (i.e., higher potential for improvement) and reflects safer roadway infrastructure with lower scores to indicate safer roads.

After estimating SSA Scores for roadway segments in the three case study cities—Austin, Cleveland, and Seattle—a structural equation modeling (SEM) approach was employed to examine the relationship between socioeconomic disadvantage (SED) and roadway safety, as measured by the SSA Score. Through SEM, the research highlights how socioeconomic disadvantages, such as high poverty or unemployment, *mediate* the impact of demographic variables on SSA Scores.

The study also introduces an interactive tool, developed using Shiny, to visualize SSA Scores and equity implications for roadway segments. This tool enables users to prioritize interventions by displaying SSA metrics, AADT, segment characteristics, and Google Street View imagery for further inspection. By integrating equity-focused SSA Scoring, the research underscores the critical need to address safety inequities in the urban infrastructure, particularly in underserved communities. The following section provides a summary of key findings, with full methodology, results, and discussions detailed in Appendix C.

Effects of Sociodemographic and Economic Factors on Roadways

Key SEM findings reveal disparities in safety alignment across three cities—Cleveland, Seattle, and Austin—showing that socioeconomically disadvantaged areas often have worse SSA Scores (indicating lower safety potential). Interestingly, disadvantaged areas in Austin showed less severe safety misalignment compared to similar areas in Cleveland and Seattle, highlighting the effectiveness of localized initiatives.

Collectively, these findings emphasize the importance of developing tailored strategies that account for the unique demographic and socioeconomic contexts of each city. Such targeted approaches are essential for effectively improving roadway safety and achieving alignment with SSA principles.

Cleveland, Ohio. In Cleveland, SED was measured using poverty and unemployment rates (Table C.11; Figure C.4). Poverty had a stronger contribution to SED, though SED was reliably captured by both indicators. SED had a significant positive effect on the SSA Score, indicating that segments in disadvantaged areas tend to be less aligned with safety objectives. Statistically significant indirect effects were found between socioeconomic factors and SSA Scores, particularly among Hispanic and Black populations, where the total effects were fully mediated by SED. For the White population, SED reduced the overall positive effect on SSA alignment by approximately one-third.

Additional factors, such as higher rates of disability and crowded housing, were also associated with poorer safety alignment, primarily through their connection to SED. These findings underscore the need for targeted safety interventions in disadvantaged or demographically vulnerable communities, particularly those with high percentages of **racial or ethnic minorities**, including Black and Hispanic, as well as **crowded housing**, to improve equity and alignment with SSA principles across Cleveland's roadway network.

Austin, Texas. In Austin, SED was measured using poverty and unemployment rates (Table C.12; Figure C.5). Poverty fully captured the construct of socioeconomic disadvantage, contributing more strongly than unemployment. In contrast to Cleveland and Seattle, Austin presents a distinct pattern. While SED remains a critical factor, it exhibits a negative association with SSA Scores. This indicates that roadway segments show improved alignment with SSA objectives as SED increases in Austin. This contrast suggests that Austin has made substantial progress in addressing safety disparities through equity-focused initiatives, such as its Vision Zero programs.

This suggests that targeted safety initiatives can effectively address disparities and improve road safety alignment, even in vulnerable areas. Austin was selected as a city with a national Vision Zero network focus in 2016 (Adler, 2016). Since then, the city has implemented numerous transportation improvement and speed management programs aimed at enhancing safety for all road users (City of Austin, n.d.-b). A notable example is Vision Zero's "*Safe for All*" initiative, which involved the development of Equity Analysis Zones (EAZs) to assist staff in analyzing and considering equity in transportation processes and decision-making (Austin Vision Zero, 2023). EAZs account for factors such as the percentage of people of color and median household income to reflect social and economic vulnerability. These zones were also integrated into Austin's former Local Area Traffic Management (LATM) program, which previously lacked a strong equity focus. This integration highlights how equity-focused approaches can reshape transportation processes to benefit all communities.

Seattle, Washington. In Seattle, SED was also measured using poverty and unemployment rates (Table C.13; Figure C.6). Poverty had a dominant contribution to SED, while unemployment played a smaller but notable role. SED had a significant positive effect on the SSA Score, indicating that segments in disadvantaged areas tend to be less aligned with safety objectives. Statistically significant indirect effects were observed between socioeconomic factors and SSA Scores, particularly for Black and Asian populations. For the Black population, SED partially offset a negative direct effect, resulting in a small overall negative total effect. For the Asian population, the total positive effect on SSA alignment was fully mediated by SED.

Additional factors, such as high rates of single-parent households and a lack of internet access, also influenced SSA alignment. While single-parent areas showed better direct alignment, SED slightly reduced this benefit. In contrast, areas with limited internet access had a strong indirect negative effect through SED, indicating lower alignment with safety objectives. These findings underscore the importance of targeted safety interventions in socioeconomically disadvantaged or demographically vulnerable areas—particularly those with **high minority populations** or **lacking internet access**—to better align with SSA principles across Seattle's roadway network.

Equity-focused Interactive SSA Framework

The contrasting findings from the SEM analysis revealed the importance of accounting for social equity factors in addressing roadway safety and its alignment with SSA objectives. As such, this study introduces an Equity Score, contributing an additional 10 points to the overall SSA Score. The Equity Score reflects the need to consider social vulnerability in safety assessments, ensuring that safety interventions are prioritized in areas where populations are more socioeconomically disadvantaged. This addition brings the total maximum score for a road segment to 117, highlighting the study's approach that not only evaluates traditional safety measures but also incorporates equity, a novel contribution to the existing FHWA scoring framework.

The SVI data was used to integrate equity considerations into roadway safety assessment, ensuring that safety measures are distributed fairly across different socioeconomic groups. This study used the percentage of the population living below 150% of the poverty threshold (EP_POV150) as the key metric to gauge social vulnerability. This measure was selected because it effectively captures the extent of economic hardship within a community, which is a critical factor when considering the equitable distribution of road safety resources. In addition, SEM measurement models for all three cities revealed poverty to be the strongest indicator of the SED construct.

Table 10 presents the scoring criteria for evaluating equity-related performance measures based on the EP_POV150 data. The scoring criteria are divided into several ranges, each corresponding to a different percentage of the population living below the 150% poverty threshold. For areas where up to 10% of the population falls below this threshold, a score of 1 was assigned. These areas are considered to have the lowest equity-related risks, as a relatively small portion of the population is economically disadvantaged. As the percentage increased, the scores rose accordingly. The highest score of 10 was assigned to areas where over 40% of the population lives below the 150% poverty threshold. These areas are identified as the most vulnerable and, therefore, the most in need of equitable distribution of road safety resources.

Table 10. Scoring Criteria for Equity-Related Performance Measures.

Road Users	Variable	Description	Category (%)	Score
Both	Equity	Equity as a measure of the percentage of the poor population	0 – 10	1
			11 – 15	2
			16 – 25	4
			25 – 40	6
			Over 40	10

Equity-Focused Interactive SSA Tool

The research team developed interactive web tools for Cleveland, Austin, and Seattle (see sample images, Figure 8 through Figure 10), enabling users to evaluate the risk levels of different road segments by providing detailed information. The central feature of the tool is a map that visually represents various roadway segments, each color-coded according to its SSA Score. This score is an aggregate measure of the safety risks associated with a specific road segment. The color scale on the left side of the screen ranges from green to red, where green indicates safer segments with lower scores and red highlights segments with higher safety risks. The SSA Score and associated metrics are crucial for understanding and managing road safety. Higher SSA Scores indicate segments with greater safety risks, guiding users to prioritize these areas for safety interventions.

Users can click on a segment within the map to assess it. This action triggers the display of the SSA Score for the selected segment, which appears as a pop-up on the map. Upon selecting a segment, the tool displays some specifics of that roadway by displaying the metrics on the right-hand side of the screen. These metrics include the following key variables:

- **AADT**: This metric shows the volume of traffic that passes through the segment daily, which is a significant factor in determining exposure risk.
- **Number of lanes**: The number of lanes on the roadway segment that impact both motor vehicle flow and pedestrian crossing difficulty.
- **Segment length**: This measure displays the segment's length; although segment length is not considered for the SSA Score.
- **MV Score** and **VRU Score**: These scores assess the exposure and risk specifically for motor vehicles and VRUs, respectively.
- **Equity Score**: This metric considers the equity implications of the road segment, reflecting whether certain communities or groups are disproportionately affected by safety risks.
- **SSA Score**: The overall SSA Score on the selected segment.

In addition to numerical data, the tool allows users to visually inspect the selected roadway segment using Google Street View. This feature is accessible through a panel on the lower right side of the screen, where users can click to view the segment in its real-world context. This function is particularly useful for assessing the presence and condition of safety features such as sidewalks, bike lanes, and road signage, which might not be fully captured through data alone.

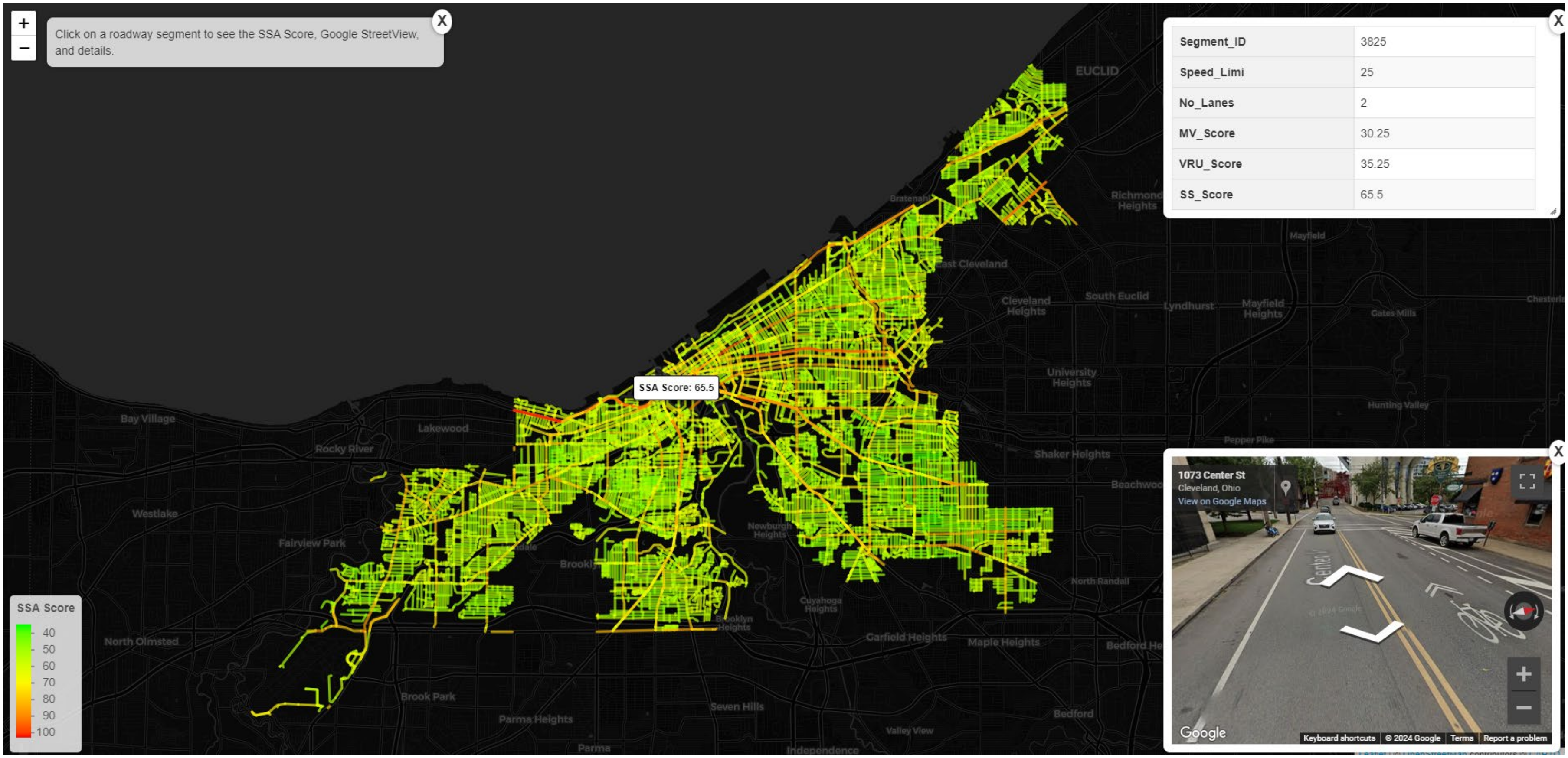


Figure 8. Interface of the SSA Tool in Cleveland, Ohio (Link to live version: Cleveland)

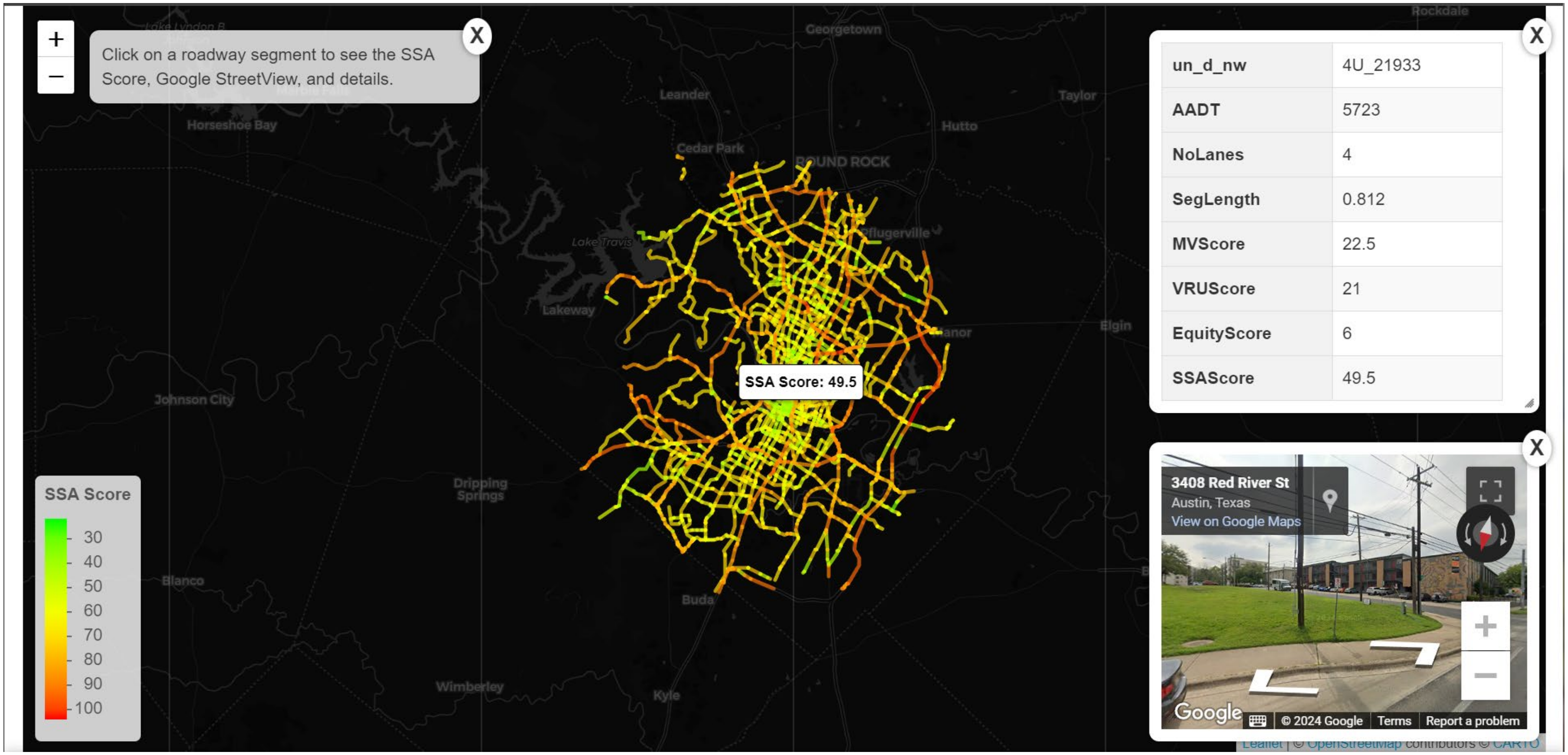


Figure 9. Interface of the SSA Tool in Austin, Texas (Link to live version: [Austin])

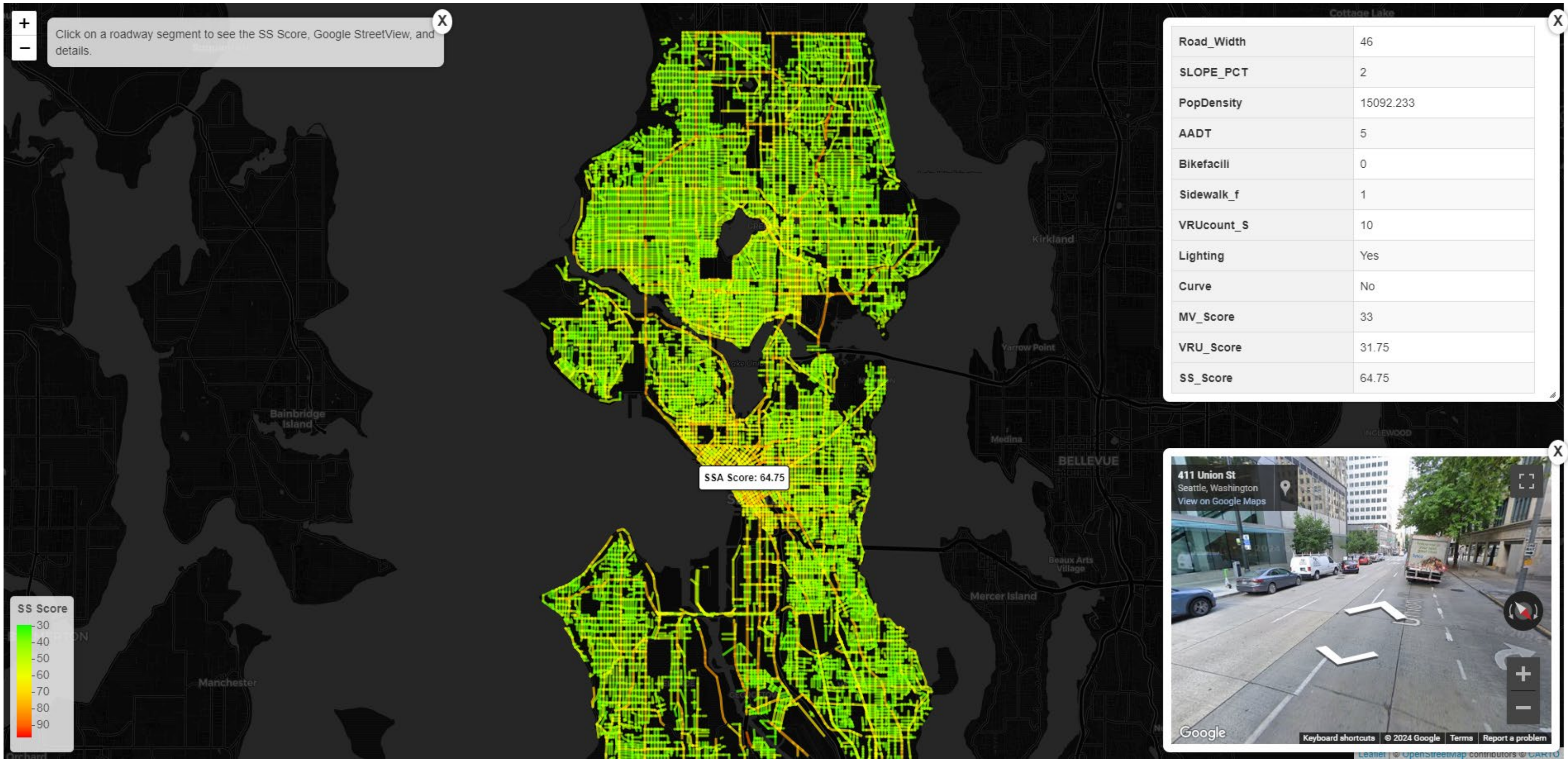


Figure 10. Interface of the SSA Tool in Seattle, Washington (Link to live version: Seattle)

Recommendations

This section provides evidence-based recommendations to address traffic safety disparities informed by findings and equity-focused literature. By synthesizing results across analyses, this study aims to identify where inequities occur and who is most affected, as well as propose best practices to mitigate these disparities. Where relevant, both the commonalities and differences between states are emphasized, and tailored recommendations for each state are proposed.

The recommendations and best practices of this research are tailored to the unique contexts, needs, and challenges that different populations and communities face. While in some cases, they may be applied broadly, in others, they may be specific to the regions and populations studied in this research. Caution against broad applications is advised. The purpose of this study is to help other researchers and policymakers in other regions create safer and more equitable environments. Given the data, analyses were unable to consider decision-making behavior or attitudes that guide decisions or perceptions of safety and equity; future research should endeavor to do so. In addition, in order to achieve equity, a holistic approach is necessary. Specifically, understanding the complex and dynamic role of many intersecting factors, such as social identities, social roles, and place-based effects, is imperative for safety.

Policy Implications and Best Practice Recommendations

Below are policy implications and best practices that have been *uniquely informed by the current analysis*. These should be considered additions and modifications to policy recommendations at each state level and not stand-alone recommendations. Table 11 summarizes policy recommendations and evidence-based example strategies, which are described in more detail in subsequent sections below. When summarizing recommendations and strategies, where relevant, supporting “case examples” are provided leveraging key outcomes from the multi-faceted data analyses. These broad recommendations are followed and augmented by more specific strategies related to SSA analysis and scoring, stemming from the road segment analysis. Table 12 depicts these SSA analysis and policy recommendations, including recommended strategies with actions, guidance, and case examples from the current research.

Table 11. Equity-Based Policy Recommendations and Strategies.

Recommendations	Strategies
Address the complexity of **human experiences**	• Disaggregate data by population demographics, such as race/ethnicity, gender, socioeconomic status, and other equity-related factors, to highlight negative impacts within traditionally marginalized populations • When possible, use an intersectional approach to disaggregate data by population demographics • Expand social demographic data collection and analyses • Consider social roles in data interpretation, policy revision, and community outreach • Communicate with and include all the above communities in transportation safety decision-making
Conduct **place-based analyses**	• Use area type (e.g., urban vs. rural) to uncover differential structures that impact safety • Use sector type (e.g., employment, retail, school) to better understand land-use patterns and their influence on crash likelihood • Consider context-dependent effects within places • When conducting place-based research, use an accompanying analysis of population demographics relevant to equity (e.g., race/ethnicity, gender, socioeconomic-related information)

Recommendation #1: Expand analyses, policies, and practices to address the complexity of human experiences

Strategy 1: *Disaggregate data by population demographics, such as race/ethnicity, gender, socioeconomic status, and other equity-related factors, to highlight negative impacts within traditionally marginalized populations.*

As others have suggested, such as in transportation scholarship and within some state DOT policies, data should be disaggregated by demographics. The data overwhelmingly highlight the importance of social demographic equity analyses in crash data.

Case example:

- In Texas, the modeling identified that males, older drivers, and those in suburban or rural areas face higher risks of sustaining fatal and severe injuries. Racial disparities are also evident in varied social demographic groups.

These data also point to the importance of using advanced analytical methods to uncover disparities when appropriate. Contingencies and important interaction effects are often lost or overlooked when using highly aggregated data. This also relates to the second strategy.

Strategy 2: *When possible, use an intersectional approach to disaggregate data by population demographics.*

An intersectional approach draws attention to the multiplicity of human experiences based on *many social group memberships* (Crenshaw, 1991). Rather than analyzing the separate effects of traffic equity by, for example, race, gender, *or* age, an intersectional approach highlights the complexity that is afforded by one's *multiple group memberships*, especially among those who belong to multiple stigmatized identities, e.g., Black women (Purdie-Vaughns & Eibach, 2008; Sesko & Biernat, 2018). It also recognizes that individuals exist within varying systems of power (like social class) that guide access to equity and life experiences (Cole, 2009). Recent work in traffic equity has begun to acknowledge the importance of such analyses (Giacomantonio et al., 2024; Roberts et al., 2019; Yuan et al., 2023). Traffic safety countermeasures should reduce assumptions that experiences are homogenous among singular social groups (e.g., among all Hispanics) and instead conduct intersectional analyses to address both the similar and differing experiences by race *and* gender (e.g., Hispanic women vs. Hispanic men), age (e.g., young Hispanic women vs. young Hispanic men), *and* social class (e.g., lower social class Whites vs. higher social class Whites), in particular, but also considering disability status, English proficiency, and other vulnerable group memberships.

Case examples:

- In Texas, Black female pedestrians are significantly overrepresented across all injury severity outcomes for all age groups (except for pedestrian fatalities involving the less than 18 years old group, which follows a similar trend but lacks statistical significance). For instance, Black females aged 55+ constitute 20.6% of pedestrian fatalities, compared to their base proportions of 9.5%, showing overrepresentation by 11.1%.
- In Texas, White males are significantly overrepresented in MVO fatalities, while Black male MVOs are significantly overrepresented in non-incapacitating injuries; both White and Black MVOs show significant overrepresentation in MVO incapacitating injuries.
- In Ohio, young and middle-aged Black male pedestrians and Black female pedestrians aged 18–34 years were significantly overrepresented in fatalities.

This sampling of data demonstrates the complexity of human experiences; intersectional analyses uncovered the consistency of risk for Black female pedestrians, differences in risk across age groups for Black and White MVOs, and differences in risk by race, gender, and age for bicyclists.

Strategy 3: *Expand social demographic data collection and analyses.*

Available data often limit the ability to conduct proper intersectional analyses. For example, access to population data by intersections may be limited (e.g., the population of low-income Hispanic women), reducing the ability to analyze fatality rates. Therefore, we also recommend a shift in data collection that considers the importance of intersectionality.

In addition, equity scholars have been drawing attention to the oversimplification of category memberships (Shih et al., 2019). For example, the category "Asian" represents a diverse group with diverse histories, cultures, socioeconomic statuses, and daily experiences. Indeed, in the current data, there was variability across and within states and measures, which may be accounted for by dehomogenizing the group (e.g., East Asian, Southeast Asian, South Asian) and focusing on multiplicities of social category memberships (e.g., low-income vs. high-income Asian groups). In addition, the AIAN group has historically been misrepresented or not at all represented, such that they are rendered invisible in scholarship, policy, and everyday discourse (Fryberg & Eason, 2017; Fryberg & Townsend, 2008). It is recommended that data collection and analyses be centered on underrepresented, misrepresented, and unrepresented groups to inform planning and policy.

Case examples:

- In Texas, the (overall) fatality rate for AIAN showed a steady increase, starting from a relatively low level in 2017 and peaking sharply in 2021 with a rate exceeding 30 fatalities per 100,000 population, remaining significantly higher than all other race/ethnicity groups in 2022. For example, AIAN fatality rates were 65% lower than those of Whites in 2017, but they increased dramatically over the years, becoming *67% higher* than those of Whites by 2022. Similarly, in Ohio, AIAN MVOs experienced increases in relative fatality rates from 2% lower to *193%* higher than Whites.
- In Washington, the NHPI relative fatality rate increased from *100% lower* than Whites in 2013 to *90% higher* in 2022.
- In Ohio, the higher the percentage of mobile homes in a tract, the stronger the association between the percentage of NHPI residents and pedestrian serious and fatal injury rates (99% increase). This suggests that considering socioeconomic status and race/ethnicity is important: NHPI individuals who are financially disadvantaged may experience different risks than those with presumably more financial security.

Strategy 4: *Consider social roles in data interpretation, policy revision, and community outreach.*

Importantly, when addressing equity concerns, group memberships should be understood based on the roles that groups commonly occupy rather than being strictly defined by demographic categories assumed to consistently perform specific roles. For example, social role theory argues that differential role occupancy (e.g., in families and occupations) can drive stereotype content (Diekman & Eagly, 2000). For example, gender stereotypes tend to be role-bound: women are stereotyped to conduct parenting activities (like picking up kids from school) more than men. Social roles are also dynamic and change: women have entered the workforce (while also remaining in caregiving roles) to a greater degree than before (Diekman & Eagly, 2000). Therefore, making policy decisions should also be informed by roles (vs. only by social demographic groups) in order to avoid creating systems that are stereotype-driven and inequitable in the future. For example, policy decisions should not be made to accommodate a particular group (like women or men), but instead, the role that is affected in traffic safety (like parents going to schools, high workplace traffic, etc.) when relevant. Certainly, though, it is equally important to acknowledge that particular groups tend to be bound to marginalized and high-risk roles; disentangling roles from social groups, therefore, is not always possible. The key, however, is to reduce the reinforcement of stereotypes while also reducing present and future inequity.

Case examples:

- In Texas, tracts with a higher number of service jobs experience higher rates of fatal and serious injuries sustained by bicyclists.
- In Ohio, the higher the percentage increase in the number of office jobs in a tract, the stronger the association between the percentage of AIAN residents and pedestrian fatal and serious injury rates.

The above sampling of data suggests roles (e.g., types of jobs that influence behavior and mode and frequency of transportation) may be an indicator of risk. Which demographic is most impacted may be context-dependent (e.g., AIAN in Ohio who occupy office jobs), but not necessarily because of race/ethnicity.

When conducting community outreach or teaching programs on risk reduction or safety skills, individual and community needs, including social roles, must be centered. For example, conducting meetings when parents are likely to be picking up kids from school reduces attendance and perceptions of inclusivity. Indeed, the WSDOT (2024) Strategic Highway Safety Plan recognizes that messaging must be accessible to all (e.g., non-English speakers), culturally relevant, and public meetings must consider the costs of travel and caregiving responsibilities. In addition, community voices, especially those that have been historically omitted, must also be present when interpreting data and making policy, leading to the next strategy.

Strategy 5: *Communicate with and include all impacted communities in transportation safety decision-making.*

To accomplish equity, individual and community voices must be centered. This means working with communities as partners to develop and implement safer systems. For example, across all states, there were significant increases in AIAN serious injuries and fatalities. To understand why this is occurring, decision-makers and researchers should discuss these data with impacted communities before suggesting infrastructure changes that may not align with community needs or values. Importantly, working with communities instead of for (or without) them creates trust and communicates that social justice is valued. In addition, when community needs are valued, the use of safe transportation systems increases. For example, higher perceived fairness is related to higher perceived quality of transit service and ease of paying for transit use, consequently increasing transit use (Kaplan et al., 2014).

Recommendation #2: Conduct place-based analyses to uncover inequities and inform policy

Place-based approaches recognize that people live in communities and spaces that inform patterns of behavior (e.g., how many people go to work, how often roads are used, how fast they can get there, transportation modality, etc.) and access (e.g., to safe road systems, hospitals).

It is also the case that social demographics (e.g., by race or socioeconomic status) may systemically vary by place (e.g., certain area types may be more likely to be home to particular racial or ethnic groups). Social identities may also inform behavior patterns, regardless of, or in interaction with, a place (e.g., cultural norms influence behavior; for a review, see the study by Karner & Niemeier (2013)). In addition, cultural-psychological frameworks and data show that inequity does not only reside in the minds of individual people (e.g., racist ideologies) but instead within the structure of our everyday worlds that are afforded by historically derived ideas and cultural patterns (Salter et al., 2018). Place-based research goes beyond location-only analyses in that it acknowledges that behavior is informed not only by the location but also by what people do in those locations and by cultural patterns that direct behavior. Therefore, to uncover disparities within structures when conducting place-based research, an accompanying analysis of population demographics is essential.

Importantly, the historical threat to the internal validity of the COVID-19 pandemic was also considered; when big events, such as a global pandemic, occur, or when a more localized event occurs, such as hurricanes, it is essential to attempt to uncover their short-term and long-term effects on behavior and in data. Below, four strategies are described that allow for place-based approaches, including area type and sector type in analyses and the application of context-dependent and population effects.

Strategy 1: *Use area type (e.g., urban vs. rural) to uncover differential structures that impact safety.*

Case examples:

- In Ohio, Texas, and Washington, rural tracts are associated with higher rates of fatal and serious injuries sustained by MVOs. In Ohio, these rates, in particular, became twice as high in the post-COVID period.
- In all three states, urban tracts experience higher rates of fatal and serious injuries sustained by vulnerable road users, particularly pedestrians, compared to suburban/town tracts.
- In Washington, while rural tracts are associated with higher rates of fatal and serious injuries sustained by MVOs, town tracts amplify the association between the percentage of people with multiple races and MVO injury rates (15% increase).
- In Washington, rural tracts with a higher percentage of Black residents are amplified by a 9% increase in pedestrian fatal and serious injury rates.
- In Texas, suburban tracts with a higher percentage of people of multiple races are amplified by a 4% increase in the pedestrian fatal and serious injury rates.
- In Ohio, fatal and serious injury rates of bicyclists in rural/town tracts are amplified if those tracts have a higher percentage of Hispanic population.

Strategy 2: *Use sector type (e.g., employment, retail, school) to better understand land-use patterns and their influence on the crash likelihood.*

Case examples (also see above strategy on the importance of social roles):

- In Washington, tracts with a higher number of retail jobs are correlated with higher rates of fatal and serious injuries sustained by MVOs and pedestrians. In Ohio, a similar association is observed for MVOs.
- In Washington, tracts with a higher number of service jobs are associated with higher rates of fatal and serious injuries sustained by bicyclists.
- In Texas, tracts with a higher number of industrial jobs experience higher fatal and serious injury rates for MVOs and bicyclists.
- In Texas, tracts with higher numbers of industrial and retail jobs are correlated with higher rates of fatal and serious injuries sustained by pedestrians.

- In Ohio, fatal and serious injury rates sustained by bicyclists are amplified in tracts with a higher density of schools and a higher percentage of people of multiple races.

Strategy 3: *Consider context-dependent effects within places.*

When conducting analyses and devising policy, it is essential that context-dependent effects of place are considered. For example, while similarities were observed across states in some findings, there were also important differences. These differences may occur for a multitude of reasons, many of which are highlighted above, including population demographics, road structures, available modes of transportation, funding, historical and current policies, land use, cultural patterns, etc. This is highlighted to acknowledge that places categorized by area type or sector in different places are not homogeneous.

Ohio case examples:

- Tracts with a higher density of multi-lane roads experience higher rates of fatal and serious injuries sustained by bicyclists.
- Census tracts with a higher density of multi-lane roads, coupled with more Asian residents, experience higher rates of fatal and serious injuries sustained by MVOs, particularly in the post-COVID period (6% increase).
- In Ohio, tracts with a higher percentage of Asian people, percentage of people without insurance, and percentage of people with a disability experience higher bicyclist fatal and serious injury rates.

Texas case examples:

- The presence of more multi-lane roads correlates with a stronger association between tracts with more people of multiple races and fatal and serious injury rates of MVOs (2% increase).
- Tracts with higher densities of roads with 30–40 mph and 45–55 mph posted speed limits or higher AADT have higher pedestrian fatal and serious injury rates.
- Tracts with a higher percentage of people of multiple races or other races are associated with lower rates of fatal and serious injuries sustained by bicyclists.

Washington case examples:

- A higher density of miles of unmarked crosswalks in tracts amplifies the association between the percentage of AIAN or Hispanic people and bicyclist fatal and serious injury rates (110% and 13% increases, respectively).

As highlighted in bold above, there was diversity in findings (e.g., unmarked crosswalks for Washington and higher density of roads by posted speed limit for Texas) and also similarities (e.g., the higher density of multi-lane roads for Ohio and Texas), but *who* was affected most and via which mode of transportation also varied across states. These data also demonstrate the need for population demographics in analyses of place, leading to our next strategy.

Strategy 4: *When conducting place-based research, use an accompanying analysis of population demographics relevant to equity (e.g., race/ethnicity, gender, socioeconomic-related information).*

Case examples:

- In Washington, tracts with higher percentages of Black, NHPI, and multiple-race populations face higher fatal and serious injury rates for MVOs.
- In Ohio, tracts with higher percentages of Black residents experience higher fatal and serious injury rates for MVOs.
- In Washington, tracts with higher percentages of Black, AIAN, and NHPI populations show increased fatal and serious injury rates for pedestrians.
- In Texas, tracts with higher percentages of Black and Hispanic populations consistently experience higher rates of fatal and serious injuries sustained by pedestrians.
- In Ohio, in tracts with a higher percentage of mobile homes, the association between higher percentages of NHPI residents and higher fatal and serious injury rates for pedestrians became stronger, particularly during the post-COVID period.
- In Washington, tracts with a higher percentage of people aged 65+ and more service jobs have higher fatal and serious injury rates for bicyclists.
- In Ohio, tracts with higher percentages of Asian and uninsured individuals experience higher rates of fatal and serious injuries sustained by bicyclists.

Recommendations for SSA Scoring and Analysis

To complement the recommendations and strategies noted above, Table 12 presents equity-based strategies, actions, and guidance that were directly informed by the SSA analyses, including case examples.

Table 12. Equity-Based SSA Scoring and Analysis Recommendations.

Strategies	Action	Guidance	Case Example
Conduct comprehensive data integration	Collect and integrate diverse data sources including roadway inventory (geometry, traffic volume, posted speed limits), crash data, and socioeconomic data (e.g., poverty rates, unemployment).	Prioritize cities or regions with comprehensive data availability to ensure reliable scoring, as demonstrated by the selection of Cleveland, Seattle, and Austin for this study.	All case studies utilized SVI to identify segments with high poverty and unemployment, highlighting areas requiring targeted safety interventions.
Develop equity-focused roadway scoring	Score roadway segments using the SSA framework that evaluates *Exposure*, *Likelihood*, and *Severity* metrics while integrating an *equity-based component* to assess socioeconomic vulnerabilities.	Use equity-related performance measures (e.g., percentage of population below 150% of the poverty threshold) to prioritize resources for underserved areas.	In Cleveland, segments in high-poverty neighborhoods showed lower safety alignment, emphasizing the need for equity considerations in roadway design and safety planning.
Conduct analysis of disparities	Assess disparities in SSA Scores across sociodemographic and socioeconomic groups, identifying systemic inequities in safety potential.	Use advanced analytical methods to uncover direct and indirect relationships between demographic factors and safety alignment, enabling informed decision-making.	SEM in Seattle revealed that segments in areas with high proportions of single-parent households or racial minorities scored lower on safety alignment, highlighting inequities in road safety outcomes.
Provide guidance on localized interventions based on case studies	Develop specific and designed safety interventions based on city-specific insights from SSA Scores and equity analysis.	Localized strategies should reflect the unique demographic and economic contexts of each city, leveraging proven approaches such as Austin's focus on vulnerable road users.	Austin's Vision Zero initiative demonstrated how targeted safety strategies, like EAZs, effectively improved safety in socioeconomically disadvantaged areas. These zones guided investments in traffic calming, speed management, and pedestrian infrastructure.

Strategies	Action	Guidance	Case Example
Develop proactive equity-centered safety planning	Prioritize equity in infrastructure planning by addressing identified safety gaps in disadvantaged neighborhoods.	Integrate equity considerations into safety policies at all planning stages, ensuring the proactive identification and mitigation of risks for vulnerable populations.	Cleveland and Seattle demonstrated that higher SSA Scores correlated with higher poverty and unemployment rates. Targeted investments in these areas can mitigate systemic disparities.
Continuous evaluation and policy adaptation	Establish benchmarks for monitoring the effectiveness of interventions and their impact on safety alignment and equity outcomes.	Cities should evaluate implemented measures periodically and adapt policies based on changing demographic and socioeconomic trends, ensuring sustained improvements in road safety equity.	The findings from Austin indicated that Vision Zero adoption and sustained equity-focused policies reduced disparities, improving alignment with SSA objectives.

Case study highlights. In addition, three stand-out state-level findings from the SSA analyses are included, along with some guidance.

- **Cleveland, Ohio**: High poverty and unemployment contributed to poor SSA alignment. Targeted interventions in high-risk areas could address inequities.
- **Seattle, Washington**: Demographic factors such as single-parent households and racial/ethnic minority populations were strongly associated with lower safety alignment, necessitating context-sensitive interventions.
- **Austin, Texas**: Early adoption of equity-focused Vision Zero policies resulted in comparatively better safety alignment in disadvantaged areas, demonstrating the effectiveness of proactive and targeted safety planning.
- Developed three demonstration versions of interactive tools to show SSA Scores on the segment level based on the Cleveland, Seattle, and Austin city case studies.

State-Level Recommendations: Key Insights

While the above takes a holistic approach, synthesizing data across states, some additional stand-out state-specific recommendations are highlighted below. In addition, the SHSP from each state is considered. An SHSP is a statewide safety framework required under the HSIP to reduce fatalities and serious injuries on public roads. The FHWA offers extensive resources, including guidance, tools, and FAQs, to assist states in developing, implementing, and improving their SHSPs. See earlier sections for details about SHSP for each state.

State-Level Recommendations: Ohio

- Data shows significant racial and demographic disparities in traffic fatalities and serious injuries, particularly for Black and AIAN populations.
    - **Community engagement** (through study surveys): Partner with local communities to ensure the data reflect lived experiences and inform equitable policy interventions.
- Black pedestrians and MVOs experience disproportionately high fatality and serious injury rates.
    - **Targeted interventions**: Increase pedestrian safety measures in urban areas with higher proportions of Black residents. Measures might include improved crosswalks, traffic calming devices, and enhanced street lighting.
- Area type-based analyses show that urban tracts experience higher rates of pedestrian fatality and serious injuries, while rural areas exhibit greater MVO injuries.
    - Prioritize pedestrian infrastructure improvements in urban tracts.
    - Expand public transit options in urban settings to reduce reliance on motor vehicles.
    - Increase visibility in rural areas through better signage and lighting.
    - Collaborate with city planners to incorporate safety considerations into land-use policies, particularly in high-risk neighborhoods.
- Adoption of the SSA can be further enhanced.
    - **Continuous monitoring**: Establish benchmarks to evaluate the effectiveness of interventions and adjust policies as necessary.
- Community-specific outreach and education are critical to improving awareness of traffic safety risks and encouraging safer behaviors.
    - **Culturally relevant messaging**: Developing culturally tailored educational campaigns to address traffic safety behaviors in diverse communities through stakeholders' collaboration, partnering with schools and local organizations to amplify safety messaging and encourage community participation.

State-Level Recommendations: Texas

- Rural census tracts are associated with higher rates of fatal and serious injuries sustained by MVOs compared to urban tracts.
    - **Implement rural roadway safety programs**: install rumble strips, widen shoulders, and improve roadway lighting in rural areas.

    - **Enhance emergency response**: expand access to trauma care and emergency services in rural regions to reduce fatalities post-crash.
- The rates of fatal and serious injuries sustained by MVOs are higher in census tracts with a higher number of industrial jobs.
    - **Introduce regulations for traffic safety audits** around industrial areas, ensuring safe ingress and egress points, and designate heavy-vehicle-only zones to minimize conflicts.
    - **Require industrial employers to collaborate** with local governments to improve transportation infrastructure near worksites, including better signage, speed management, and lighting.
- The rates of fatal and serious injuries sustained by pedestrians are higher in tracts with higher numbers of service and industrial jobs; with Black pedestrians at a higher risk of sustaining fatal and serious injuries compared to White and Hispanic pedestrians.
    - **Prioritize pedestrian infrastructure improvements** (e.g., crosswalks, sidewalks, lighting) in tracts with high concentrations of service and industrial jobs, focusing on communities with racial safety disparities.
    - **Launch a targeted public safety campaign** addressing pedestrian safety in high-risk areas, including culturally tailored and community-informed outreach to Black communities.
- The rates of fatal and serious injuries sustained by bicyclists are higher in tracts with higher percentages of mobile homes, individuals with a disability, and individuals living below 150% of the poverty estimate.
    - **Develop bike-friendly infrastructure,** such as protected bike lanes and traffic calming measures, in low-income and mobile home communities.
    - **Create subsidy programs for free or low-cost bicycle safety equipment** (e.g., helmets, lights) and offer safety training for individuals with disabilities and low-income populations.
- Roadway segments in socioeconomically disadvantaged areas in Austin demonstrated good alignment with SSA objectives, likely due to Austin's proactive adoption of safety strategies like Vision Zero.
    - **Investment in SSA strategies**, such as traffic calming measures, protected pedestrian and bicycle infrastructure, and speed management, with a focus on socioeconomically disadvantaged areas.
    - **Establish equity-focused performance metrics** within Vision Zero to ensure ongoing monitoring and prioritization of safety improvements in disadvantaged neighborhoods, addressing any emerging gaps.

State-Level Recommendations: Washington

- Rural census tracts are associated with higher rates of fatal and serious injuries sustained by MVOs compared to urban tracts.
  - **Implement rural roadway safety programs**: install rumble strips, widen shoulders, and improve roadway lighting in rural areas.
  - **Enhance emergency response**: expand access to trauma care and emergency services in rural regions to reduce fatalities post-crash.
- Census tracts with higher percentages of Black, NHPI, and other racial populations are associated with higher fatal and serious injury rates among MVOs.
  - **Equity-focused funding**: allocate targeted funds to improve infrastructure in racial/ethnic minority-dense tracts, such as adding median barriers and protected lanes.
  - **Community engagement**: work directly with underserved communities to identify high-risk areas and prioritize safety improvements.
- Compared to urban tracts, town, and suburban tracts exhibit lower rates of fatal and serious injuries sustained by pedestrians.
  - **Urban pedestrian safety improvements**: implement traffic calming measures, such as speed humps, narrower lanes, and pedestrian-exclusive signal phases at intersections in urban areas.
  - **Expand walkability initiatives**: create safer pedestrian paths and enhance visibility with improved street lighting.
- Census tracts with higher percentages of Black, AIAN, and NHPI populations are associated with increased fatal and serious injury rates among pedestrians.
  - **Crosswalk upgrades**: increase marked and signalized pedestrian crossings in underserved areas.
  - **Address systemic inequities**: provide equitable investment in safe pedestrian infrastructure, particularly in racial/ethnic minority communities, through federal and local safety grants.
- Tracts with a higher percentage of individuals with a disability show a significant association with higher fatal and serious pedestrian injury rates.
  - **Accessible pedestrian infrastructure**: install curb ramps, tactile paving, and auditory pedestrian signals.
  - **Targeted education and enforcement**: promote driver awareness campaigns emphasizing pedestrian rights, particularly for individuals with disabilities.

- Tracts with a higher density of unmarked crosswalks are correlated with higher fatal and serious pedestrian injury rates.
    - **Improve crosswalk visibility**: mark all crosswalks with high-visibility striping and add pedestrian signage.
    - **Traffic calming at crossings**: install pedestrian refuge islands or curb extensions near unmarked crosswalk locations.
- Tracts with higher percentages of individuals aged 65+ or under 18 are linked to increased fatal and serious injury rates of bicyclists.
    - **Dedicated bicycle lanes**: create protected and buffered bike lanes to separate cyclists from vehicle traffic.
    - **Educational programs**: offer cycling safety programs targeted at older adults and youth to promote safer riding behaviors.
- Tracts with a greater prevalence of service-sector jobs are also associated with higher fatal and serious bicyclist injury rates.
    - **Bicycle network expansion**: develop bike-friendly commuting routes near service-sector job hubs.
    - **Employer collaboration**: Encourage service-sector employers to support safe commuting options, such as secure bike parking and incentives for alternative transportation.
- Segments in disadvantaged areas (higher poverty/unemployment rates) in Seattle tend to show reduced alignment with safety objectives. Notably, areas with higher proportions of single-parent households or racial/ethnic minority populations score lower on safety alignment, underscoring inequities in road safety outcomes.
    - **Equitable road safety audits**: Conduct regular safety audits in disadvantaged areas to identify gaps in infrastructure.
    - **Incentivize safety funding**: Provide additional funding and resources to these areas for projects that align with Vision Zero or similar safety programs.

Across the country, efforts are underway at both the state and city levels to improve transportation safety through an equity lens. For example, in Washington State, the bill WA HB1772 is currently in progress (Washington State Legislature, 2025a). This legislation focuses on establishing shared streets that prioritize bicycle and pedestrian safety, including setting speed limits as low as 10 mph in designated areas. Another Washington State House Transportation SB 5581 bill concerns SSA strategies for active transportation infrastructure (Washington State Legislature, 2025b). In Texas, SB1013 expands transportation law to protect sidewalk users—now defined to include people using bikes, scooters, mobility devices, skateboards, and similar modes. The bill requires drivers entering or exiting alleys, driveways, or buildings to stop before crossing sidewalks, yield to pedestrians and sidewalk users, and yield to oncoming traffic when entering a roadway (Texas Legislature, 2025).

Limitations

There were some quality data limitations that should be noted. First, race and ethnicity information was only available for crashes that occurred in recent years, which limited the ability to assess disparities across demographic groups over the entire decade. Another limitation is the small number of crash counts for certain race/ethnic groups in some of the states. In some cases, this caused sharp fluctuations across some years, which can give a misleading impression of an excessively high or changing risk.

Second, in many cases detailed traffic exposure data and speed information was only available for major roads. In many cases, detailed traffic-related exposure data, such as Average Annual Daily Traffic (AADT), pedestrian counts, and bicycle volumes, were limited and not disaggregated by the different races or ethnicities, which may have masked important variations in risk for vulnerable road users. As a result, the study relied on population data and other surrogate measures, which may have reduced the precision and limited the ability to fully capture safety inequities.

Third, the population and demographic data obtained from KFF did not include estimates for the year 2020 due to disruptions caused by the COVID-19 pandemic. To address this gap, the 2020 population for each race and ethnicity group was estimated by averaging the estimates for 2019 and 2021.

In addition, the CRIS database used in this study does not explicitly define the guidelines or protocols employed in collecting ethnicity data of individuals involved in a crash. The lack of standardized data collection methods may lead to inconsistencies or inaccuracies in how race and ethnicity are recorded. In the analysis, race/ethnicity data were classified according to the OMB guidelines. However, this classification approach may differ from the methodologies used by TxDOT in collecting race/ethnicity data.

Finally, crash data for the year 2020 were not considered in the neighborhood-level analysis due to the unprecedented and disruptive impacts of the COVID-19 pandemic. The pandemic led to significant and atypical changes in travel behavior, including widespread lockdowns, reduced traffic volumes, shifts in modal choice, and changes in roadway usage patterns. As a result, crash patterns during 2020 were highly irregular and not representative of typical conditions. To ensure the validity and consistency of the models, the analysis was instead based on two-year periods immediately before and after 2020, allowing for more reliable comparisons and minimizing the influence of pandemic-related anomalies.

By integrating equity considerations through SSA, the project provides a roadmap for developing comprehensive approaches that prioritize equity-focused interventions.

However, further research is needed to evaluate the long-term effectiveness of such interventions. Expanding this research to include additional geographic regions across the nation would help refine policies and strategies that ensure traffic safety improvements benefit all communities equitably.

References

Adler, S. (2016). *Austin selected as national vision zero network focus city*. City of Austin Mayor's Office. https://www.mayoradler.com/austin-selected-as-national-vision-zero-network-focus-city/

Aguinis, H., Gottfredson, R. K., & Joo, H. (2013). Best-practice recommendations for defining, identifying, and handling outliers. *Organizational Research Methods* 16(2), 270–301. https://doi.org/10.1177/1094428112470848

Ahmad, S., Zulkurnain, N., & Khairushalimi, F. (2016). Assessing the validity and reliability of a measurement model in structural equation modeling (SEM). *British Journal of Mathematics & Computer Science*, 15(3), 1–8. https://doi.org/10.9734/bjmcs/2016/25183

American Association of State Highway and Transportation Officials. (2018). *A policy on geometric design of highways and streets* (7th ed.).

Anastasopoulos, P. C., & Mannering, F. L. (2011). An empirical assessment of fixed and random parameter logit models using crash-and non-crash-specific injury data. *Accident Analysis & Prevention*, 43(3), 1140–1147. https://doi.org/10.1016/j.aap.2010.12.024

Association of Washington Cities. (2021). *AWC Equity Resource Guide: Tools and case studies for Washington cities.* Published on Nov 30, 2021. https://wacities.org/data-resources/articles/2021/11/30/awc-equity-resource-guide-tools-and-case-studies-for-washington-cities

Austin Vision Zero. (2023). *Safe for all: 2023 update. vision zero's role in advancing racial equity in Austin.* https://storymaps.arcgis.com/stories/3a3a426a303c41bab65936eda0d58fde

Baayen, R. H., Davidson, D. J., & Bates, D. M. (2008). Mixed-effects modeling with crossed random effects for subjects and items. *Journal of Memory and Language*, 59(4), 390–412. https://doi.org/10.1016/j.jml.2007.12.005

Barajas, J. M. (2018). Not all crashes are created equal: associations between the built environment and disparities in bicycle collisions. *Journal of Transport and Land Use*, 11(1). https://doi.org/10.5198/jtlu.2018.1145

Barber, A., Berkson, B., Furness, N., & Thorsteinson, S. (2021). *WSDOT equity study*. Center for Economic and Business Research, Western Washington University. https://wsdot.wa.gov/sites/default/files/2021-11/WSDOT-Equity-Study.pdf

Behnood, A., & Mannering, F. (2017). Determinants of bicyclist injury severities in bicycle-vehicle crashes: A random parameters approach with heterogeneity in means and variances. *Analytic Methods in Accident Research*, 16, 35–47. https://doi.org/10.1016/j.amar.2017.08.001

Bentler, P. M. (2010). SEM with simplicity and accuracy. *Journal of Consumer Psychology*, 20(2), 215–220. https://doi.org/10.1016/j.jcps.2010.03.002

BERK Consluting. (2020). *Joint Transportation Committee: Statewide Transportation Needs Assessment*. https://leg.wa.gov/media/wbylt12h/statewidetransportationneedsfinalphase1.pdf

Braveman, P., Arkin, E., Orleans, T., Proctor, D., Acker, J., & Plough, A. (2018). What is Health Equity? *Behavioral Science & Policy*, *4*(1), 1–14. https://doi.org/10.1177/237946151800400102

Capital Area Metropolitan Planning Organization. (2015). *Capital Area Metropolitan Planning Organization (CAMPO) 2040 Regional Transportation Plan.* https://www.campotexas.org/regional-transportation-plans/2040-plan/

Centers for Disease Control and Prevention/ Agency for Toxic Substances and Disease Registry. (2022). *CDC/ATSDR Social Vulnerability Index 2022 Database* [Data set]. Geospatial Research, Analysis, and Services Program. Retrieved August 21, 2024. https://www.atsdr.cdc.gov/placeandhealth/svi/data_documentation_download.html

Cheung, G. W., Cooper-Thomas, H. D., Lau, R. S., & Wang, L. C. (2024). Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations. *Asia Pacific Journal of Management*, 41(2), 745–783. https://doi.org/10.1007/s10490-023-09871-y

City of Austin. (n.d.-a). *Transportation urban trails network*. Retrieved August 21, 2024. https://data.austintexas.gov/dataset/TRANSPORTATION_urban_trails_network/jdwm-wfps/about_data

City of Austin. (n.d.-b). *Vision Zero Programs and Initiatives*. Retrieved October 9, 2024. https://www.austintexas.gov/page/vision-zero-programs-and-initiatives

City of Austin. (n.d.-c). *Sidewalks* | Open Data. Retrieved August 21, 2024. https://data.austintexas.gov/dataset/Sidewalks/vchz-d9ng/about_data

City of Dallas. (2024). *Housing and neighborhood revitalization*. https://dallascityhall.com/departments/housing-neighborhood-revitalization/Pages/Infrastructure.aspx

City of Seattle. (2024). *Seattle streets*. https://data-seattlecitygis.opendata.arcgis.com/datasets/d716876edede4fbd9c614978683b1c91_0/explore

Cole, E. R. (2009). Intersectionality and research in psychology. *American Psychologist*, 64(3), 170–180. https://doi.org/10.1037/a0014564

Coughenour, C., Abelar, J., Pharr, J., Chien, L.-C., & Singh, A. (2020). Estimated car cost as a predictor of driver yielding behaviors for pedestrians. *Journal of Transport & Health*, 16, 100831. https://doi.org/10.1016/j.jth.2020.100831

Cousineau, D., & Allan, T. A. (2015). Likelihood and its use in parameter estimation and model comparison. *Mesure et Évaluation En Éducation*, 37(3), 63–98. https://doi.org/10.7202/1036328ar

Crenshaw, K. (1991). Mapping the Margins: Intersectionality, Identity Politics, and Violence against Women of Color. *Stanford Law Review*, 43(6), 1241. https://doi.org/10.2307/1229039

Cui, H., & Xie, K. (2021). An accelerated hierarchical Bayesian crash frequency model with accommodation of spatiotemporal interactions. *Accident Analysis & Prevention*, 153, 106018. https://doi.org/10.1016/j.aap.2021.106018

Das, S., & Mills, D. (2024). *Texas Driveway Navigator*.

Dash, G., & Paul, J. (2021). CB-SEM vs PLS-SEM methods for research in social sciences and technology forecasting. *Technological Forecasting and Social Change*, 173. https://doi.org/10.1016/j.techfore.2021.121092

Davis, V. O. (2023). *Inclusive Transportation: A Manifesto for Repairing Divided Communities.* Island Press.

DeWine, M., & Marchbanks, J. (2021). *Walk. Bike. Ohio policy plan: statewide bike and pedestrian plan*. https://www.transportation.ohio.gov/programs/walkbikeohio

Diekman, A. B., & Eagly, A. H. (2000). Stereotypes as dynamic constructs: women and men of the past, present, and future. *Personality and Social Psychology Bulletin*, 26(10), 1171–1188. https://doi.org/10.1177/0146167200262001

Dixon, W. J. (1953). Processing Data for Outliers. *Biometrics*, 9(1), 74–89. https://doi.org/10.2307/3001634

Dong, C., Clarke, D. B., Yan, X., Khattak, A., & Huang, B. (2014). Multivariate random-parameters zero-inflated negative binomial regression model: An application to estimate crash frequencies at intersections. *Accident Analysis & Prevention*, 70, 320–329. https://doi.org/10.1016/j.aap.2014.04.018

Dumbaugh, E., Li, Y., Saha, D., & Marshall, W. (2022). Why do lower-income areas experience worse road safety outcomes? Examining the role of the built environment in Orange County, Florida. *Transportation Research Interdisciplinary Perspectives*, 16, 100696. https://doi.org/10.1016/j.trip.2022.100696

Federal Highway Administration (2022). *Special Edition of Public Roads Magazine—The Safe System Approach*. https://highways.dot.gov/safety/learn-safety/special-edition-public-roads-magazine-safe-system-approach

Federal Highway Administration. (2024). Exploring risk factors to disparities in pedestrian and bicyclist fatalities and serious injuries. https://doi.org/https://doi.org/10.21949/1521546

Federal Highway Administration. (n.d.). *Safe system project-based alignment framework*. Retrieved August 21, 2024. https://highways.dot.gov/safety/zero-deaths/safe-system-project-based-alignment-framework

Fryberg, S. A., & Eason, A. E. (2017). Making the invisible visible: acts of commission and omission. *Current Directions in Psychological Science*, 26(6), 554–559. https://doi.org/10.1177/0963721417720959

Fryberg, S. A., & Townsend, S. S. M. (2008). The psychology of invisibility. In G. Adams, M. Biernat, N. R. Branscombe, C. S. Crandall, & L. S. Wrightsman (Eds.), *Commemorating Brown: The social psychology of racism and discrimination* (pp. 173–193). American Psychological Association. https://doi.org/10.1037/11681-010

Geverdt, D. (2019). *Education Demographic and Geographic Estimates Program (EDGE): Locale Boundaries File Documentation, 2017* (NCES 2018-115). U.S. Department of Education. Washington, DC: National Center for Education Statistics. https://nces.ed.gov/programs/edge/docs/EDGE_NCES_LOCALE.pdf

Giacomantonio, S., Mitra, R., & Ravensbergen, L. (2024). Bicycle facilities and women's cycling frequency – An intersectional analysis of gendered travel behaviour. *Transportation Research Part A: Policy and Practice*, 184, 104094. https://doi.org/10.1016/j.tra.2024.104094

Glassbrenner, D., Herbert, G., Reish, L., Webb, C., & Lindsey, T. (2022). *Evaluating disparities in traffic fatalities by race, ethnicity, and income (Report No. DOT HS 813 188)*. National Highway Traffic Safety Administration.

Goddard, T., Kahn, K. B., & Adkins, A. (2015). Racial bias in driver yielding behavior at crosswalks. *Transportation Research Part F: Traffic Psychology and Behaviour*, 33, 1–6. https://doi.org/10.1016/j.trf.2015.06.002

Governors Highway Safety Association. (2021). *An analysis of traffic fatalities by race and ethnicity*. https://www.ghsa.org/sites/default/files/2025-01/race_2021.pdf

Graham, M. A., Neath, S., Buchanan, K. M., Mulligan, K., Lloyd, T., & Solomon, P. A. (2024). *Racial disparities in use of force at traffic stops*. https://policingequity.org/wp-content/uploads/2024/08/CPE-Use-of-Force-at-Traffic-Stops-Data-Brief-2024.pdf

Guerra, E., Dong, X., & Kondo, M. (2019). Do denser neighborhoods have safer streets? Population Density and Traffic Safety in the Philadelphia Region. *Journal of Planning Education and Research*, 0739456X1984504. https://doi.org/10.1177/0739456X19845043

Guo, Y., Chen, Z., Stuart, A., Li, X., & Zhang, Y. (2020). A systematic overview of transportation equity in terms of accessibility, traffic emissions, and safety outcomes: From conventional to emerging technologies. *Transportation Research Interdisciplinary Perspectives*, 4, 100091. https://doi.org/10.1016/j.trip.2020.100091

Hansmann, K. J., Grabow, M., & McAndrews, C. (2022). Health equity and active transportation: A scoping review of active transportation interventions and their impacts on health equity. *Journal of Transport & Health*, 25, 101346. https://doi.org/10.1016/j.jth.2022.101346

Harper, S., Charters, T. J., & Strumpf, E. C. (2015). Trends in Socioeconomic Inequalities in Motor Vehicle Accident Deaths in the United States, 1995–2010. *American Journal of Epidemiology*, 182(7), 606–614. https://doi.org/10.1093/aje/kwv099

Haskins, A. E., Clark, D. E., & Travis, L. L. (2013). Racial disparities in survival among injured drivers. *American Journal of Epidemiology*, 177(5), 380–387. https://doi.org/10.1093/aje/kws242

Henning-Smith, C., Evenson, A., Kozhimannil, K., & Moscovice, I. (2018). Geographic variation in transportation concerns and adaptations to travel-limiting health conditions in the United States. *Journal of Transport & Health*, 8, 137–145. https://doi.org/10.1016/j.jth.2017.11.146

Holdridge, J. M., Shankar, V. N., & Ulfarsson, G. F. (2005). The crash severity impacts of fixed roadside objects. *Journal of Safety Research*, 36(2), 139–147. https://doi.org/10.1016/j.jsr.2004.12.005

Igolkina, A. A., & Meshcheryakov, G. (2020). semopy: A Python Package for Structural Equation Modeling. *Structural Equation Modeling: A Multidisciplinary Journal*, *27*(6), 952–963. https://doi.org/10.1080/10705511.2019.1704289

Jalayer, M., Shabanpour, R., Pour-Rouholamin, M., Golshani, N., & Zhou, H. (2018). Wrong-way driving crashes: A random-parameters ordered probit analysis of injury severity. *Accident Analysis & Prevention*, 117, 128–135. https://doi.org/10.1016/j.aap.2018.04.019

Kaplan, S., de Abreu e Silva, J., & Di Ciommo, F. (2014). The relationship between young people׳s transit use and their perceptions of equity concepts in transit service provision. *Transport Policy*, 36, 79–87. https://doi.org/10.1016/j.tranpol.2014.08.004

Karner, A., & Niemeier, D. (2013). Civil rights guidance and equity analysis methods for regional transportation plans: a critical review of literature and practice. *Journal of Transport Geography*, 33, 126–134. https://doi.org/10.1016/j.jtrangeo.2013.09.017

Kaiser Family Foundation. (2023). *Demographics and the Economy*. https://www.kff.org/state-category/demographics-and-the-economy/population/

Kim, J.-K., Kim, S., Ulfarsson, G. F., & Porrello, L. A. (2007). Bicyclist injury severities in bicycle–motor vehicle accidents. *Accident Analysis & Prevention*, 39(2), 238–251. https://doi.org/10.1016/j.aap.2006.07.002

Kposowa, A. J., & Adams, M. (1998). Motor vehicle crash fatalities: the effects of race and marital status. *Applied Behavioral Science Review*, 6(1), 69–91. https://doi.org/10.1016/S1068-8595(99)80005-1

Kumar, S. (2024). Handling Missing Values with Random Forest. https://www.analyticsvidhya.com/blog/2022/05/handling-missing-values-with-random-forest/

Kwak, S. K., & Kim, J. H. (2017). Statistical data preparation: Management of missing values and outliers. In Korean Journal of Anesthesiology (Vol. 70, Issue 4, pp. 407–411). *Korean Society of Anesthesiologists*. https://doi.org/10.4097/kjae.2017.70.4.407

Lin, P.-S., Guo, R., Bialkowska-Jelinska, E., Kourtellis, A., & Zhang, Y. (2019). Development of countermeasures to effectively improve pedestrian safety in low-income areas. *Journal of Traffic and Transportation Engineering (English Edition)*, 6(2), 162–174. https://doi.org/10.1016/j.jtte.2019.02.001

Liu, J., Das, S., & Khan, M. N. (2024). Decoding the impacts of contributory factors and addressing social disparities in crash frequency analysis. *Accident Analysis & Prevention*, 194, 107375. https://doi.org/10.1016/j.aap.2023.107375

Longford, N. T. (1994). Logistic regression with random coefficients. *Computational Statistics & Data Analysis*, 17(1), 1–15. https://doi.org/10.1016/0167-9473(92)00062-V

Mansfield, T. J., Peck, D., Morgan, D., McCann, B., & Teicher, P. (2018). The effects of roadway and built environment characteristics on pedestrian fatality risk: A national assessment at the neighborhood scale. *Accident Analysis & Prevention*, 121, 166–176. https://doi.org/10.1016/j.aap.2018.06.018

Merlin, L. A., Guerra, E., & Dumbaugh, E. (2020). Crash risk, crash exposure, and the built environment: A conceptual review. *Accident Analysis & Prevention*, 134, 105244. https://doi.org/10.1016/j.aap.2019.07.020

Mőller, H., Rogers, K., Cullen, P., Senserrick, T., Boufous, S., & Ivers, R. (2021). Socioeconomic status during youth and risk of car crash during adulthood. Findings from the DRIVE cohort study. *Journal of Epidemiology and Community Health*, 75(8), 755–763. https://doi.org/10.1136/jech-2020-214083

Mudrazija, S., & Butrica, B. A. (2024). *Estimating Disparities Using Structural Equation Models*. Working Paper 2024-2. Chestnut Hill, MA: Center for Retirement Research at Boston College. https://crr.bc.edu/wp-content/uploads/2024/01/wp_2024-2.pdf

Mueller, R. O., & Hancock, G. R. (2018). *Structural equation modeling*. In The reviewer's guide to quantitative methods in the social sciences (pp. 445–456). Routledge.

National Academies of Sciences, Engineering, and Medicine. 2022. *Human Factors Guidelines for Road Systems 2021 Update, Volume 1: Updated and New Chapters.* Washington, DC: The National Academies Press. https://doi.org/10.17226/26473

National Highway Traffic Safety Administration. (2022). *Fatality Analysis Reporting System*. https://www.nhtsa.gov/Crash-Data-Systems/Fatality-Analysis-Reporting-System.

National Highway Safety Administration. (2024). *Traffic Safety Facts Annual Report Tables*. U.S. Department of Transportation. https://cdan.dot.gov/tsftables/tsfar.htm

National Safety Council. (1990). *National Safety Council KABCO Injury Classification Scale and Definitions*. https://highways.dot.gov/media/20141

Neuroth, L. M., Singichetti, B., Harmon, K. J., Waller, A. E., & Naumann, R. B. (2024). Racial and ethnic disparities in motor vehicle crash-related outcomes in North Carolina surrounding the COVID-19 pandemic. *Injury Prevention*, 30(1), 84–88. https://doi.org/10.1136/ip-2023-045005

Noël, R. A. (2018). *Race, economics, and social status*. Bureau of labor statistics. https://www.bls.gov/spotlight/2018/race-economics-and-social-status/pdf/race-economics-and-social-status.pdf

Nordback, K., Sellinger, M., & Phillips, T. (2017). *Estimating Walking and Bicycling at the State Level*. NITC-RR-564. Portland, OR: Transportation Research and Education Center (TREC). https://doi.org/10.15760/trec.163

Northeast Ohio Areawide Coordinating Agency. (n.d.). *GIS Portal*. Retrieved September 13, 2024. https://gis.noaca.org/portal/

Norton, E. C., & Dowd, B. E. (2018). Log odds and the interpretation of logit models. *Health Services Research*, 53(2), 859–878. https://doi.org/10.1111/1475-6773.12712

Office of Disease Prevention and Health Promotion. (2024). *Healthy People 2030: Building a healthier future for all.* U.S. Department of Health and Human Services. https://odphp.health.gov/healthypeople

Office of Management and Budget. (1997). *Appendix A Standards for Maintaining, Collecting, and Presenting Federal Data on Race and Ethnicity*. https://obamawhitehouse.archives.gov/omb/fedreg_1997standards

Ohio Department of Transportation. (2020). *Strategic Highway Safety Plan (SHSP)*. https://www.transportation.ohio.gov/working/publications/strategic-highway-safety-plan

Ohio Department of Transportation. (2023). *Ohio Vulnerable Road User Assessment 2023*. https://www.transportation.ohio.gov/working/publications/vulnerable-road-user-assessment

Ohio Department of Transportation. (2024). *Safe Routes to School Program: 2024 Application Guidance*. https://www.transportation.ohio.gov/programs/safe-routes-srts/apply-srts-funding/02-srts-guidance

Osborne, J. W., & Overbay, A. (2014). The power of outliers and fringeliers (and why researchers should ALWAYS check for them). *Practical Assessment, Research, and Evaluation,* 9(6).

OpenStreetMap Foundation. (n.d.). *OpenStreetMap*. Retrieved July 16, 2024. https://www.openstreetmap.org/#map=15/41.49093/-81.69588

Pantanowitz, A., & Marwala, T. (2009). Missing data imputation through the use of the random forest algorithm. *Advances in Computational Intelligence*, 53–62. https://doi.org/10.1007/978-3-642-03156-4_6

Pirdavani, A., Daniels, S., van Vlierden, K., Brijs, K., & Kochan, B. (2017). Socioeconomic and sociodemographic inequalities and their association with road traffic injuries. *Journal of Transport and Health*, 4, 152–161. https://doi.org/10.1016/j.jth.2016.12.001

Powell, J., Menendian, S., & Ake, W. (2019). *Targeted universalism: Policy & Practice*. Haas Institute for a Fair and Inclusive Society, University of California, Berkeley. https://haasinstitute.berkeley.edu/targeteduniversalism

Puget Sound Regional Council. (2022). *Puget Sound Regional Council Regional Transportation Plan.* https://www.psrc.org/media/5934

Purdie-Vaughns, V., & Eibach, R. P. (2008). Intersectional Invisibility: The Distinctive Advantages and Disadvantages of Multiple Subordinate-Group Identities. *Sex Roles*, 59(5–6), 377–391. https://doi.org/10.1007/s11199-008-9424-4

Ramthun, M. (n.d.). *Roadway Design Manual: Rumble Strips*. Retrieved August 21, 2024. https://onlinemanuals.txdot.gov/TxDOTOnlineManuals/TxDOTManuals/rdw/rumble_strips.htm

Revised Code of Washington. (2022). *RCW 47.04.035: Street access—Principles of complete streets—Requirements.* https://app.leg.wa.gov/rcw/default.aspx?cite=47.04.035

Roberts, J. D., Mandic, S., Fryer, C. S., Brachman, M. L., & Ray, R. (2019). Between Privilege and Oppression: An Intersectional Analysis of Active Transportation Experiences Among Washington D.C. Area Youth. *International Journal of Environmental Research and Public Health*, 16(8), 1313. https://doi.org/10.3390/ijerph16081313

Roll, J., & McNeil, N. (2022). Race and income disparities in pedestrian injuries: Factors influencing pedestrian safety inequity. *Transportation Research Part D: Transport and Environment*, 107, 103294. https://doi.org/10.1016/j.trd.2022.103294

Rue, H., Martino, S., & Chopin, N. (2009). Approximate Bayesian Inference for Latent Gaussian models by using Integrated Nested Laplace Approximations. Journal of the Royal Statistical Society Series B: *Statistical Methodology*, 71(2), 319–392. https://doi.org/10.1111/j.1467-9868.2008.00700.x

Saha, D., Alluri, P., Gan, A., & Wu, W. (2018). Spatial analysis of macro-level bicycle crashes using the class of conditional autoregressive models. *Accident Analysis & Prevention*, 118, 166–177. https://doi.org/10.1016/j.aap.2018.02.014

Salter, P. S., Adams, G., & Perez, M. J. (2018). Racism in the structure of everyday worlds: a cultural-psychological perspective. *Current Directions in Psychological Science*, 27(3), 150–155. https://doi.org/10.1177/0963721417724239

Sanders, R. L., & Schneider, R. J. (2022). An exploration of pedestrian fatalities by race in the United States. *Transportation Research Part D: Transport and Environment*, 107. https://doi.org/10.1016/j.trd.2022.103298

Schwartz, N., Buliung, R., Daniel, A., & Rothman, L. (2022). Disability and pedestrian road traffic injury: A scoping review. *Health & Place*, 77, 102896. https://doi.org/10.1016/j.healthplace.2022.102896

Serhiyenko, V., Mamun, S. A., Ivan, J. N., & Ravishanker, N. (2016). Fast Bayesian inference for modeling multivariate crash counts. *Analytic Methods in Accident Research*, 9, 44–53. https://doi.org/10.1016/j.amar.2016.02.002

Sesko, A. K., & Biernat, M. (2018). Invisibility of Black women: Drawing attention to individuality. *Group Processes & Intergroup Relations*, 21(1), 141–158. https://doi.org/10.1177/1368430216663017

Shih, K. Y., Chang, T., & Chen, S. (2019). Impacts of the model minority myth on Asian American individuals and families: social justice and critical race feminist perspectives. *Journal of Family Theory & Review*, 11(3), 412–428. https://doi.org/10.1111/jftr.12342

Smart Growth America. (2024). *Best Complete Streets Policies 2023*. https://www.smartgrowthamerica.org/knowledge-hub/resources/the-best-complete-streets-policies-2023/

Sroka, C. J., & Nagaraja, H. N. (2018). Odds ratios from logistic, geometric, Poisson, and negative binomial regression models. *BMC Medical Research Methodology*, 18(1). https://doi.org/10.1186/s12874-018-0568-9

Stacy, C., Ramos, K., Harvey, D., Rodriguez, S. D., Morales-Burnett, J., & Morris, M. (2022). *Recommendations for increasing transportation equity in South Dallas*. https://www.urban.org/sites/default/files/2022-12/Recommendations%20for%20Increasing%20Transportation%20Equity%20in%20South%20Dallas.pdf

Stoker, P., Garfinkel-Castro, A., Khayesi, M., Odero, W., Mwangi, M. N., Peden, M., & Ewing, R. (2015). Pedestrian safety and the built environment. journal of planning literature, 30(4), 377–392. https://doi.org/10.1177/0885412215595438

Tefft, B. C., & Wang, M. (2022). *Traffic Safety Impact of the COVID-19 Pandemic: Fatal Crashes Relative to Pre-Pandemic Trends, United States, May–December 2020 (Research Brief)*. Washington, D.C.: AAA Foundation for Traffic Safety. https://aaafoundation.org/traffic-safety-impact-of-the-covid-19-pandemic-fatal-crashes-relative-to-pre-pandemic-trends-united-states-may-december-2020/

Texas A&M Transportation Institute (TTI). (n.d.). *Texas Bicycle and Pedestrian Count Exchange (BP|CX) - Mobility Division*. Retrieved August 21, 2024, from https://mobility.tamu.edu/bikepeddata/

Texas Department of Transportation. (2021). *Texas Strategic Highway Safety Plan 2022–2027*. https://www.texasshsp.com/wp-content/uploads/2023/05/2022-2027-Texas-SHSP-2.pdf

Texas Department of Transportation. (2022). *Statewide Transportation Enhancement Program*. https://www.txdot.gov/projects/planning/stip.html

Texas Department of Transportation. (2023). *TxDOT's push to end 23 years of daily deaths on Texas roads*. Press Release dated 7 November 2023. https://www.txdot.gov/about/newsroom/statewide/2023/txdots-push-to-end-23-years-of-daily-deaths-on-texas-roads.html

Texas Department of Transporation. (2024). *Crash Records Information System*. https://cris.dot.state.tx.us/Public/Query/App/Home

Texas Department of Transportation. (n.d.-a). *Crash data analysis and statistics*. Retrieved November 7, 2024. https://www.txdot.gov/data-maps/crash-reports-records/crash-data-analysis-statistics.html

Texas Department of Transportation. (n.d.-b). *Roadway Inventory*. Retrieved August 21, 2024. http://txdot.gov/en/home/data-maps/roadway-inventory.html

Texas Legislature. (2025). SB 1013, *89th Legislature, Regular Session: Relating to the right-of-way of pedestrians and other sidewalk users*. Texas Legislature Online. https://capitol.texas.gov/BillLookup/History.aspx?LegSess=89R&Bill=SB1013

Toole Design. (2023). *Transportation Equity in Washington's Cities*. https://leg.wa.gov/media/t3kpmstl/finalreport_transpoequity.pdf

Toward Zero Deaths. (2024). *How Ohio DOT Advanced Equity in Traffic Safety with HSIP Funds*. https://www.towardzerodeaths.org/ohio-dot-equity-in-traffic-safety/

Transportation Equity Act for the 21st Century, H.R. 2400, 105th Cong. (1997). https://www.congress.gov/bill/105th-congress/house-bill/2400

Transporation Information Mapping System. (n.d.). *Data Download*. Ohio Department of Transportation. Retrieved August 14, 2024. https://gis.dot.state.oh.us/tims_classic/Data/Download

Turner, B., Jurewicz, C., Pratt, K., Corben, B., & Woolley, J. (2016). *Safe system assessment framework (Austroads Publication No. AP-R509-16)*. Austroads. https://www.researchgate.net/profile/Chris-Jurewicz/publication/294428116_Safe_System_Assessment_Framework/links/56c0ddbb08aeedba0564867e/Safe-System-Assessment-Framework.pdf

U.S. Census Bureau. (2024). *American Community Survey*. https://www.census.gov/programs-surveys/acs

U.S. Department of Transportation. (2022a). *Justice40*. https://www.transportation.gov/sites/dot.gov/files/2022-11/Justice4011141722.pdf

U.S. Department of Transportation. (2022b, October 13). *What is a Safe System Approach?* https://www.transportation.gov/NRSS/SafeSystem

U.S. Department of Transportation. (2023a, November). *RAISE Discretionary Grants*.

U.S. Department of Transportation. (2023b). *Safe Streets and Roads for All (SS4A) Grant Program.* https://www.transportation.gov/grants/SS4A

U.S. Environmental Protection Agency, & U.S. Department of Transportation. (2020). *Smart Location Database, version 3* [Data set]. U.S. Environmental Protection Agency. https://www.epa.gov/smartgrowth/smart-location-mapping#SLD

U.S. Geological Survey. (2018, December). *The National Elevation Dataset*. https://www.usgs.gov/Publications/National-Elevation-Dataset.

Vingilis, E., Beirness, D., Boase, P., Byrne, P., Johnson, J., Jonah, B., Mann, R. E., Rapoport, M. J., Seeley, J., Wickens, C. M., & Wiesenthal, D. L. (2020). Coronavirus disease 2019: What could be the effects on Road safety? *Accident Analysis & Prevention*, 144. https://doi.org/10.1016/j.aap.2020.105687

Vision Zero Chicago. (2017). *Action Plan 2017–2019: Chicago's initiative to eliminate traffic fatalities and serious injuries by 2026*. https://www.chicago.gov/content/dam/city/sites/complete-streets/pdfs/17_0612%20VZ%20Action%20Plan_FOR%20WEB.pdf

Waseem, M., Ahmed, A., & Saeed, T. U. (2019). Factors affecting motorcyclists' injury severities: An empirical assessment using random parameters logit model with heterogeneity in means and variances. *Accident Analysis & Prevention*, 123, 12–19. https://doi.org/10.1016/j.aap.2018.10.022

Washington State Department of Transportation. (2021a). *The Highway System Plan's Approach to Equity*. https://wsdot.wa.gov/sites/default/files/2021-07/HSP-Equity-approach.pdf

Washington State Department of Transportation. (2021b). *Secretary's Executive Order E 1119.00: Anti-Racism Policy and Diversity, Equity, and Inclusion Planning*. https://wsdot.wa.gov/sites/default/files/2021-11/Anti-Racism-Policy-DEI-Planning-E119.pdf

Washington State Department of Transportation. (2021c). *Washington State Active Transportation Plan.* https://wsdot.wa.gov/construction-planning/statewide-plans/active-transportation-plan

Washington State Department of Transportation. (2021d). *Strategic Planning Listening Sessions & Organizational Equity Readiness Baseline Assessment.* https://wsdot.wa.gov/sites/default/files/2021-11/Strategic-Planning-Listening-Sessions-Organizational-Equity-Readiness-Baseline-Assessment.pdf

Washington State Department of Transportation. (2024). *Washington State Strategic Highway Safety Plan 2024*. https://wtsc.wa.gov/wp-content/uploads/dlm_uploads/2024/07/WA-SHSP-TargetZero_Public-Draft-July15.pdf

Washington State Legislature. (2025a). *HB 1772: Establishing shared streets*. https://app.leg.wa.gov/BillSummary/?BillNumber=1772&Year=2025&Initiative=false

Washington State Legislature. (2025b). *HB 5581: Implementing Safe System Approach Strategies for Active Transportation Infrastructure*. https://app.leg.wa.gov/billsummary/?BillNumber=5581&Year=2025&Initiative=false

Washington Traffic Safety Commission. (2021). *FFY 2022 Washington Highway Safety Plan*. https://wtsc.wa.gov/wp-content/uploads/dlm_uploads/2022/08/2023-HSP-Final.pdf

Washington State Transportation Commission. (2018). *Washington Transportation Plan 2040 & Beyond, Your Washington State Policy Plan.* https://www.wtp2040andbeyond.com/

West, B. A., & Naumann, R. B. (2005). Motor vehicle–related deaths—United States, 2005 and 2009. *Morbidity and Mortality Weekly Report (MMWR)*, 62(03), 176–178.

Yu, C.-Y., Zhu, X., & Lee, C. (2022). Income and racial disparity and the role of the built environment in pedestrian injuries. *Journal of Planning Education and Research*, 42(2), 136–149. https://doi.org/10.1177/0739456X18807759

Yuan, Y., Masud, M., Chan, H., Chan, W., & Brubacher, J. R. (2023). Intersectionality and urban mobility: A systematic review on gender differences in active transport uptake. *Journal of Transport & Health*, 29, 101572. https://doi.org/10.1016/j.jth.2023.101572

Zeng, T. (2011). *Essays on the random parameters logit model (Doctoral dissertation)*. Louisiana State University. https://repository.lsu.edu/gradschool_dissertations/1584/

Zhai, G., Xie, K., Yang, H., & Yang, D. (2023). Are ride-hailing services safer than taxis? A multivariate spatial approach with accommodation of exposure uncertainty. *Accident Analysis & Prevention*, 193, 107281. https://doi.org/10.1016/j.aap.2023.107281

Zhu, C., Dadashova, B., Lee, C., Ye, X., & Brown, C. T. (2024). Equity in non-motorist safety: Exploring two pathways in Houston. *Transportation Research Part D: Transport and Environment*, 132. https://doi.org/10.1016/j.trd.2024.104239

Zygmont, C., & Smith, M. R. (2014). Robust factor analysis in the presence of normality violations, missing data, and outliers: Empirical questions and possible solutions. *The Quantitative Methods for Psychology*, 10(1), 40–55. https://doi.org/10.20982/tqmp.10.1.p040

APPENDIX A: INDIVIDUAL ANALYSIS APPENDICES

Appendix A.1: Results of Traffic Injury Trends by Race/Ethnicity Group

A.1.1 Ohio

Table A.1. Fatalities in Traffic Crashes in Ohio, by Race/Ethnicity, 2013–2022

Year	Hispanic		White		Black		AIAN		Asian		NHPI		Multiracial		All Others		Unknown		Total
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	
2013	18	1.8	834	84.3	114	11.5	1	0.1	5	0.51	0	0.0	2	0.2	3	0.3	12	1.2	989
2014	25	2.5	857	85.2	110	10.9	2	0.2	3	0.3	0	0.0	1	0.1	3	0.3	5	0.5	1006
2015	46	4.1	911	82.1	135	12.2	1	0.1	5	0.45	0	0.0	1	0.1	5	0.5	6	0.5	1110
2016	33	2.9	914	80.7	159	14.1	1	0.1	5	0.44	1	0.1	4	0.4	8	0.7	7	0.6	1132
2017	29	2.5	947	80.3	181	15.4	2	0.2	5	0.42	0	0.0	5	0.4	8	0.7	2	0.2	1179
2018	35	3.3	817	76.5	187	17.5	2	0.2	13	1.22	0	0.0	3	0.3	7	0.7	4	0.4	1068
2019	38	3.3	926	80.3	168	14.6	2	0.2	8	0.69	0	0.0	2	0.2	9	0.8	0	0.0	1153
2020	54	4.4	917	74.6	219	17.8	1	0.1	4	0.33	0	0.0	9	0.7	10	0.8	16	1.3	1230
2021	59	4.4	991	73.2	267	19.7	1	0.1	12	0.89	0	0.0	10	0.7	13	1.0	1	0.1	1354
2022	55	4.3	951	74.6	234	18.4	3	0.2	7	0.55	0	0.0	5	0.4	17	1.3	3	0.2	1275

Table A.2. Relative Fatality Rate in Traffic Crashes in Ohio, by Race/Ethnicity, 2013–2022

Race/Ethnicity	Relative Traffic Fatalities per 100,000 Population									
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Hispanic	0.53	0.69	1.15	0.81	0.65	0.88	0.81	1.10	1.06	1.01
AIAN	0.88	1.30	0.67	0.75	1.10	1.14	1.22	0.72	0.79	2.56
Asian	0.27	0.15	0.22	0.22	0.19	0.55	0.30	0.15	0.39	0.23
Black	0.93	0.86	0.99	1.14	1.26	1.49	1.17	1.57	1.80	1.59
NHPI	0.00	0.00	0.00	3.07	0.00	0.00	0.00	0.00	0.00	0.00
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table A.3. Fatalities in Traffic Crashes in Ohio, by Race/Ethnicity and Road User Type, 2013–2022

Years	Hispanic		White		Black		AIAN		Asian		NHPI		Total*
	N	%	N	%	N	%	N	%	N	%	N	%	
Pedestrian													
2013	2	2.35	63	74.12	19	22.35	0	0.00	0	0.00	0	0.00	85
2014	5	5.75	66	75.86	15	17.24	0	0.00	1	1.15	0	0.00	87
2015	7	6.03	82	70.69	26	22.41	0	0.00	1	0.86	0	0.00	116
2016	9	6.72	82	61.19	40	29.85	0	0.00	2	1.49	0	0.00	134
2017	6	4.23	95	66.90	39	27.46	0	0.00	0	0.00	0	0.00	142
2018	11	8.66	79	62.20	33	25.98	0	0.00	4	3.15	0	0.00	127
2019	5	4.03	94	75.81	23	18.55	0	0.00	2	1.61	0	0.00	124
2020	11	6.92	98	61.64	44	27.67	0	0.00	1	0.63	0	0.00	159
2021	8	4.76	109	64.88	43	25.60	0	0.00	5	2.98	0	0.00	168
2022	4	2.50	104	65.00	44	27.50	0	0.00	2	1.25	0	0.00	160
Total	**68**	**5.22**	**872**	**66.97**	**326**	**25.04**	**0**	**0.00**	**18**	**1.38**	**0**	**0.00**	**1302**
Bicyclist													
2013	1	4.55	19	86.36	2	9.09	0	0.00	0	0.00	0	0.00	22
2014	0	0.00	10	66.67	5	33.33	0	0.00	0	0.00	0	0.00	15
2015	1	4.00	19	76.00	4	16.00	0	0.00	0	0.00	0	0.00	25
2016	0	0.00	17	94.44	1	5.56	0	0.00	0	0.00	0	0.00	18
2017	0	0.00	18	85.71	2	9.52	0	0.00	1	4.76	0	0.00	21
2018	0	0.00	19	67.86	9	32.14	0	0.00	0	0.00	0	0.00	28
2019	1	3.45	25	86.21	3	10.34	0	0.00	0	0.00	0	0.00	29
2020	1	4.76	18	85.71	0	0.00	0	0.00	1	4.76	0	0.00	21
2021	2	5.71	20	57.14	10	28.57	0	0.00	1	2.86	0	0.00	35
2022	0	0.00	10	76.92	2	15.38	0	0.00	1	7.69	0	0.00	13
Total	**6**	**2.64**	**175**	**77.09**	**38**	**16.74**	**0**	**0.00**	**4**	**1.76**	**0**	**0.00**	**227**
MVO													
2013	15	1.71	749	85.21	93	10.58	1	0.11	5	0.57	0	0.00	879
2014	20	2.22	779	86.46	89	9.88	2	0.22	2	0.22	0	0.00	901
2015	38	3.94	807	83.63	105	10.88	1	0.10	4	0.41	0	0.00	965
2016	24	2.47	808	83.04	118	12.13	1	0.10	3	0.31	1	0.10	973
2017	23	2.28	827	81.96	140	13.88	2	0.20	4	0.40	0	0.00	1009
2018	24	2.63	717	78.70	145	15.92	2	0.22	9	0.99	0	0.00	911
2019	32	3.20	806	80.68	142	14.21	2	0.20	6	0.60	0	0.00	999
2020	42	4.01	799	76.24	175	16.70	1	0.10	2	0.19	0	0.00	1048
2021	49	4.28	857	74.78	214	18.67	1	0.09	6	0.52	0	0.00	1146
2022	51	4.66	830	75.80	188	17.17	3	0.27	4	0.37	0	0.00	1095
Total	**318**	**3.20**	**7979**	**80.38**	**1409**	**14.20**	**16**	**0.16**	**45**	**0.45**	**1**	**0.01**	**9926**

Note: *Includes other race/ethnicity groups (i.e., multiracial, all others, and unknown).

Table A.4. Relative Fatality Rate in Traffic Crashes in Ohio, by Race/Ethnicity and Road User Type, 2013–2022

Race/Ethnicity	Relative Pedestrian Fatalities per 100,000 Population									
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Pedestrian										
Hispanic	0.79	1.80	1.95	2.45	1.35	2.88	1.06	2.10	1.32	0.67
AIAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Asian	0.00	0.64	0.50	0.98	0.00	1.75	0.73	0.34	1.48	0.59
Black	2.04	1.52	2.12	3.22	2.71	2.73	1.59	2.94	2.63	2.73
NHPI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Bicyclist										
Hispanic	1.29	0.00	1.19	0.00	0.00	0.00	0.79	1.05	1.78	0.00
AIAN	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Asian	0.00	0.00	0.00	0.00	2.00	0.00	0.00	1.90	1.61	3.18
Black	0.71	3.36	1.43	0.37	0.75	3.10	0.79	0.00	3.30	1.36
NHPI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MVO										
Hispanic	0.50	0.61	1.07	0.66	0.59	0.69	0.78	0.99	1.02	1.07
AIAN	0.98	1.43	0.76	0.85	1.26	1.30	1.40	0.82	0.92	2.93
Asian	0.30	0.11	0.20	0.15	0.17	0.43	0.25	0.08	0.23	0.15
Black	0.85	0.77	0.87	0.96	1.12	1.32	1.14	1.44	1.66	1.46
NHPI	0.00	0.00	0.00	3.47	0.00	0.00	0.00	0.00	0.00	0.00
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

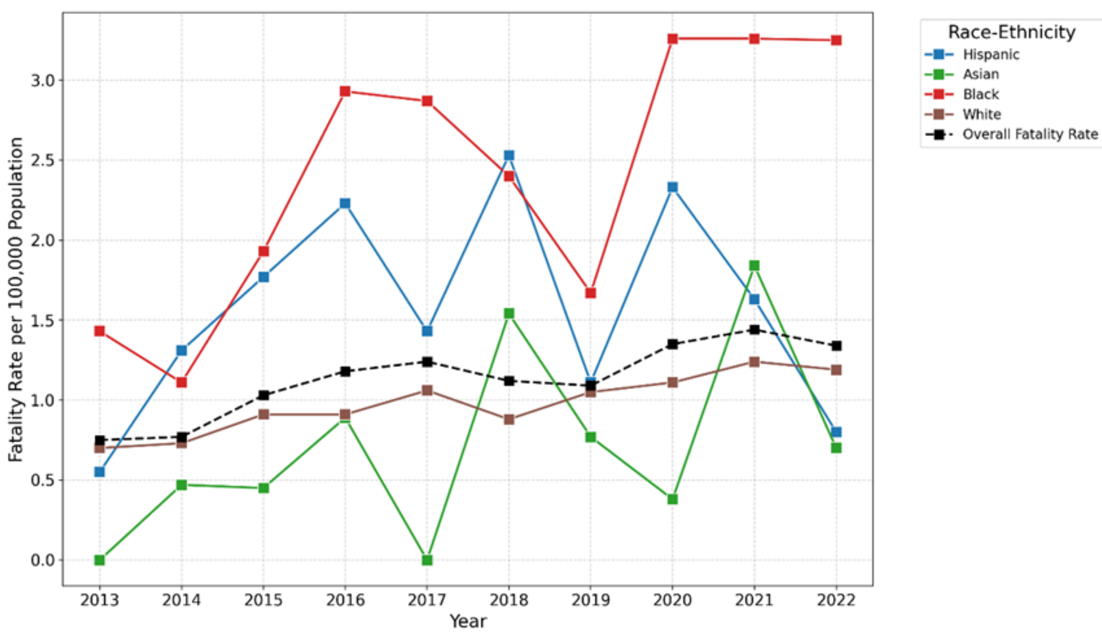


Figure A.1. Pedestrian Fatality Rate in Traffic Crashes Per 100,000 Population in Ohio, by Race/Ethnicity, 2013–2022

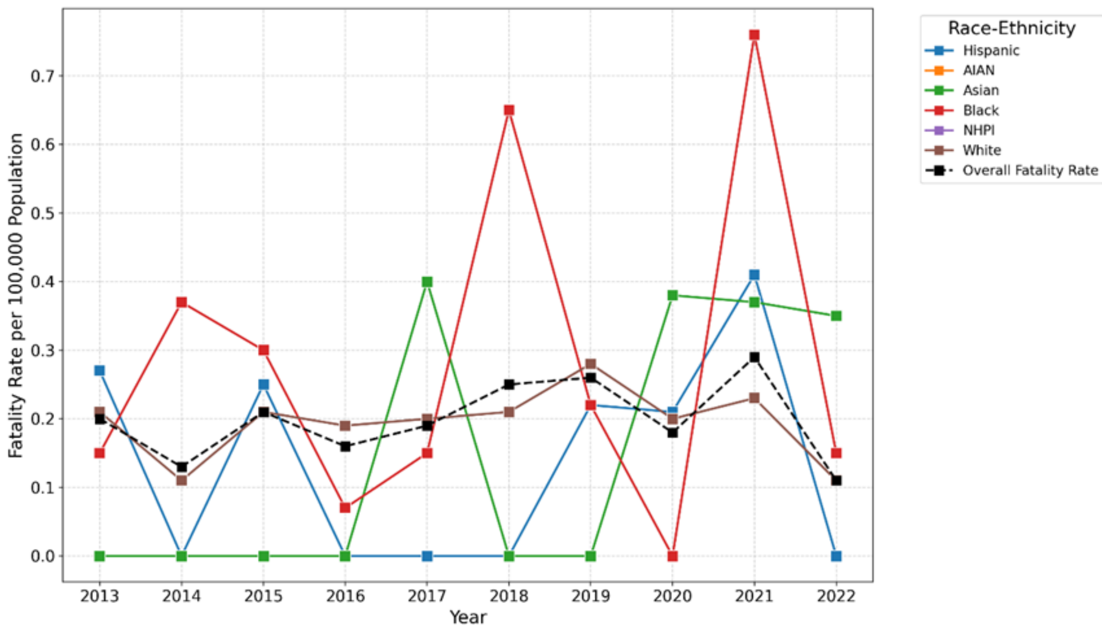


Figure A.2. Bicyclist Fatality Rate in Traffic Crashes Per 100,000 Population in Ohio, by Race/Ethnicity, 2013–2022

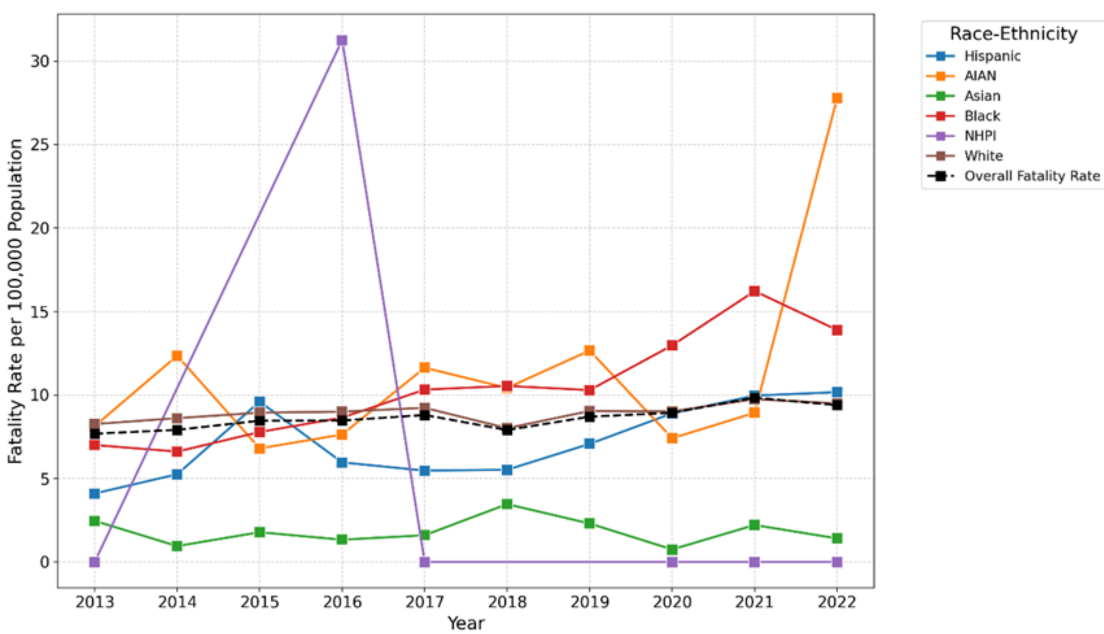


Figure A.3. MVO Fatality Rate in Traffic Crashes Per 100,000 Population in Ohio, by Race/Ethnicity, 2013–2022

A.1.2 Texas

Table A.5. Fatalities, Incapacitating, and Non-Incapacitating Injury Crash Count in Texas, by Race/Ethnicity in Texas, 2017–2022

Year	Hispanic		White		Black		AIAN		Asian		Others		Unknown		Total
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	
Fatalities															
2017	1123	30	1913	51.1	572	15.3	4	0.1	54	1.4	62	1.7	15	0.4	3743
2018	1160	31.4	1846	49.9	539	14.6	6	0.2	62	1.7	70	1.9	16	0.4	3699
2019	1177	32.1	1806	49.3	532	14.5	13	0.4	74	2	52	1.4	13	0.4	3667
2020	1344	34.2	1800	45.8	657	16.7	12	0.3	73	1.9	34	0.9	6	0.2	3926
2021	1558	34.7	2051	45.6	760	16.9	13	0.3	71	1.6	18	0.4	22	0.5	4493
2022	1610	36.4	1989	44.9	679	15.3	12	0.3	97	2.2	14	0.3	25	0.6	4426
Incapacitating Injuries															
2017	5448	30.5	8655	48.5	2969	16.6	25	0.1	382	2.1	315	1.8	65	0.4	17859
2018	4812	31.6	7154	46.9	2547	16.7	33	0.2	304	2	329	2.2	64	0.4	15243
2019	5389	33.4	7336	45.4	2800	17.3	28	0.2	305	1.9	228	1.4	63	0.4	16149
2020	4962	33.3	6562	44	2911	19.5	54	0.4	294	2	91	0.6	42	0.3	14916
2021	6764	34.2	8719	44	3754	19	54	0.3	366	1.8	72	0.4	73	0.4	19802
2022	6737	35.1	8254	43	3489	18.2	81	0.4	447	2.3	102	0.5	86	0.4	19196
Non-Incapacitating Injuries															
2017	26969	32.8	35879	43.6	14995	18.2	107	0.1	2315	2.8	1685	2	331	0.4	82281
2018	25488	33.7	31784	42	13976	18.5	132	0.2	2265	3	1814	2.4	280	0.4	75739
2019	26195	34.7	30709	40.6	14693	19.4	134	0.2	2309	3.1	1241	1.6	267	0.4	75548
2020	22429	35.2	25277	39.6	13569	21.3	109	0.2	1725	2.7	483	0.8	191	0.3	63783
2021	31055	36.8	32279	38.3	17553	20.8	263	0.3	2383	2.8	488	0.6	290	0.3	84311
2022	35359	38.1	34960	37.7	18322	19.7	344	0.4	2965	3.2	525	0.6	324	0.3	92799

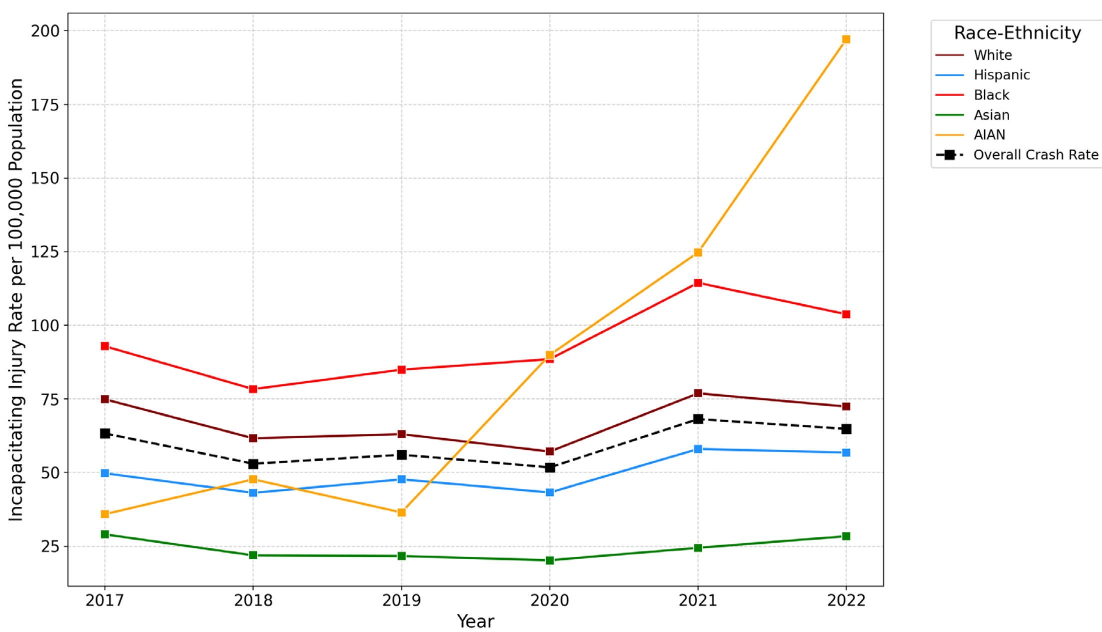


Figure A.4. Incapacitating Injury Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

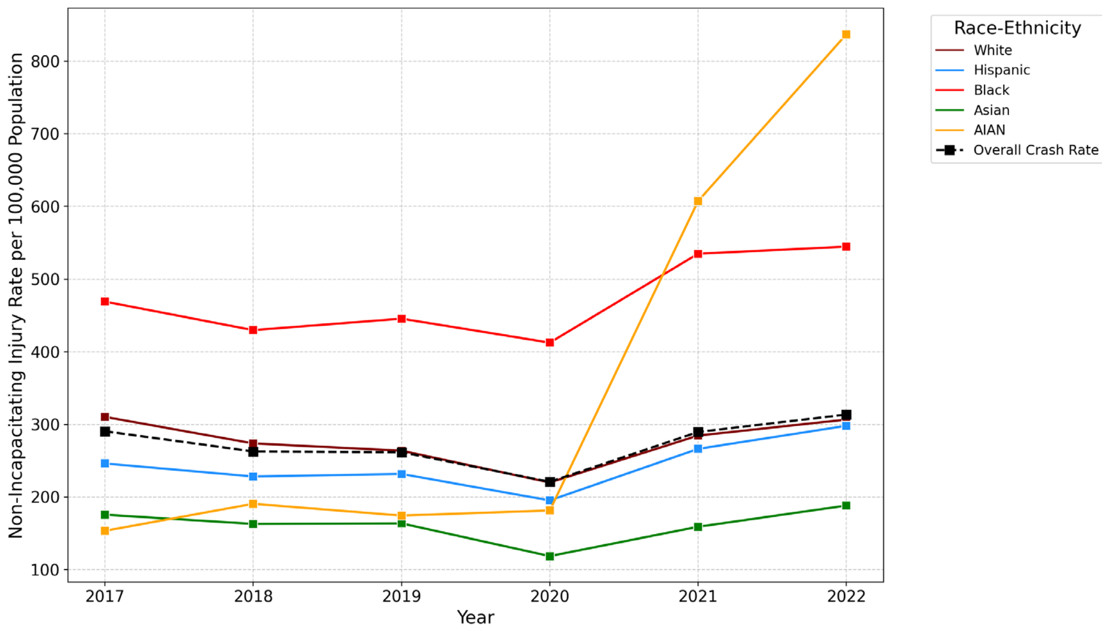


Figure A.5. Non-Incapacitating Injury Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

Table A.6. Relative Injury Severity Rates in Traffic Crashes in Texas, by Race/Ethnicity, 2017–2022

Race/Ethnicity	Year					
	2017	2018	2019	2020	2021	2022
Relative Fatality Rate per 100,000 Population						
Hispanic	0.62	0.65	0.67	0.75	0.74	0.78
AIAN	0.35	0.55	1.09	1.28	1.66	1.67
Asian	0.25	0.28	0.34	0.32	0.26	0.35
Black	1.08	1.04	1.04	1.27	1.28	1.16
White	1.00	1.00	1.00	1.00	1.00	1.00
Relative Incapacitating Injury Rate per 100,000 Population						
Hispanic	0.66	0.70	0.76	0.76	0.75	0.79
AIAN	0.48	0.77	0.58	1.57	1.62	2.72
Asian	0.39	0.36	0.34	0.35	0.32	0.39
Black	1.24	1.27	1.35	1.55	1.49	1.43
White	1.00	1.00	1.00	1.00	1.00	1.00
Relative Non-Incapacitating Injury Rate per 100,000 Population						
Hispanic	0.79	0.83	0.88	0.89	0.94	0.97
AIAN	0.50	0.70	0.66	0.83	2.13	2.73
Asian	0.57	0.60	0.62	0.54	0.56	0.61
Black	1.51	1.57	1.69	1.88	1.88	1.78
White	1.00	1.00	1.00	1.00	1.00	1.00

Table A.7. Fatalities in Traffic Crashes in Texas, by Race/Ethnicity and Road User Type, 2017–2022

Year	Hispanic		White		Black		AIAN		Asian		Other		Unknown		Total
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	
Pedestrian															
2017	199	31.3	274	43.1	135	21.2	0	0.0	14	2.2	9	1.4	5	0.8	636
2018	216	32.7	283	42.9	131	19.9	1	0.2	8	1.2	13	2.0	8	1.2	660
2019	243	35.1	259	37.4	144	20.8	3	0.4	23	3.3	13	1.9	8	1.2	693
2020	261	35.5	294	40.0	155	21.1	3	0.4	13	1.8	7	1.0	2	0.3	735
2021	303	36.0	327	38.9	184	21.9	2	0.2	12	1.4	2	0.2	11	1.3	841
2022	306	36.6	325	38.9	177	21.2	2	0.2	15	1.8	3	0.4	8	1.0	836
Bicyclist															
2017	12	20.7	34	58.6	10	17.2	0	0.0	2	3.5	0	0.0	0	0.0	58
2018	21	29.6	36	50.7	8	11.3	0	0.0	4	5.6	2	2.8	0	0.0	71
2019	19	28.8	28	42.4	14	21.2	0	0.0	4	6.1	1	1.5	0	0.0	66
2020	22	27.9	38	48.1	15	19.0	0	0.0	3	3.8	1	1.3	0	0.0	79
2021	32	35.6	46	51.1	10	11.1	0	0.0	1	1.1	1	1.1	0	0.0	90
2022	25	27.2	49	53.3	13	14.1	0	0.0	4	4.4	0	0.0	1	1.1	92
MVO															
2017	815	32.0	1270	49.9	367	14.4	4	0.2	34	1.3	48	1.9	9	0.4	2547
2018	853	33.5	1239	48.7	352	13.8	2	0.1	46	1.8	45	1.8	7	0.3	2544
2019	824	33.2	1241	50.0	330	13.3	9	0.4	40	1.6	32	1.3	5	0.2	2481
2020	949	36.4	1148	44.0	431	16.5	7	0.3	53	2.0	20	0.8	3	0.1	2611
2021	1107	36.7	1322	43.8	500	16.6	9	0.3	55	1.8	14	0.5	10	0.3	3017
2022	1160	39.6	1244	42.4	431	14.7	8	0.3	67	2.3	10	0.3	13	0.4	2933

Table A.8. Incapacitating Injuries in Traffic Crashes in Texas, by Race/Ethnicity and Road User Type, 2017–2022

Year	Hispanic		White		Black		AIAN		Asian		Other		Unknown		Total
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	
Pedestrian															
2017	424	31.5	558	41.4	312	23.2	1	0.1	28	2.1	23	1.7	2	0.2	1348
2018	443	33.2	516	38.6	298	22.3	2	0.2	33	2.5	35	2.6	9	0.7	1336
2019	528	35.6	546	36.8	343	23.1	5	0.3	40	2.7	17	1.2	4	0.3	1483
2020	441	33.3	493	37.3	329	24.9	2	0.2	38	2.9	19	1.4	1	0.1	1323
2021	571	35.7	582	36.4	379	23.7	4	0.3	44	2.8	9	0.6	10	0.6	1599
2022	572	34.4	608	36.5	407	24.4	7	0.4	48	2.9	11	0.7	12	0.7	1665
Bicyclist															
2017	93	26.4	185	52.6	55	15.6	1	0.3	9	2.6	6	1.7	3	0.9	352
2018	77	28.0	131	47.6	52	18.9	2	0.7	6	2.2	5	1.8	2	0.7	275
2019	87	27.0	167	51.9	59	18.3	0	0.0	7	2.2	2	0.6	0	0.0	322
2020	79	26.6	148	49.8	57	19.2	0	0.0	8	2.7	4	1.4	1	0.3	297
2021	89	26.2	179	52.7	52	15.3	1	0.3	13	3.8	2	0.6	4	1.2	340
2022	104	30.9	175	51.9	43	12.8	2	0.6	10	3.0	2	0.6	1	0.3	337
MVO															
2017	4510	32.2	6453	46.1	2383	17.0	19	0.1	325	2.3	255	1.8	56	0.4	14001
2018	3956	34.0	5145	44.2	1975	17.0	23	0.2	243	2.1	255	2.2	43	0.4	11640
2019	4439	35.6	5324	42.7	2207	17.7	19	0.2	237	1.9	193	1.6	53	0.4	12472
2020	4056	35.7	4681	41.2	2282	20.1	39	0.3	226	2.0	58	0.5	32	0.3	11374
2021	5603	36.3	6395	41.4	3028	19.6	43	0.3	274	1.8	57	0.4	50	0.3	15450

Table A.9. Non-Incapacitating Injuries in Traffic Crashes in Texas, by Race/Ethnicity and Road User Type, 2017–2022

Year	Hispanic		White		Black		AIAN		Asian		Other		Unknown		Total
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	
Pedestrian															
2017	1047	33.6	1189	38.2	687	22.1	5	0.2	103	3.3	63	2.0	18	0.6	3112
2018	1046	35.9	1093	37.6	608	20.9	5	0.2	99	3.4	49	1.7	11	0.4	2911
2019	1005	34.7	1085	37.5	666	23.0	3	0.1	80	2.8	48	1.7	8	0.3	2895
2020	767	34.8	832	37.7	509	23.1	2	0.1	67	3.0	18	0.8	10	0.5	2205
2021	962	34.8	1016	36.8	669	24.2	9	0.3	79	2.9	17	0.6	9	0.3	2761
2022	1131	36.4	1109	35.7	719	23.1	11	0.4	102	3.3	18	0.6	18	0.6	3108
Bicyclist															
2017	360	26.1	725	52.5	220	15.9	0	0.0	38	2.8	33	2.4	6	0.4	1382
2018	330	28.2	593	50.7	191	16.3	2	0.2	35	3.0	13	1.1	6	0.5	1170
2019	341	27.5	621	50.1	212	17.1	1	0.1	42	3.4	18	1.5	4	0.3	1239
2020	308	29.9	530	51.5	150	14.6	0	0.0	33	3.2	3	0.3	5	0.5	1029
2021	345	30.0	559	48.6	191	16.6	4	0.4	38	3.3	9	0.8	5	0.4	1151
2022	369	29.3	626	49.7	200	15.9	2	0.2	46	3.7	7	0.6	9	0.7	1259
MVO															
2017	24899	33.6	31580	42.6	13661	18.4	97	0.1	2116	2.9	1538	2.1	294	0.4	74185
2018	23544	34.4	28031	40.9	12812	18.7	118	0.2	2100	3.1	1679	2.5	249	0.4	68533
2019	24241	35.4	27179	39.7	13450	19.6	120	0.2	2137	3.1	1132	1.7	220	0.3	68479
2020	20670	35.8	22235	38.5	12494	21.7	100	0.2	1576	2.7	454	0.8	171	0.3	57700
2021	28925	37.5	28792	37.3	16257	21.1	239	0.3	2222	2.9	453	0.6	263	0.3	77151
2022	33030	38.9	31161	36.7	16983	20.0	319	0.4	2752	3.2	489	0.6	288	0.3	85022

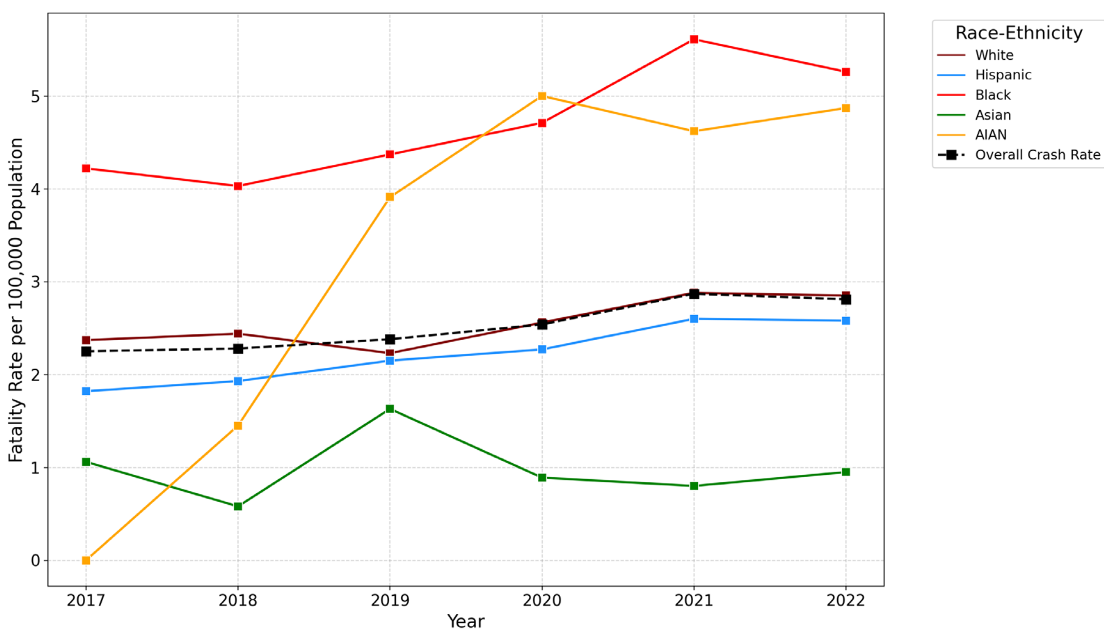


Figure A.6. Pedestrian Fatality Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

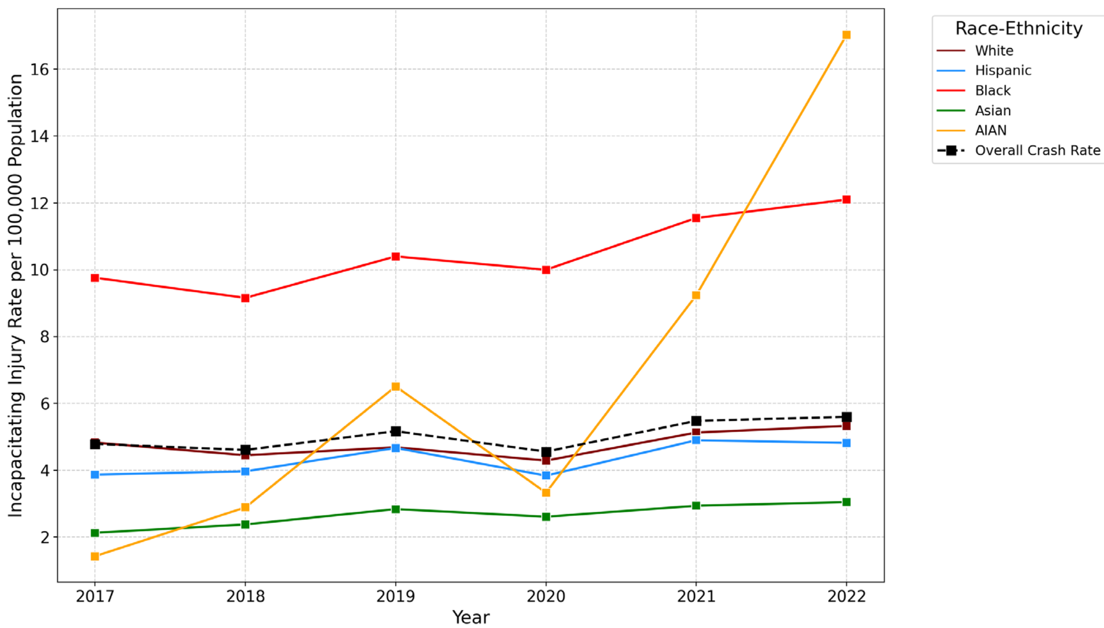


Figure A.7. Pedestrian Incapacitating Injury Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

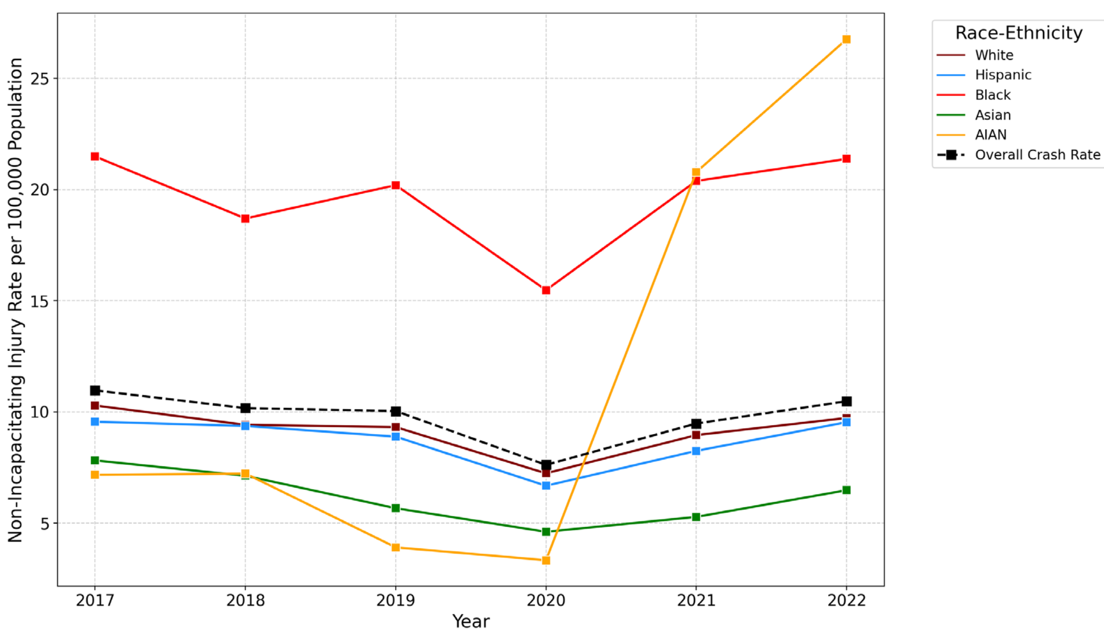
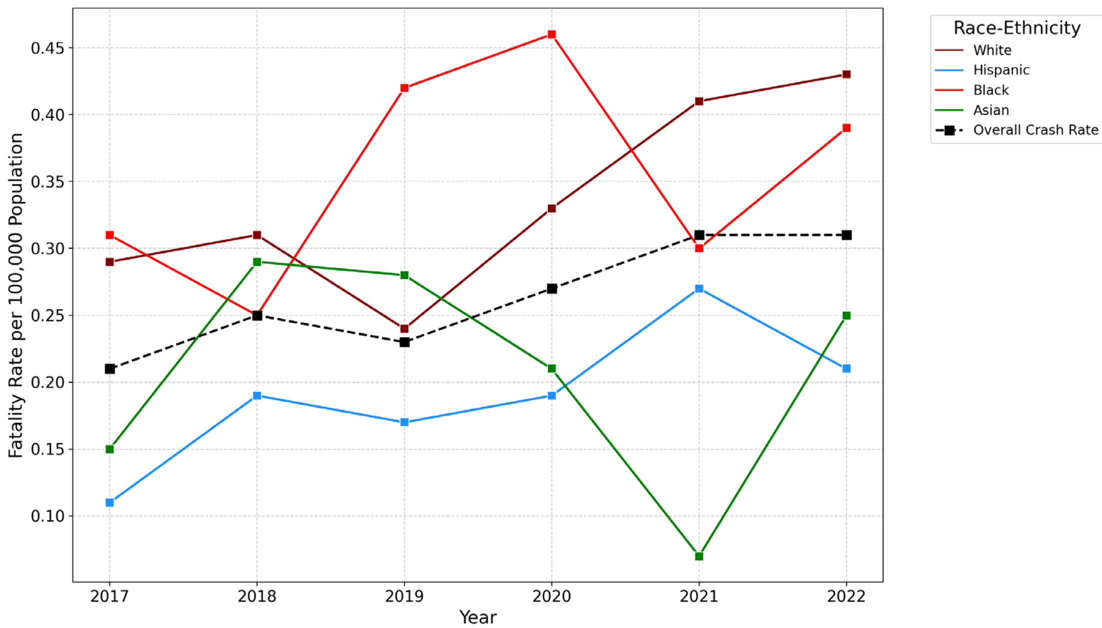


Figure A.8. Pedestrian Non-Incapacitating Injury Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022



Note: No AIAN bicyclist fatalities were recorded between 2017 and 2022; therefore, fatality rates for this group are not reported

Figure A.9. Bicyclist Fatality Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022.

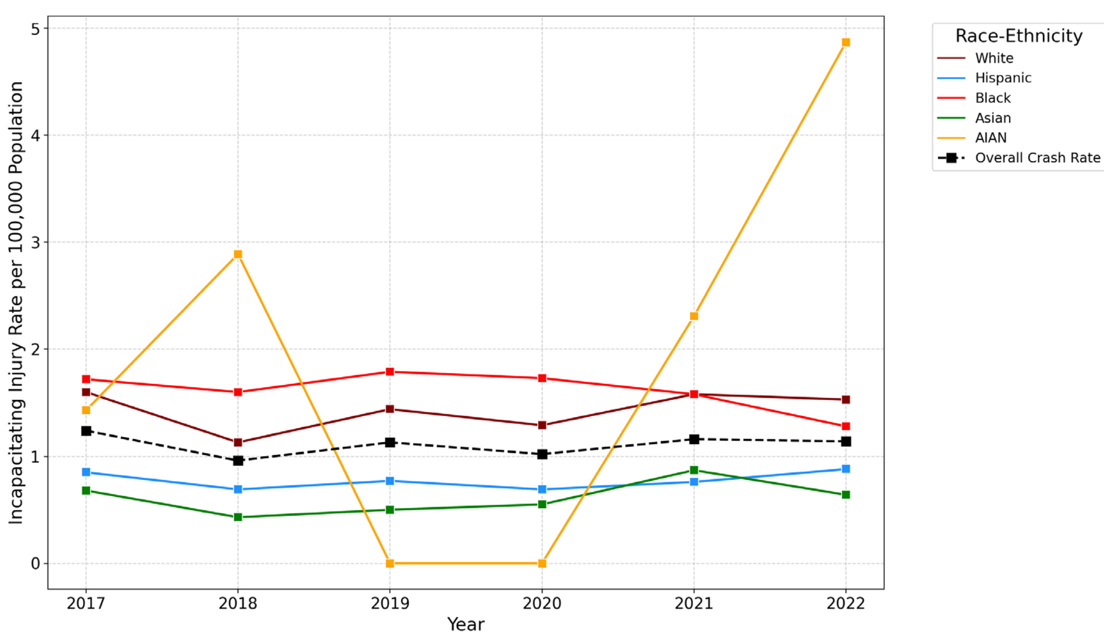


Figure A.10. Bicyclist Incapacitating Injury Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

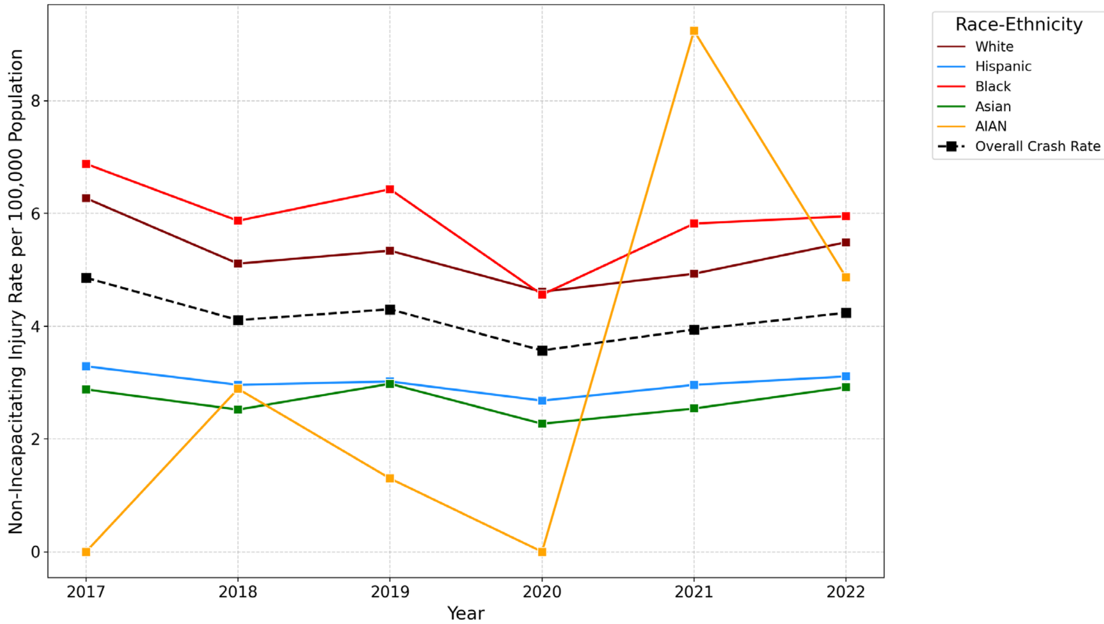


Figure A.11. Bicyclist Non-Incapacitating Injury Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

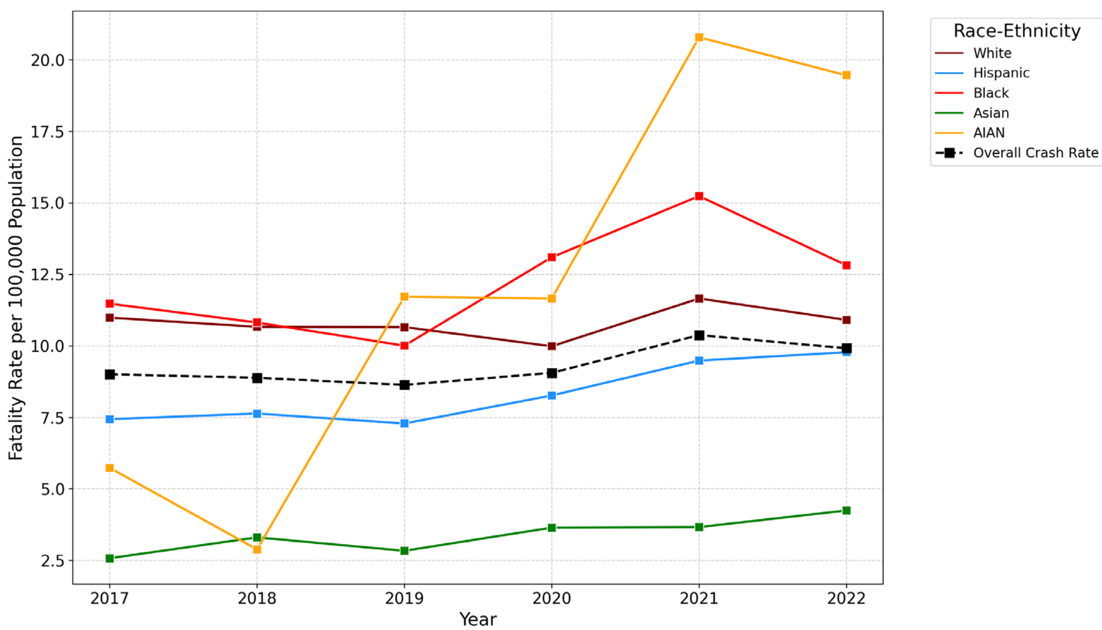


Figure A.12. MVO Fatality Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

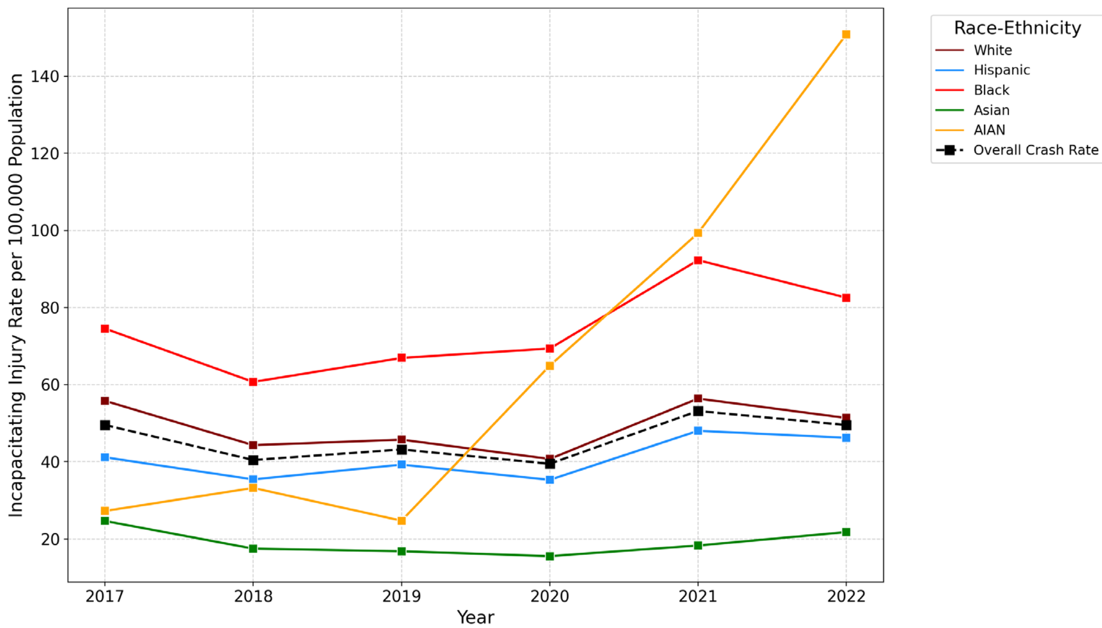


Figure A.13. MVO Incapacitating Injury Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

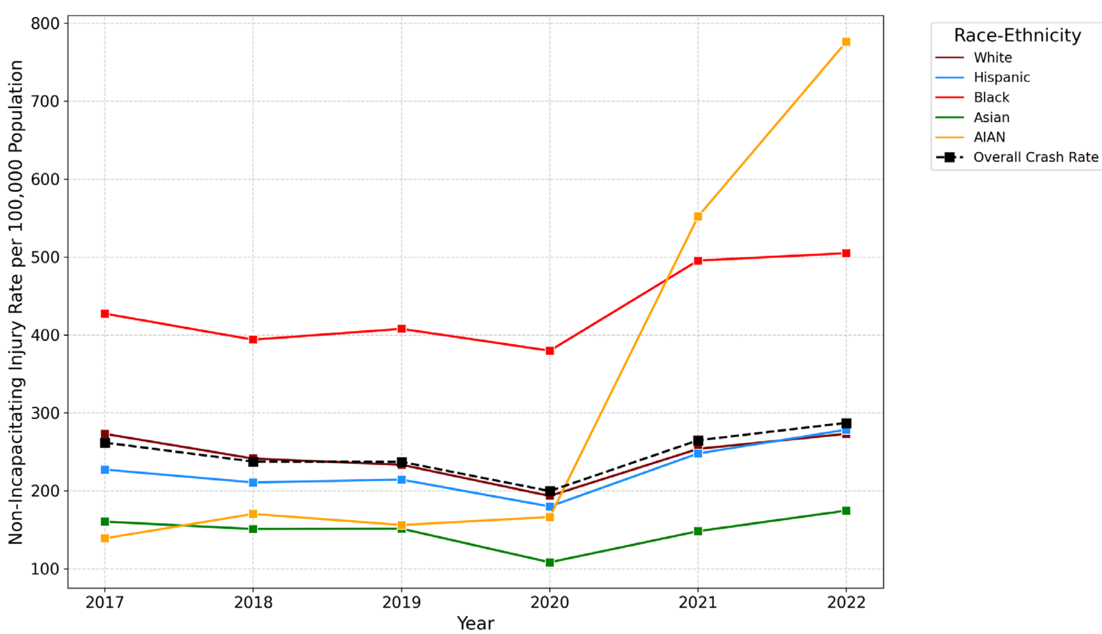


Figure A.14. MVO Non-Incapacitating Injury Rate in Traffic Crashes Per 100,000 Population in Texas, by Race/Ethnicity, 2017–2022

Table A.10. Pedestrian Relative Injury Rate in Traffic Crashes in Texas, by Race/Ethnicity, 2017–2022

Race/Ethnicity	Year					
	2017	2018	2019	2020	2021	2022
Relative Pedestrian Fatality Rates per 100,000 Population						
Hispanic	0.77	0.79	0.96	0.89	0.90	0.91
AIAN	0.00	0.59	1.75	1.95	1.60	1.71
Asian	0.45	0.24	0.73	0.35	0.28	0.33
Black	1.78	1.65	1.96	1.84	1.95	1.85
White	1.00	1.00	1.00	1.00	1.00	1.00
Relative Pedestrian Incapacitating Injury Rates per 100,000 Population						
Hispanic	0.80	0.89	1.00	0.90	0.96	0.90
AIAN	0.30	0.65	1.39	0.78	1.80	3.20
Asian	0.44	0.54	0.61	0.61	0.57	0.57
Black	2.02	2.06	2.22	2.33	2.25	2.27
White	1.00	1.00	1.00	1.00	1.00	1.00
Relative Pedestrian Non-Incapacitating Injury Rates per 100,000 Population						
Hispanic	0.929	0.995	0.954	0.923	0.921	0.98
AIAN	0.697	0.768	0.42	0.46	2.32	2.75
Asian	0.76	0.757	0.608	0.637	0.589	0.666
Black	2.088	1.985	2.167	2.138	2.276	2.197
White	1.00	1.00	1.00	1.00	1.00	1.00

Table A.11. Bicyclist Relative Injury Rate in Traffic Crashes in Texas, by Race/Ethnicity, 2017–2022

Race/Ethnicity	Year					
	2017	2018	2019	2020	2021	2022
Relative Bicyclist Fatality Rates per 100,000 Population						
Hispanic	0.38	0.61	0.71	0.58	0.66	0.49
Asian	0.52	0.94	1.17	0.64	0.17	0.58
Black	1.07	0.81	1.75	1.39	0.73	0.91
White	1.00	1.00	1.00	1.00	1.00	1.00
Relative Bicyclist Incapacitating Injury Rates per 100,000 Population						
Hispanic	0.51	0.61	0.56	0.54	0.53	0.56
AIAN	0.76	2.01	0.00	0.00	1.17	2.49
Asian	0.44	0.50	0.46	0.47	0.47	0.45
Black	1.07	1.29	1.32	1.35	0.96	0.85
White	1.00	1.00	1.00	1.00	1.00	1.00
Relative Bicyclist Non-Incapacitating Injury Rates per 100,000 Population						
Hispanic	0.57	0.61	0.63	0.63	0.66	0.58
AIAN	0.28	0.64	0.29	0.42	1.84	0.88
Asian	0.47	0.53	0.61	0.58	0.59	0.56
Black	1.30	1.35	1.43	1.15	1.37	1.24
White	1.00	1.00	1.00	1.00	1.00	1.00

***Note**: No AIAN bicyclist fatalities were recorded between 2017 and 2022; therefore, fatality rates for this group are not reported.*

Table A.12. MVO Relative Injury Rate in Traffic Crashes in Texas, by Race/Ethnicity, 2017–2022

Race/Ethnicity	Year					
	2017	2018	2019	2020	2021	2022
Relative MVO Fatality Rates per 100,000 Population						
Hispanic	0.68	0.72	0.68	0.83	0.81	0.90
AIAN	0.52	0.27	1.10	1.17	1.78	1.78
Asian	0.24	0.31	0.27	0.37	0.32	0.39
Black	1.05	1.01	0.94	1.31	1.31	1.18
White	1.00	1.00	1.00	1.00	1.00	1.00
Relative MVO Incapacitating Injury Rates per 100,000 Population						
Hispanic	0.73	0.78	0.83	0.86	0.85	0.90
AIAN	0.49	0.66	0.65	1.51	1.77	2.73
Asian	0.41	0.38	0.35	0.38	0.32	0.42
Black	1.29	1.30	1.36	1.63	1.58	1.53
White	1.00	1.00	1.00	1.00	1.00	1.00
Relative MVO Non-Incapacitating Injury Rates per 100,000 Population						
Hispanic	0.98	1.00	1.06	1.08	1.10	1.13
AIAN	0.64	0.81	0.76	1.11	2.18	3.05
Asian	0.70	0.72	0.74	0.62	0.69	0.75
Black	1.89	1.93	2.03	2.30	2.22	2.11
White	1.00	1.00	1.00	1.00	1.00	1.00

A.1.3 Washington

Table A.13. Fatalities in Traffic Crashes in Washington, by Race/Ethnicity, 2013–2022

Year	Hispanic		White		Black		AIAN		Asian		NHPI		Multiracial		All Others		Unknown		Total
	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	N	%	
2013	63	14.5	328	75.2	14	3.2	18	4.1	4	0.92	0	0.0	0	0.0	7	1.6	2	0.5	436
2014	51	11.0	348	75.3	14	3.0	22	4.8	10	2.16	1	0.2	1	0.2	14	3.0	1	0.2	462
2015	65	11.8	398	72.2	21	3.8	29	5.3	26	4.72	3	0.5	0	0.0	8	1.5	1	0.2	551
2016	76	14.2	369	68.8	23	4.3	32	6.0	18	3.36	2	0.4	0	0.0	13	2.4	3	0.6	536
2017	88	15.6	370	65.7	31	5.5	28	5.0	21	3.73	4	0.7	1	0.2	16	2.8	4	0.7	563
2018	90	16.7	365	67.7	18	3.3	30	5.6	15	2.78	8	1.5	0	0.0	13	2.4	0	0.0	539
2019	76	14.1	373	69.3	20	3.7	19	3.5	16	2.97	1	0.2	24	4.5	6	1.1	3	0.6	538
2020	96	16.7	376	65.5	27	4.7	21	3.7	20	3.48	1	0.2	30	5.2	3	0.5	0	0.0	574
2021	110	16.3	406	60.2	38	5.6	44	6.5	26	3.86	4	0.6	31	4.6	15	2.2	0	0.0	674
2022	114	15.6	465	63.4	38	5.2	37	5.1	21	2.86	9	1.2	22	3.0	18	2.5	9	1.2	733

Table A.14. Relative Fatality Rate in Traffic Crashes in Washington, by Race/Ethnicity, 2013–2022

Race/Ethnicity	Relative Traffic Fatalities per 100,000 Population									
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Hispanic	1.14	0.85	0.93	1.15	1.29	1.30	1.06	1.27	1.29	1.12
AIAN	3.39	4.08	4.60	5.55	5.49	5.28	3.10	4.00	9.52	5.78
Asian	0.11	0.26	0.58	0.42	0.46	0.32	0.33	0.38	0.44	0.29
Black	0.89	0.86	1.07	1.26	1.69	0.92	0.95	1.26	1.61	1.37
NHPI	0.00	0.32	0.81	0.60	1.27	2.28	0.28	0.27	0.99	1.90
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Table A.15. Fatalities in Traffic Crashes in Washington, by Race/Ethnicity and Road User Type, 2013–2022

Years	Hispanic		White		Black		AIAN		Asian		NHPI		Total*
	N	%	N	%	N	%	N	%	N	%	N	%	
Pedestrian													
2013	6	12.24	31	63.27	3	6.12	5	10.20	2	4.08	0	0.00	49
2014	8	10.67	50	66.67	2	2.67	4	5.33	3	4.00	1	1.33	75
2015	12	14.29	53	63.10	5	5.95	5	5.95	8	9.52	0	0.00	84
2016	10	12.05	50	60.24	4	4.82	6	7.23	8	9.64	1	1.20	83
2017	18	17.31	62	59.62	5	4.81	7	6.73	5	4.81	1	0.96	104
2018	15	15.15	71	71.72	4	4.04	4	4.04	2	2.02	0	0.00	99
2019	17	16.67	56	54.90	6	5.88	6	5.88	10	9.80	0	0.00	102
2020	7	6.67	68	64.76	7	6.67	7	6.67	11	10.48	0	0.00	105
2021	17	11.89	79	55.24	11	7.69	11	7.69	11	7.69	0	0.00	143
2022	15	11.90	82	65.08	7	5.56	8	6.35	3	2.38	0	0.00	126
Total	**125**	**12.89**	**602**	**62.06**	**54**	**5.57**	**63**	**6.49**	**63**	**6.49**	**3**	**0.31**	**970**
Bicyclist													
2013	2	16.67	8	66.67	0	0.00	2	16.67	0	0.00	0	0.00	12
2014	0	0.00	8	80.00	0	0.00	0	0.00	1	10.00	0	0.00	10
2015	2	14.29	12	85.71	0	0.00	0	0.00	0	0.00	0	0.00	14
2016	0	0.00	14	82.35	1	5.88	1	5.88	0	0.00	0	0.00	17
2017	2	10.00	15	75.00	1	5.00	0	0.00	2	10.00	0	0.00	20
2018	3	15.00	16	80.00	0	0.00	1	5.00	0	0.00	0	0.00	20
2019	1	7.14	13	92.86	0	0.00	0	0.00	0	0.00	0	0.00	14
2020	2	11.11	11	61.11	2	11.11	0	0.00	1	5.56	0	0.00	18
2021	2	11.76	14	82.35	0	0.00	1	5.88	0	0.00	0	0.00	17
2022	1	7.14	11	78.57	0	0.00	0	0.00	1	7.14	0	0.00	14
Total	**15**	**9.62**	**122**	**78.21**	**4**	**2.56**	**5**	**3.21**	**5**	**3.21**	**0**	**0.00**	**156**
MVO													
2013	55	14.67	289	77.07	11	2.93	11	2.93	2	0.53	0	0.00	375
2014	43	11.41	290	76.92	12	3.18	18	4.77	6	1.59	0	0.00	377
2015	50	11.09	332	73.61	16	3.55	24	5.32	18	3.99	3	0.67	451
2016	66	15.38	300	69.93	17	3.96	24	5.59	10	2.33	1	0.23	429
2017	68	15.49	293	66.74	25	5.69	21	4.78	14	3.19	3	0.68	439
2018	72	17.14	278	66.19	14	3.33	25	5.95	13	3.10	8	1.90	420
2019	58	13.74	304	72.04	14	3.32	13	3.08	6	1.42	1	0.24	422
2020	87	19.33	296	65.78	18	4.00	14	3.11	8	1.78	1	0.22	450
2021	90	17.58	313	61.13	27	5.27	32	6.25	15	2.93	4	0.78	512
2022	98	16.55	371	62.67	31	5.24	29	4.90	17	2.87	9	1.52	592
Total	**687**	**15.38**	**3066**	**68.64**	**185**	**4.14**	**211**	**4.72**	**109**	**2.44**	**30**	**0.67**	**4467**

Note: **Includes other race/ethnicity groups (i.e., multiracial, all others, and unknown).*

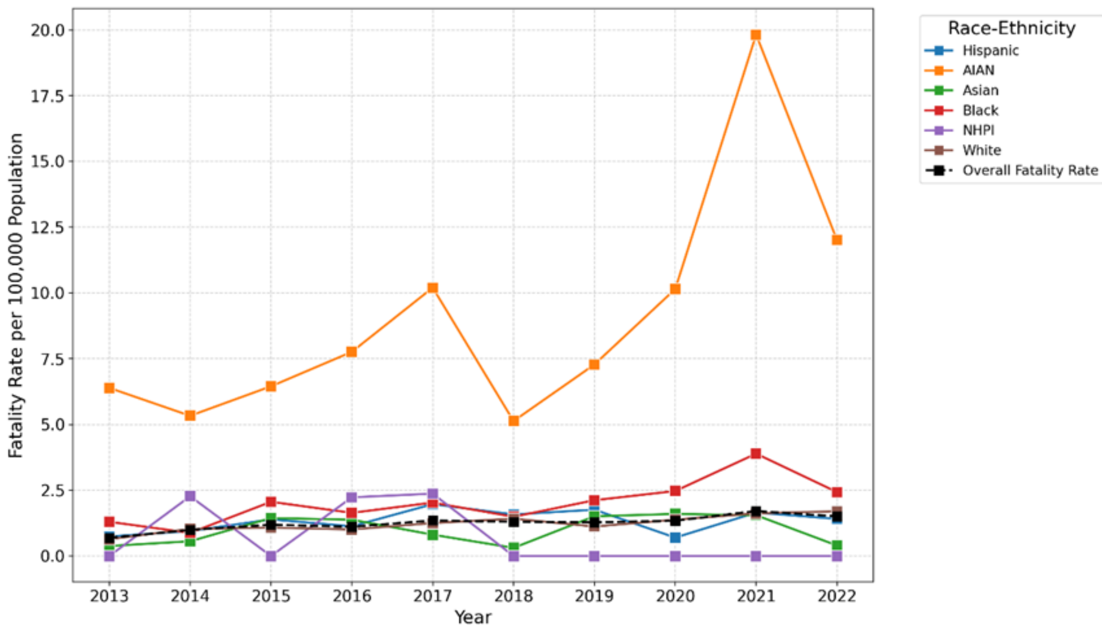


Figure A.15. Pedestrian Fatality Rate in Traffic Crashes Per 100,000 Population in Washington, by Race/Ethnicity, 2013–2022

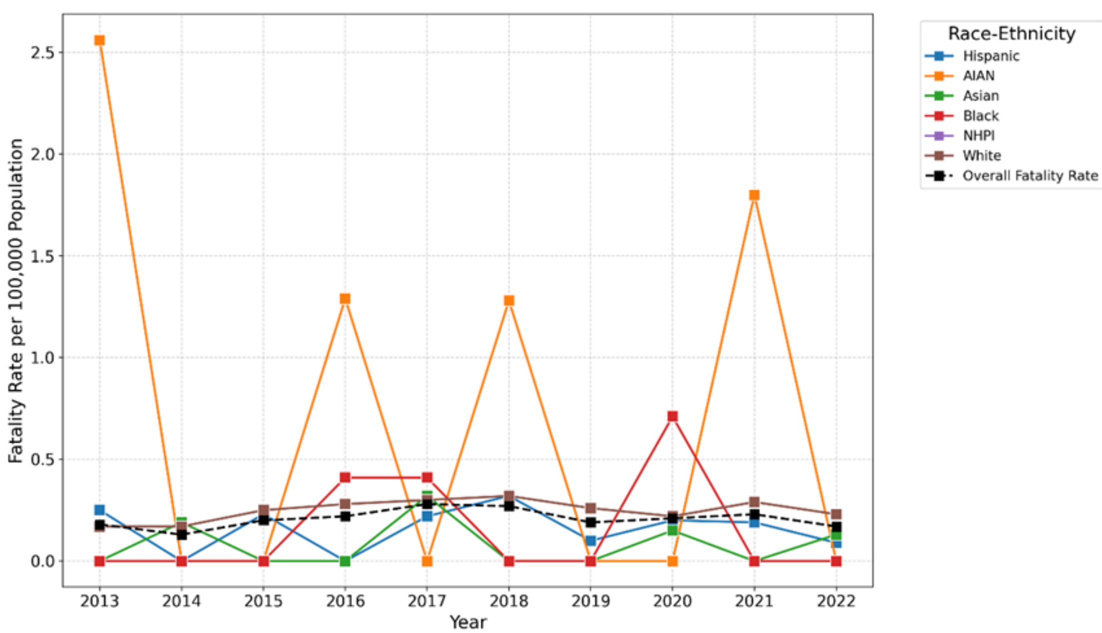


Figure A.16. Bicyclist Fatality Rate in Traffic Crashes Per 100,000 Population in Washington, by Race/Ethnicity, 2013–2022

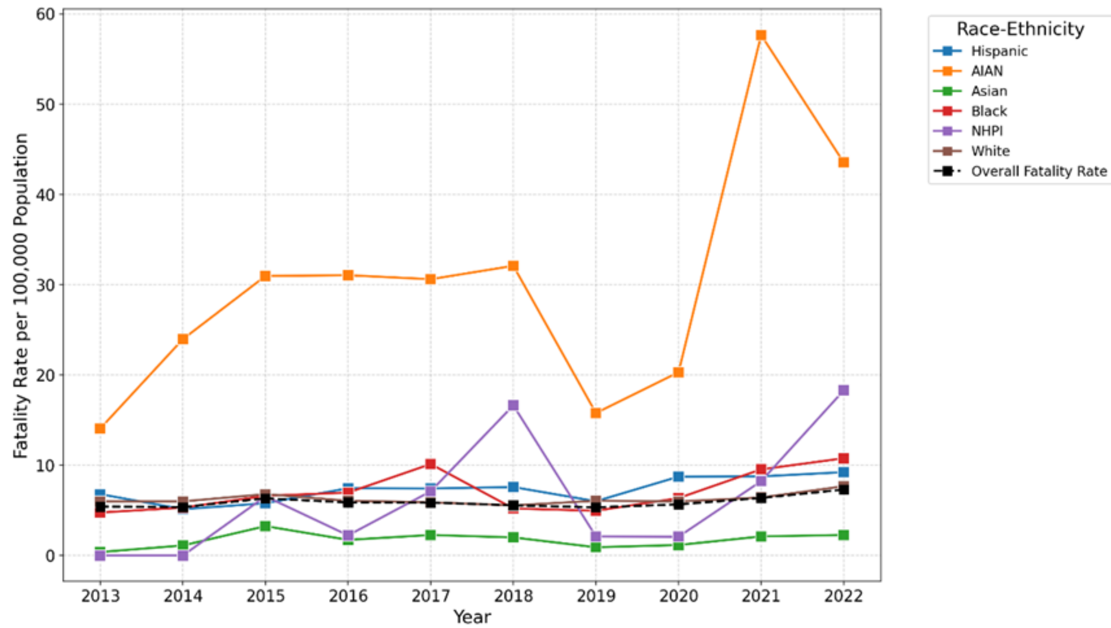


Figure A.17. MVO Fatality Rate in Traffic Crashes Per 100,000 Population in Washington, by Race/Ethnicity, 2013–2022

Table A.16. Relative Fatality Rate in Traffic Crashes in Washington, by Race/Ethnicity and Road User Type, 2013–2022

Race/Ethnicity	Relative Pedestrian Fatalities per 100,000 Population									
	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Pedestrian										
Hispanic	1.16	0.92	1.29	1.12	1.58	1.11	1.57	0.51	1.02	0.83
AIAN	9.98	5.18	5.97	7.68	8.16	3.61	6.50	7.36	12.24	7.07
Asian	0.59	0.54	1.33	1.37	0.65	0.22	1.35	1.16	0.96	0.24
Black	2.03	0.85	1.91	1.62	1.62	1.05	1.89	1.79	2.40	1.43
NHPI	0.00	2.20	0.00	2.21	1.90	0.00	0.00	0.00	0.00	0.00
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Bicyclist										
Hispanic	1.47	0.00	0.92	0.00	0.73	1.00	0.39	0.91	0.66	0.39
AIAN	15.06	0.00	0.00	4.61	0.00	4.00	0.00	0.00	6.21	0.00
Asian	0.00	1.12	0.00	0.00	1.07	0.00	0.00	0.68	0.00	0.57
Black	0.00	0.00	0.00	1.46	1.37	0.00	0.00	3.23	0.00	0.00
NHPI	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
MVO										
Hispanic	1.13	0.86	0.85	1.23	1.26	1.37	0.99	1.46	1.36	1.20
AIAN	2.35	4.00	4.56	5.12	5.20	5.78	2.60	3.39	8.98	5.68
Asian	0.06	0.19	0.48	0.29	0.39	0.36	0.15	0.19	0.33	0.30
Black	0.80	0.89	0.97	1.15	1.72	0.94	0.82	1.06	1.49	1.40
NHPI	0.00	0.00	0.97	0.37	1.21	3.00	0.35	0.35	1.28	2.39
White	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Appendix A.2: Detailed Methodology of Intersectional Analysis by Race/Ethnicity, Gender, and Age

An intersectional analysis was performed to assess whether a particular group's involvement in traffic-related injuries is disproportionately high or low compared to their share of the median population. The intersectional analysis calculates injury outcomes for road user's gender and age within each race/ethnic group and standardizes these counts by percentages of the median population. This approach offers a clear comparison of traffic safety disparities across demographic groups by revealing whether certain groups are overrepresented or underrepresented in traffic fatalities.

The following formulas illustrate the method used to compute disparities based on race/ethnicity, gender, and age, which includes:

(i) calculating the percentage of traffic injury outcomes by road user's gender and age within each race/ethnicity group (Equation A-1) and

(ii) determining counts and percentages per 1,000 of the median population for each gender and age group within each race/ethnicity (Equation A-2).

This method indicates if a particular group's injury involvement is above or below its median population share, providing insight into relative impacts across demographics.

$$P_{\text{road user category|race−ethnicity by gender \& age}} = \frac{\text{Injury counts in a race−ethnicity by gender\& age}}{\text{Injury across all race−ethnicity by gender \& age}} \quad \text{(A-1)}$$

$$P_{\text{pop|race−ethnicity by gender \& age}} = \frac{\text{Median population in a race−ethnicity group by gender\&age}}{\text{Median population across all race−ethnicity by gender \& age}} \quad \text{(A-2)}$$

where, $P_{\text{road user category|race−ethnicity by gender \& age}}$ = percentage of injury severity outcome for a specific road user's gender and age category within the race/ethnicity group and $P_{\text{pop|race−ethnicity by gender \& age}}$ = median population percentage expressed per 1,000 of each gender and age group for the race/ethnicity category. Disparities were assessed by comparing $P_{\text{pop|race−ethnicity by gender \& age}}$ with $P_{\text{road user category|race−ethnicity by gender \& age}}$. Overrepresentation occurs when $P_{\text{road user category|race−ethnicity by gender \& age}}$ significantly exceeds $P_{\text{pop|race−ethnicity by gender \& age}}$, indicating that a specific group experiences a higher injury severity than expected.

Table A.17 through Table A.28 summarize the intersectional analysis findings for each race/ethnicity and gender group across age categories and road user types. These tables provide the count, proportion, and proportional differences to indicate overrepresentation (red bars) or underrepresentation (green bars) in each category. Findings significant at the 95% confidence interval for different groups are described in the Results Section for Intersectional Analysis in more detail.

Appendix A.3: Results of Intersectional Analysis

Note: Prop = Proportion; Popn = Median population; Crashes = Crash count; Diff = Difference; Results in bold imply the overrepresentation of the respective group in crashes is significant at the 95% confidence level.

A.3.1 Ohio

Table A.17. Intersectional Analysis for Pedestrian Fatalities in Ohio

Race	Gender	Prop	Popn<18)	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn>=55	Crashes>=55	Diff (%)
Hispanic	Female	Count	22	9		17	4		25	8		6	3	
		%	6.9	16.4	9.4	4.6	3.9	-0.7	3.5	7.1	3.6	1.3	2.0	0.7
	Male	Count	23.07	4.00		18.46	14.00		26.90	18.00		4.84	23.07	
		%	6.9	7.1	0.3	5.1	7.1	2.0	3.8	6.1	2.3	1.3	7.0	5.7
White	Female	Count	237	24		278	62		573	74		387	111	
		%	74.5	43.6	**-30.9**	77.5	60.8	**-16.7**	80.5	65.5	**-15.0**	87.7	74.0	**-13.7**
	Male	Count	251	27		283	129		575	205		324	240	
		%	74.8	48.2	**-26.6**	77.8	65.2	**-12.7**	81.5	69.3	**-12.2**	89.1	72.9	**-16.2**
Black	Female	Count	51	21		52	35		92	31		42	29	
		%	16.0	38.2	22.2	14.5	34.3	**19.8**	13.0	27.4	14.5	9.6	19.3	9.8
	Male	Count	53	25		50	54		84	72		30	59	
		%	15.8	44.6	**28.8**	13.8	27.3	13.4	11.8	24.3	**12.5**	8.2	17.9	9.8
AIAN	Female	Count	1	0		1	0		1	0		1	0	
		%	0.2	0.0	-0.2	0.2	0.0	-0.2	0.2	0.0	-0.2	0.2	0.0	-0.2
	Male	Count	1	0		1	0		2	0		0	0	
		%	0.2	0.0	-0.2	0.2	0.0	-0.2	0.3	0.0	-0.3	0.1	0.0	-0.1
Asian	Female	Count	8	1		11	1		20	0		6	7	
		%	2.4	1.8	-0.6	3.2	1.0	-2.2	2.8	0.0	-2.8	1.3	4.7	3.4
	Male	Count	7	0		11	1		18	1		5	7	
		%	2.2	0.0	-2.2	3.0	0.5	-2.5	2.6	0.3	-2.2	1.2	2.1	0.9
NHIP	Female	Count	0	0		0	0		0	0		0	0	
		%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Male	Count	0	0		0	0		0	0		0	0	
		%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table A.18. Intersectional Analysis for Bicyclist Fatalities in Ohio

Race	Gender	Prop	Popn<18)	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn>=55	Crashes>=55	Diff (%)
Hispanic	Female	Count	22	0		17	0		25	0		6	0	
		%	6.9	0.0	-6.9	4.6	0.0	-4.6	3.5	0.0	-3.5	1.3	0.0	-1.3
	Male	Count	23	1		18	0		27	2		5	3	
		%	6.9	2.9	-4.0	5.1	0.0	-5.1	3.8	4.7	0.8	1.3	3.4	2.0
White	Female	Count	237	7		278	9		573	8		387	7	
		%	74.5	87.5	13.0	77.5	90.0	12.5	80.5	100.0	**19.5**	87.7	77.8	-9.9
	Male	Count	251	27		283	14		575	31		324	72	
		%	74.8	77.1	2.3	77.8	66.7	-11.2	81.5	72.1	-9.4	89.1	80.9	-8.2
Black	Female	Count	51	1		52	1		92	0		42	2	
		%	16.0	12.5	-3.5	14.5	10.0	-4.5	13.0	0.0	**-13.0**	9.6	22.2	**12.7**
	Male	Count	53	6		50	6		84	9		30	13	
		%	15.8	17.1	1.3	13.8	28.6	14.7	11.8	0.0	-11.8	8.2	14.6	6.4
AIAN	Female	Count	1	0		1	0		1	0		1	0	
		%	0.2	0.0	-0.2	0.2	0.0	-0.2	0.2	0.0	-0.2	0.2	0.0	-0.2
	Male	Count	1	0		1	0		2	0		0	0	
		%	0.2	0.0	-0.2	0.2	0.0	-0.2	0.3	0.0	-0.3	0.1	0.0	-0.1
Asian	Female	Count	8	0		11	0		20	0		6	0	
		%	2.4	0.0	-2.4	3.2	0.0	-3.2	2.8	0.0	-2.8	1.3	0.0	-1.3
	Male	Count	7	1		11	1		18	1		5	1	
		%	2.2	2.9	0.6	3.0	4.8	1.7	2.6	2.3	-0.3	1.2	1.1	-0.1
NHIP	Female	Count	0	0		0	0		0	0		0	0	
		%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Male	Count	0	0		0	0		0	0		0	0	
		%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table A.19. Intersectional Analysis for MVO Fatalities in Ohio

Race	Gender	Prop	Popn<18)	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn>=55	Crashes>=55	Diff (%)
Hispanic	Female	Count	22	14		17	34		25	20		6	19	
		%	6.9	4.7	-2.2	4.6	4.0	-0.6	3.5	2.6	-0.9	1.3	1.7	0.5
	Male	Count	23	22		18	123		27	69		5	17	
		%	6.9	4.7	-2.2	5.1	5.7	0.6	3.8	3.4	-0.5	1.3	0.8	-0.5
White	Female	Count	237	236		278	608		573	642		387	990	
		%	74.5	80.0	5.5	77.5	71.9	-5.6	80.5	83.2	2.6	87.7	90.7	2.9
	Male	Count	251	355		283	1602		575	1660		324	1885	
		%	74.8	75.9	1.0	77.8	74.3	-3.5	81.5	80.7	-0.8	89.1	90.6	1.5
Black	Female	Count	51	44		52	194		92	105		42	79	
		%	16.0	14.9	-1.1	14.5	22.9	8.4	13.0	13.6	0.6	9.6	7.2	-2.3
	Male	Count	53	88		50	419		84	313		30	167	
		%	15.8	18.8	3.0	13.8	19.4	5.6	11.8	15.2	3.4	8.2	8.0	-0.2
AIAN	Female	Count	1	0		1	3		1	1		1	0	
		%	0.2	0.0	-0.2	0.2	0.4	0.2	0.2	0.1	-0.1	0.2	0.0	-0.2
	Male	Count	1	0		1	5		2	1		0	6	
		%	0.2	0.0	-0.2	0.2	0.2	0.0	0.3	0.0	-0.2	0.1	0.3	0.2
Asian	Female	Count	8	1		11	7		20	4		6	4	
		%	2.4	0.3	-2.0	3.2	0.8	-2.4	2.8	0.5	-2.3	1.3	0.4	-0.9
	Male	Count	7	3		11	7		18	13		5	6	
		%	2.2	0.6	-1.6	3.0	0.3	-2.7	2.6	0.6	-1.9	1.2	0.3	-1.0
NHIP	Female	Count	0	0		0	0		0	0		0	0	
		%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	Male	Count	0	0		0	0		0	1		0	0	
		%	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

A.3.2 Texas

Table A.20. Intersectional Analysis for Pedestrian Fatalities in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	Female	Count	486	78		407	359		704	342		184	369	
		%	47.7	46.4	-1.3	40.2	40.8	0.6	36.6	34.2	-2.4	**22.4**	**34.7**	**12.3**
	Male	Count	507	48		442	99		713	103		148	109	
		%	47.6	45.3	-2.3	41.2	31.9	-9.2	36.7	25.8	-10.9	21.5	27.7	6.1
White	Female	Count	305	43		357	297		749	412		497	434	
		%	30.0	25.6	-4.4	35.3	33.8	-1.5	38.9	41.2	2.3	60.7	40.8	-19.9
	Male	Count	322	30		375	119		773	211		434	204	
		%	30.2	28.3	-1.9	34.9	38.4	3.5	**39.8**	**52.9**	**13.1**	63.0	51.8	-11.2
Black	Female	Count	118	41		132	195		235	211		77	219	
		%	11.6	24.4	12.8	**13.0**	**22.2**	**9.2**	**12.2**	**21.1**	**8.9**	**9.5**	**20.6**	**11.1**
	Male	Count	122	23		131	85		216	79		56	65	
		%	11.5	21.7	10.2	**12.2**	**27.4**	**15.3**	11.1	19.8	8.7	8.1	16.5	8.4
AIAN	Female	Count	4	0		5	2		9	2		3	4	
		%	0.4	0.0	-0.4	0.5	0.2	-0.3	0.5	0.2	-0.3	0.4	0.4	0.0
	Male	Count	4	0		5	1		10	2		3	0	
		%	0.4	0.0	-0.4	0.5	0.3	-0.2	0.5	0.5	0.0	0.4	0.0	-0.4
Asian	Female	Count	42	3		48	10		111	20		31	30	
		%	4.1	1.8	-2.3	4.8	1.1	-3.6	5.8	2.0	-3.8	3.8	2.8	-0.9
	Male	Count	43	4		48	3		104	2		25	13	
		%	4.0	3.8	-0.2	4.5	1.0	-3.5	5.3	0.5	-4.8	3.7	3.3	-0.4

Table A.21. Intersectional Analysis for Pedestrian Incapacitating Injuries in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	Female	Count	486	288		407	708		704	641		184	375	
		%	47.7	42.1	-5.6	40.2	38.9	-1.3	36.6	36.0	-0.6	22.4	28.5	6.0
	Male	Count	507	159		442	302		713	234		148	228	
		%	47.6	39.2	-8.5	41.2	34.0	-7.2	36.7	26.7	-10.0	21.5	27.4	5.8
White	Female	Count	305	181		357	623		749	661		497	574	
		%	30.0	26.5	-3.5	35.3	34.2	-1.1	38.9	37.1	-1.8	60.7	43.6	-17.1
	Male	Count	322	112		375	336		773	373		434	412	
		%	30.2	27.6	-2.7	34.9	37.8	3.0	39.8	42.6	2.8	63.0	49.5	-13.5
Black	Female	Count	118	179		132	414		235	425		77	309	
		%	**11.6**	**26.2**	**14.5**	**13.0**	**22.7**	**9.7**	**12.2**	**23.9**	**11.6**	**9.5**	**23.5**	**14.0**
	Male	Count	122	119		131	215		216	226		56	148	
		%	**11.5**	**29.3**	**17.8**	**12.2**	**24.2**	**12.1**	**11.1**	**25.8**	**14.7**	**8.1**	**17.8**	**9.7**
AIAN	Female	Count	4	1		5	9		9	5		3	0	
		%	0.4	0.1	-0.2	0.5	0.5	0.0	0.5	0.3	-0.2	0.4	0.0	-0.4
	Male	Count	4	0		5	3		10	0		3	3	
		%	0.4	0.0	-0.4	0.5	0.3	-0.2	0.5	0.0	-0.5	0.4	0.4	-0.1
Asian	Female	Count	42	22		48	43		111	27		31	45	
		%	4.1	3.2	-0.9	4.8	2.4	-2.4	5.8	1.5	-4.3	3.8	3.4	-0.3
	Male	Count	43	11		48	24		104	29		25	28	
		%	4.0	2.7	-1.3	4.5	2.7	-1.8	5.3	3.3	-2.0	3.7	3.4	-0.3

Table A.22. Intersectional Analysis for Pedestrian Non-incapacitating Injuries in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	Female	Count	486	795		407	1084		704	938		184	704	
		%	47.7	43.1	-4.6	40.2	37.2	-3.0	36.6	35.4	-1.2	**22.4**	**29.9**	**7.4**
	Male	Count	507	527		442	676		713	644		148	541	
		%	47.6	43.2	-4.4	41.2	32.3	-8.9	36.7	34.5	-2.2	**21.5**	**29.5**	**8.0**
White	Female	Count	305	497		357	990		749	1030		497	1075	
		%	30.0	27.0	-3.0	35.3	34.0	-1.3	38.9	38.9	-0.1	60.7	45.6	-15.1
	Male	Count	322	319		375	763		773	713		434	883	
		%	30.2	26.2	-4.1	34.9	36.4	1.5	39.8	38.2	-1.6	63.0	48.2	-14.8
Black	Female	Count	118	478		132	706		235	587		77	488	
		%	**11.6**	**25.9**	**14.3**	**13.0**	**24.2**	**11.2**	**12.2**	**22.2**	**9.9**	**9.5**	**20.7**	**11.2**
	Male	Count	122	319		131	530		216	409		56	309	
		%	**11.5**	**26.2**	**14.7**	**12.2**	**25.3**	**13.1**	**11.1**	**21.9**	**10.8**	**8.1**	**16.9**	**8.8**
AIAN	Female	Count	4	0		5	10		9	4		3	6	
		%	0.4	0.0	-0.4	0.5	0.3	-0.1	0.5	0.2	-0.3	0.4	0.3	-0.1
	Male	Count	4	2		5	7		10	4		3	2	
		%	0.4	0.2	-0.2	0.5	0.3	-0.2	0.5	0.2	-0.3	0.4	0.1	-0.3
Asian	Female	Count	42	56		48	78		111	62		31	60	
		%	4.1	3.0	-1.1	4.8	2.7	-2.1	5.8	2.3	-3.5	3.8	2.5	-1.2
	Male	Count	43	36		48	80		104	69		25	84	
		%	4.01	2.95	-1.05	4.46	3.82	-0.65	5.34	3.70	-1.64	3.70	4.58	0.89

Table A.23. Intersectional Analysis for Bicyclist Fatalities in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	Female	Count	486	15		407	17		704	43		184	48	
		%	47.7	48.4	0.7	40.2	26.2	-14.0	36.6	31.9	-4.7	22.4	30.2	7.7
	Male	Count	507	2		442	4		713	1		148	1	
		%	47.6	28.6	-19.0	41.2	22.2	-19.0	36.7	4.5	-32.2	21.5	7.1	-14.4
White	Female	Count	305	8		357	33		749	67		497	84	
		%	30.0	25.8	-4.1	35.3	50.8	15.5	38.9	49.6	10.7	60.7	52.8	-7.9
	Male	Count	322	4		375	7		773	15		434	10	
		%	30.2	57.1	26.9	34.9	38.9	4.0	**39.8**	**68.2**	**28.4**	63.0	71.4	8.4
Black	Female	Count	118	6		132	12		235	21		77	20	
		%	11.6	19.4	7.7	13.0	18.5	5.4	12.2	15.6	3.3	9.5	12.6	3.1
	Male	Count	122	1		131	4		216	5		56	1	
		%	11.5	14.3	2.8	12.2	22.2	10.1	11.1	22.7	11.6	8.1	7.1	-0.9
AIAN	Female	Count	4	0		5	0		9	0		3	0	
		%	0.4	0.0	-0.4	0.5	0.0	-0.5	0.5	0.0	-0.5	0.4	0.0	-0.4
	Male	Count	4	0		5	0		10	0		3	0	
		%	0.4	0.0	-0.4	0.5	0.0	-0.5	0.5	0.0	-0.5	0.4	0.0	-0.4
Asian	Female	Count	42	2		48	2		111	2		31	7	
		%	4.1	6.5	2.4	4.8	3.1	-1.7	5.8	1.5	-4.3	3.8	4.4	0.6
	Male	Count	43	0		48	3		104	0		25	2	
		%	4.0	0.0	-4.0	4.5	16.7	12.2	5.3	0.0	-5.3	3.7	14.3	10.6

Table A.24. Intersectional Analysis for Bicyclist Incapacitating Injuries in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	Female	Count	486	78		407	125		704	155		184	104	
		%	47.7	30.7	-17.0	40.2	30.2	-10.0	36.6	31.8	-4.8	22.4	**23.2**	**0.8**
	Male	Count	507	19		442	22		713	18		148	6	
		%	47.6	39.6	-8.0	41.2	22.9	-18.3	36.7	20.9	-15.8	21.5	9.2	-12.3
White	Female	Count	305	104		357	202		749	246		497	242	
		%	30.0	40.9	11.0	**35.3**	**48.8**	**13.5**	**38.9**	**50.5**	**11.6**	60.7	54.0	-6.7
	Male	Count	322	21		375	58		773	54		434	51	
		%	**30.2**	**43.8**	**13.5**	**34.9**	**60.4**	**25.5**	**39.8**	**62.8**	**23.0**	63.0	78.5	15.5
Black	Female	Count	118	54		132	66		235	72		77	86	
		%	11.6	21.3	9.6	13.0	15.9	2.9	**12.2**	**14.8**	**2.6**	9.5	19.2	9.7
	Male	Count	122	8		131	10	-121	216	14		56	4	
		%	11.5	16.7	5.2	12.2	10.4		**11.1**	**16.3**	**5.1**	8.1	6.2	-1.9
AIAN	Female	Count	4	0		5	2		9	1		3	2	
		%	0.4	0.0	-0.4	0.5	0.5	0.0	0.5	0.2	-0.3	0.4	0.4	0.1
	Male	Count	4	0		5	0		10	0		3	1	
		%	0.4	0.0	-0.4	0.5	0.0	-0.5	0.5	0.0	-0.5	0.4	1.5	1.1
Asian	Female	Count	42	16		48	10		111	8		31	10	
		%	4.1	6.3	2.2	4.8	2.4	-2.3	5.8	1.6	-4.1	3.8	2.2	-1.5
	Male	Count	43	0		48	5		104	0		25	3	
		%	4.0	0.0	-4.0	4.5	**5.2**	0.7	5.3	0.0	-5.3	3.7	4.6	0.9

Table A.25. Intersectional Analysis for Bicyclist Non-incapacitating Injuries in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	**Female**	Count	486	427		407	544		704	458		184	315	
		%	47.7	**31.4**	-16.3	40.2	31.6	-8.6	36.6	29.7	-6.8	22.4	**26.1**	**3.7**
	Male	Count	507	97		442	114		713	61		148	18	
		%	47.6	29.3	-18.3	41.2	22.0	-19.2	36.7	18.8	-17.9	21.5	13.1	-8.4
White	**Female**	Count	305	583		357	828		749	791		497	649	
		%	**30.0**	**42.9**	**12.9**	**35.3**	**48.2**	**12.9**	**38.9**	**51.4**	**12.4**	60.7	53.9	-6.9
	Male	Count	322	154		375	313		773	210		434	97	
		%	**30.2**	**46.5**	**16.3**	**34.9**	**60.4**	**25.5**	**39.8**	**64.8**	**25.0**	63.0	**70.8**	**7.8**
Black	**Female**	Count	118	281		132	254		235	237		77	206	
		%	**11.6**	**20.7**	**9.1**	13.0	**14.8**	1.7	12.2	**15.4**	3.2	9.5	**17.1**	**7.6**
	Male	Count	122	65		131	59		216	37		56	15	
		%	11.5	**19.6**	8.2	12.2	**11.4**	-0.8	11.1	**11.4**	0.3	8.1	10.9	2.9
AIAN	**Female**	Count	4	1		5	4		9	2		3	1	
		%	0.4	0.1	-0.3	0.5	0.2	-0.2	0.5	0.1	-0.3	0.4	0.1	-0.3
	Male	Count	4	0		5	1		10	0		3	0	
		%	0.4	0.0	-0.4	0.5	0.2	-0.3	0.5	0.0	-0.5	0.4	0.0	-0.4
Asian	**Female**	Count	42	55		48	61		111	35		31	23	
		%	4.1	**4.0**	0.0	4.8	3.5	-1.2	5.8	2.3	-3.5	3.8	**1.9**	**-1.8**
	Male	Count	43	13		48	24		104	11		25	6	
		%	4.0	3.9	-0.1	4.5	**4.6**	0.2	5.3	3.4	-1.9	3.7	**4.4**	**0.7**

Table A.26. Intersectional Analysis for MVO Fatalities in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	Female	Count	486	466		407	1895		704	1133		184	596	
		%	47.7	46.6	-1.1	**40.2**	**45.9**	**5.7**	36.6	37.3	0.7	22.4	21.7	-0.7
	Male	Count	507	271		442	639		713	381		148	303	
		%	47.6	41.0	-6.6	41.2	38.1	-3.1	36.7	30.7	-6.1	21.5	19.4	-2.1
White	Female	Count	305	328		357	1446		749	1282		497	1720	
		%	30.0	32.8	2.8	35.3	35.0	-0.2	38.9	42.2	3.3	60.7	62.8	2.0
	Male	Count	322	285		375	705		773	640		434	1048	
		%	**30.2**	**43.1**	**12.9**	**34.9**	**42.0**	**7.1**	**39.8**	**51.5**	**11.7**	63.0	67.3	4.3
Black	Female	Count	118	168		132	647		235	527		77	346	
		%	11.6	16.8	5.2	13.0	15.7	2.6	12.2	17.4	5.1	9.5	12.6	3.2
	Male	Count	122	84		131	291		216	184		56	160	
		%	11.5	12.7	1.2	12.2	17.3	5.2	11.1	14.8	3.7	8.1	10.3	2.2
AIAN	Female	Count	4	4		5	13		9	9		3	9	
		%	0.4	0.4	0.0	0.5	0.3	-0.2	0.5	0.3	-0.2	0.4	0.3	-0.1
	Male	Count	4	1		5	2		10	1		3	0	
		%	0.4	0.2	-0.3	0.5	0.1	-0.4	0.5	0.1	-0.4	0.4	0.0	-0.4
Asian	Female	Count	42	20		48	68		111	56		31	49	
		%	4.1	2.0	-2.1	4.8	1.6	-3.1	5.8	1.8	-3.9	3.8	1.8	-2.0
	Male	Count	43	14		48	25		104	26		25	37	
		%	4.0	2.1	-1.9	4.5	1.5	-3.0	5.3	2.1	-3.2	3.7	2.4	-1.3

Table A.27. Intersectional Analysis for MVO Incapacitating Injuries in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	Female	Count	486	1919		407	8445		704	4340		184	1714	
		%	47.7	45.5	2.2	40.2	43.0	2.8	36.6	34.8	1.8	22.4	22.3	-0.1
	Male	Count	507	1707		442	5064		713	3158		148	1492	
		%	47.6	43.8	3.8	41.2	35.8	5.3	36.7	32.7	4.1	21.5	20.7	-0.9
White	Female	Count	305	1488		357	6994		749	5156		497	4486	
		%	30.0	35.3	5.3	35.3	35.6	0.4	38.9	41.4	2.4	60.7	58.5	-2.3
	Male	Count	322	1458		375	5517		773	4229		434	4409	
		%	30.2	37.4	7.2	34.9	39.1	4.2	39.8	43.8	4.0	63.0	61.1	-1.9
Black	Female	Count	118	712		132	3539		235	2536		77	1169	
		%	11.6	16.9	5.3	13.0	18.0	5.0	12.2	20.4	8.1	9.5	15.2	5.8
	Male	Count	122	623		131	3073		216	1905		56	1013	
		%	11.5	16.0	4.5	12.2	21.8	9.6	11.1	19.7	8.6	8.1	14.0	6.0
AIAN	Female	Count	4	6		5	60		9	29		3	23	
		%	0.4	0.1	0.2	0.5	0.3	0.2	0.5	0.2	0.2	0.4	0.3	-0.1
	Male	Count	4	7		5	48		10	21		3	11	
		%	0.4	0.2	0.2	0.5	0.3	0.2	0.5	0.2	0.3	0.4	0.2	-0.3
Asian	Female	Count	42	55		48	292		111	268		31	213	
		%	4.1	1.3	2.8	4.8	1.5	3.3	5.8	2.2	3.6	3.8	2.8	-1.0
	Male	Count	43	77		48	245		104	251		25	236	
		%	4.0	2.0	2.0	4.5	1.7	2.7	5.3	2.6	2.7	3.7	3.3	-0.4

Table A.28. Intersectional Analysis for MVO Non-incapacitating Injuries in Texas

Race-Ethnicity	Gender	Prop	Popn<18	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn ≥55	Crashes≥55	Diff (%)
Hispanic	Female	Count	486	10754		407	36282		704	19963		184	9424	
		%	47.7	45.8	-1.9	40.2	41.6	1.4	36.6	35.8	-0.8	22.4	24.8	2.4
	Male	Count	507	11654		442	32828		713	22300		148	11295	
		%	47.6	44.4	-3.2	41.2	36.5	-4.6	36.7	35.3	-1.4	21.5	25.8	4.3
White	Female	Count	305	7558		357	29084		749	21219		497	20825	
		%	30.0	32.2	2.2	35.3	33.3	-1.9	38.9	38.0	-0.9	60.7	54.8	-5.9
	Male	Count	322	8919		375	32585		773	24540		434	23632	
		%	30.2	34.0	3.8	34.9	36.3	1.4	39.8	38.8	-0.9	63.0	53.9	-9.0
Black	Female	Count	118	4348		132	17785		235	11796		77	6036	
		%	**11.6**	**18.5**	**6.9**	**13.0**	**20.4**	**7.4**	**12.2**	**21.1**	**8.9**	9.5	15.9	6.4
	Male	Count	122	4833		131	20468		216	13062		56	6901	
		%	**11.5**	**18.4**	**6.9**	**12.2**	**22.8**	**10.6**	**11.1**	**20.7**	**9.5**	**8.1**	**15.8**	**7.7**
AIAN	Female	Count	4	35		5	257		9	130		3	79	
		%	0.4	0.1	-0.2	0.5	0.3	-0.2	0.5	0.2	-0.2	0.4	0.2	-0.2
	Male	Count	4	35		5	226		10	155		3	72	
		%	0.4	0.1	-0.3	0.5	0.3	-0.2	0.5	0.2	-0.3	0.4	0.2	-0.3
Asian	Female	Count	42	525		48	2281		111	1919		31	1263	
		%	4.1	2.2	-1.9	4.8	2.6	-2.2	5.8	3.4	-2.4	3.8	3.3	-0.4
	Male	Count	43	545		48	2337		104	2391		25	1579	
		%	4.0	2.1	-1.9	4.5	2.6	-1.9	5.3	3.8	-1.6	3.7	3.6	-0.1

A.3.3 Washington

Table A.29. Intersectional Analysis for Pedestrian Fatalities in Washington

Race	Gender	Prop	Popn<18)	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn>=55	Crashes>=55	Diff (%)
Hispanic	Female	Count	48	2		36	9		53	12		8	15	
		%	24.0	14.3	-9.7	15.7	15.8	0.1	11.7	15.0	3.3	3.4	10.4	7.0
	Male	Count	50	8		41	23		59	35		8	21	
		%	23.8	27.6	3.7	16.5	16.3	-0.1	12.6	16.7	4.2	3.6	8.9	5.3
White	Female	Count	123	11		155	33		324	58		210	102	
		%	61.1	78.6	17.4	67.0	57.9	-9.1	71.3	72.5	1.2	86.0	70.8	**-15.1**
	Male	Count	130	14		166	84		337	128		189	171	
		%	61.9	48.3	-13.6	66.3	59.6	-6.7	71.9	61.2	**-10.6**	87.1	72.8	**-14.3**
Black	Female	Count	4	0		3	4		6	2		2	3	
		%	1.7	0.0	-1.7	1.4	7.0	5.7	1.3	2.5	1.2	1.0	2.1	1.1
	Male	Count	3	2		4	13		6	17		2	13	
		%	1.5	6.9	5.4	1.5	9.2	7.7	1.2	8.1	6.9	0.9	5.5	4.6
AIAN	Female	Count	16	0		24	10		52	4		18	5	
		%	7.8	0.0	-7.8	10.5	17.5	7.1	11.4	5.0	-6.4	7.4	3.5	-3.9
	Male	Count	15	3		25	13		43	17		13	11	
		%	7.4	10.3	3.0	9.8	9.2	-0.6	9.2	8.1	-1.1	5.9	4.7	-1.3
Asian	Female	Count	9	1		11	1		16	4		5	19	
		%	4.6	7.1	2.6	4.6	1.8	-2.8	3.5	5.0	1.5	1.9	13.2	11.3
	Male	Count	10	2		13	7		21	10		5	19	
		%	4.6	6.9	2.3	5.1	5.0	-0.2	4.5	4.8	0.3	2.1	8.1	6.0
NHIP	Female	Count	1	0		2	0		3	0		1	0	
		%	0.7	0.0	-0.7	0.9	0.0	-0.9	0.7	0.0	-0.7	0.3	0.0	-0.3
	Male	Count	2	0		2	1		3	2		1	0	
		%	0.8	0.0	-0.8	0.9	0.7	-0.2	0.7	1.0	0.3	0.3	0.0	-0.3

Table A.30. Intersectional Analysis for Bicyclist Fatalities in Washington

Race	Gender	Prop	Popn<18)	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn>=55	Crashes>=55	Diff (%)
Hispanic	Female	Count	48	0		36	0		53	0		8	0	
		%	24.0	0.0	**-24.0**	15.7	0.0	**-15.7**	11.7	0.0	**-11.7**	3.4	0.0	-3.4
	Male	Count	50	3		41	2		59	3		8	7	
		%	23.8	20.0	-3.8	16.5	10.0	**-6.5**	12.6	8.3	-4.2	2.2	11.5	9.2
White	Female	Count	123	2		155	2		324	5		210	6	
		%	61.1	100.0	**38.9**	67.0	66.7	**-0.3**	71.3	100.0	**28.7**	86.0	100.0	**14.0**
	Male	Count	130	11		166	15		337	31		324	50	
		%	61.9	73.3	11.5	66.3	75.0	8.7	71.9	86.1	**14.3**	92.1	82.0	-10.1
Black	Female	Count	4	0		3	0		6	0		2	0	
		%	1.7	0.0	-1.7	1.4	0.0	**-1.4**	1.3	0.0	-1.3	1.0	0.0	-1.0
	Male	Count	3	0		4	2		6	0		2	2	
		%	1.5	0.0	-1.5	1.5	10.0	8.5	1.2	0.0	-1.2	0.6	3.3	2.7
AIAN	Female	Count	16	0		24	0		52	0		18	0	
		%	7.8	0.0	-7.8	10.5	0.0	**-10.5**	11.4	0.0	**-11.4**	7.4	0.0	-7.4
	Male	Count	15	1		25	1		43	0		13	0	
		%	7.4	0.1	-7.3	9.8	5.0	**-4.8**	9.2	0.0	**-9.2**	3.7	0.0	-3.7
Asian	Female	Count	9	0		11	1		16	0		5	0	
		%	4.6	0.0	-4.6	4.6	33.3	28.8	3.5	0.0	-3.5	1.9	0.0	-1.9
	Male	Count	10	0		13	0		21	2		5	2	
		%	4.6	0.0	-4.6	5.1	0.0	**-5.1**	4.5	5.6	1.1	1.3	3.3	2.0
NHIP	Female	Count	1	0		2	0		3	0		1	0	
		%	0.7	0.0	-0.7	0.9	0.0	-0.9	0.7	0.0	-0.7	0.3	0.0	-0.3
	Male	Count	2	0		2	0		3	0		1	0	
		%	0.8	0.0	-0.8	0.9	0.0	-0.9	0.7	0.0	-0.7	0.2	0.0	-0.2

Table A.31. Intersectional Analysis for MVO Fatalities in Washington

Race	Gender	Prop	Popn<18)	Crashes<18	Diff (%)	Popn (18-34)	Crashes (18-34)	Diff (%)	Popn (35-54)	Crashes (35-54)	Diff (%)	Popn>=55	Crashes>=55	Diff (%)
Hispanic	Female	Count	48	23		36	81		53	43		8	30	
		%	24.0	17.8	-6.2	15.7	21.6	5.9	11.7	14.3	2.6	3.4	6.9	3.5
	Male	Count	50	59		41	266		59	118		8	58	
		%	23.8	30.6	6.7	16.5	25.4	9.0	12.6	13.8	1.3	2.2	6.3	4.0
White	Female	Count	123	82		155	226		324	205		210	353	
		%	61.1	63.6	2.4	67.0	60.3	-6.7	71.3	68.1	-3.2	86.0	81.7	-4.3
	Male	Count	130	112		166	629		337	639		324	802	
		%	61.9	58.0	-3.8	66.3	60.1	-6.2	71.9	74.9	3.1	92.1	86.6	**-5.4**
Black	Female	Count	4	5		3	21		6	14		2	6	
		%	1.7	3.9	2.1	1.4	5.6	4.2	1.3	4.7	3.3	1.0	1.4	0.4
	Male	Count	3	6		4	72		6	41		2	17	
		%	1.5	3.1	1.6	1.5	6.9	5.4	1.2	4.8	3.6	0.6	1.8	1.3
AIAN	Female	Count	16	14		24	40		52	28		18	16	
		%	7.8	10.9	3.0	10.5	10.7	0.2	11.4	9.3	-2.1	7.4	3.7	-3.7
	Male	Count	15	9		25	49		43	31		13	22	
		%	7.4	4.7	-2.7	9.8	4.7	-5.1	9.2	3.6	-5.6	3.7	2.4	-1.3
Asian	Female	Count	9	4		11	6		16	9		5	25	
		%	4.6	3.1	-1.5	4.6	1.6	-3.0	3.5	3.0	-0.5	1.9	5.8	3.9
	Male	Count	10	6		13	21		21	14		5	24	
		%	4.6	3.1	-1.5	5.1	2.0	-3.1	4.5	1.6	-2.8	1.3	2.6	1.3
NHIP	Female	Count	1	1		2	1		3	2		1	2	
		%	0.7	0.8	0.0	0.9	0.3	-0.7	0.7	0.7	-0.1	0.3	0.5	0.2
	Male	Count	2	1		2	10		3	10		1	3	
		%	0.8	0.5	-0.3	0.9	1.0	0.1	0.7	1.2	0.5	0.2	0.3	0.1

Appendix A.4: Statistical Analysis of Texas Using Binary Logit Model with Random Parameters

This section presents the analysis performed exclusively for the state of Texas to identify disparities across different racial/ethnic groups using CRIS data (TxDOT, 2024). There are three key differences in the analysis performed for Texas:

1. Instead of employing national databases like FARS, this study utilizes a state-specific dataset due to its unique inclusion of race and ethnicity data, which provides a more granular perspective on demographic factors.
2. Rather than focusing on historical trends or crash rates, the approach shifts to predicting injury severity outcomes among pedestrians, bicyclists, and MVOs. A severity analysis reveals conditions and disparities that lead to more severe outcomes, particularly among racial and ethnic groups. This is achieved through the application of Random Parameter (RP) binary models, allowing a deeper understanding of factors influencing inequities in injury severity outcomes.
3. The analysis captures travel patterns during pre-COVID (2018–2019) and post-COVID (2021–2022) periods (Vingilis et al., 2020).

By focusing on severity, this study aims to address these structural issues and reduce unequal risks of serious injury or death, ensuring that traffic safety initiatives prioritize the most vulnerable populations.

This study uses exploratory data analysis and a random parameter (RP) logistic regression model to examine how demographic, socioeconomic, and built environment factors affect traffic safety outcomes in Texas. The model evaluates risks of fatal and serious injuries, with the findings informing recommendations to reduce disparities and promote equitable outcomes for all road users.

A.4.1 Descriptive Statistics of Injury Severity

The analysis begins by presenting descriptive statistics on injury severity across various crash attributes for different road user categories: pedestrians, bicyclists, and MVOs. It explores a broad range of crash-related characteristics, including road-user demographics, road infrastructure, environmental conditions, vehicle factors, and behaviors contributing to crash occurrences. Key attributes taken from the CRIS database, such as the day of the week, weather conditions, vehicle age, and road-user attributes, are examined to identify patterns in injury severity outcomes. General trends in crash occurrences are analyzed based on the severity of injuries sustained, with total counts and percentages reported for crash-related attributes grouped by road-user category. These variables were selected for their relevance to road-user safety based on insights from existing literature and for their potential to highlight how various factors impact road users across different injury outcomes.

Pedestrians. The descriptive statistics for pedestrian crashes (Table A.32) provide valuable insights into injury severity and associated factors. Out of 18,985 total cases, 62.3% resulted in minor or possible injuries, while 37.7% were KA injuries. The proportion of KA injuries increased post-COVID (41.9% compared to 33.8% pre-COVID). Age distribution showed a relatively even spread among the 19–34 (29.2%) and 35–54 (29.2%) age groups, with individuals aged 55+ accounting for 24.1% of the total cases. Male pedestrians were involved in the majority of incidents (64%). By race/ethnicity, White pedestrians comprised 36.8% of cases, followed by Hispanic (35.5%) and Black (23.4%) pedestrians. Lighting conditions played a significant role, with 48.8% of crashes occurring during daylight and a notable 20.2% occurring in dark, unlit conditions. Most crashes happened on roads with speed limits of 30–40 mph (62.3%), and nearly two-thirds (64.4%) were not at intersections. Traffic signals were the most common control type involved (61.5%). Light trucks, SUVs, and vans were the most frequently involved vehicle types (51.3%). Hit-and-run incidents accounted for 6% of cases. Geographically, urban areas saw the majority of pedestrian crashes, with 66.6% occurring in cities, while rural areas accounted for 10.5%.

Table A.32. Descriptive Statistics for Pedestrian Injury Crashes and Related Variables in Texas

Variable	Category	Count	%	Count	%	Count	%
		Pre-COVID		Post-COVID		Total	
		9,820		9,165		18,985	
Injury Severity	Minor or Possible Injury	6,503	66.22	5,325	58.10	11,828	62.30
	Fatal or Serious Injury	3,317	33.78	3,840	41.90	7,157	37.70
Age (years)	<=18	1,852	18.86	1,463	15.96	3,315	17.46
	19–34	2,828	28.80	2,715	29.62	5,543	29.20
	35–54	2,767	28.18	2,778	30.31	5,545	29.21
	>=55	2,373	24.16	2,209	24.10	4,582	24.13
Gender	Female	3,658	37.25	3,187	34.77	6,845	36.05
	Male	6,162	62.75	5,978	65.23	12,140	63.95
Race/Ethnicity	White	3,621	36.87	3,371	36.78	6,992	36.83
	Hispanic	3,462	35.25	3,284	35.83	6,746	35.53
	Black	2,275	23.17	2,158	23.55	4,433	23.35
	Asian	275	2.80	266	2.90	541	2.85
	Other	171	1.74	57	0.62	228	1.20
	AIAN	16	0.16	29	0.32	45	0.24
Alcohol/Drug Related	No	9,621	97.97	8,998	98.18	18,619	98.07
	Yes	199	2.03	167	1.82	366	1.93
Lighting Condition	Daylight	5,010	51.02	4,258	46.46	9,268	48.82
	Dark–Lighted	2,715	27.65	2,686	29.31	5,401	28.45
	Dark–Not Lighted	1,814	18.47	2,011	21.94	3,825	20.15
	Dawn/Dusk	281	2.86	210	2.29	491	2.59
Speed Limit (mph)	<=25	526	5.36	504	5.50	1,030	5.43
	30–40	6,429	65.47	5,403	58.95	11,832	62.32
	>= 45	2,865	29.18	3,258	35.55	6,123	32.25
Intersection Related	No	6,163	62.76	6,068	66.21	12,231	64.42
	Yes	3,657	37.24	3,097	33.79	6,754	35.58
Traffic Control Type	Traffic Signal	5,727	58.32	5,939	64.80	11,666	61.45
	Human control	117	1.19	75	0.82	192	1.01
	Traffic Sign	1,883	19.18	1,457	15.90	3,340	17.59
	No Traffic Control	1,940	19.76	1,479	16.14	3,419	18.01
	Other Controls	153	1.56	215	2.35	368	1.94
Vehicle Body Size	Light trucks, SUV, Van	4,994	50.86	4,742	51.74	9,736	51.28
	Passenger cars, Motorcycles	4,592	46.76	4,194	45.76	8,786	46.28
	Heavy trucks and Buses	234	2.38	229	2.50	463	2.44
Hit and Run	No	9,251	94.21	8,602	93.86	17,853	94.04
	Yes	569	5.79	563	6.14	1,132	5.96
Area Type	City	6,722	68.45	5,918	64.57	12,640	66.58
	Suburban	1,565	15.94	1,629	17.77	3,194	16.82
	Town	576	5.87	585	6.38	1,161	6.12
	Rural	957	9.75	1,033	11.27	1,990	10.48

Bicyclists. The descriptive statistics of bicycle injury severity (Table A.33) reveal notable patterns across different categories and time periods. Overall, there were 7,224 bicycle-related injuries, with minor or possible injuries being the most common (82.2%), while KA injuries constituted 17.8% of the total. Comparing pre- and post-COVID periods, a slight increase in the proportion of KA injuries was observed post-COVID (20.1% vs.

15.7%). Age distribution showed a higher incidence among individuals aged 19–34 (26.5%) and 35–54 (27.9%), with a relatively lower proportion in the 55+ group. Males accounted for a substantial majority (82.4%) of the injuries, consistent across both periods. White individuals were the largest racial/ethnic group involved (49.8%), followed by Hispanic (29.3%) and Black (16.2%) individuals. Most incidents occurred in daylight (72.9%) and on roads with speed limits between 30-40 mph (72.6%). Intersection-related crashes were prevalent (60.8%), as were those at traffic signals (62.5%). Light trucks, SUVs, and vans were the most common vehicle types involved (52.4%). Most injuries occurred in urban areas, with cities accounting for 63.9% of the total cases. These statistics highlight critical areas for targeted interventions to enhance bicyclist safety.

Table A.33. Descriptive Statistics for Bicyclist Injury Crashes and Related Variables in Texas

Variable	Category	Count	%	Count	%	Count	%
		Pre-COVID		Post-COVID		Total	
		3,767		3,457		7,224	
Injury Severity	Minor or Possible Injury	3,175	84.28	2,762	79.90	5,937	82.18
	Fatal or Serious Injury	592	15.72	695	20.10	1,287	17.82
Age (years)	<=18	930	24.69	778	22.51	1,708	23.64
	19–34	1,045	27.74	872	25.22	1,917	26.54
	35–54	1,032	27.40	981	28.38	2,013	27.87
	>=55	760	20.18	826	23.89	1,586	21.95
Gender	Female	688	18.26	584	16.89	1,272	17.61
	Male	3,079	81.74	2,873	83.11	5,952	82.39
Race/Ethnicity	White	1,850	49.11	1,744	50.45	3,594	49.75
	Hispanic	1,103	29.28	1,010	29.22	2,113	29.25
	Black	631	16.75	538	15.56	1,169	16.18
	Asian	122	3.24	130	3.76	252	3.49
	Other	55	1.46	28	0.81	83	1.15
	AIAN	6	0.16	7	0.20	13	0.18
Alcohol/Drug Related	No	3,734	99.12	3,435	99.36	7,169	99.24
	Yes	33	0.88	22	0.64	55	0.76
Lighting Condition	Daylight	2,755	73.14	2,508	72.55	5,263	72.85
	Dark−Lighted	577	15.32	529	15.30	1,106	15.31
	Dark−Not Lighted	315	8.36	319	9.23	634	8.78
	Dawn/Dusk	120	3.19	101	2.92	221	3.06
Speed Limit (mph)	<=25	209	5.55	203	5.87	412	5.70
	30–40	2,801	74.36	2,444	70.70	5,245	72.61
	>= 45	757	20.10	810	23.43	1,567	21.69
Intersection Related	No	1,497	39.74	1,337	38.68	2,834	39.23
	Yes	2,270	60.26	2,120	61.32	4,390	60.77
Traffic Control Type	Traffic Signal	2,300	61.06	2,218	64.16	4,518	62.54
	Human control	9	0.24	7	0.20	16	0.22
	Traffic Sign	781	20.73	677	19.58	1,458	20.18
	No Traffic Control	601	15.95	458	13.25	1,059	14.66
	Other Controls	76	2.02	97	2.81	173	2.39
Vehicle Body Size	Light trucks, SUV, Van	1,893	50.25	1,890	54.67	3,783	52.37
	Passenger cars, Motorcycles	1,821	48.34	1,518	43.91	3,339	46.22
	Heavy trucks and Buses	53	1.41	49	1.42	102	1.41
Area Type	City	2,477	65.76	2,136	61.79	4,613	63.86
	Suburban	774	20.55	787	22.77	1,561	21.61
	Town	254	6.74	238	6.88	492	6.81
	Rural	262	6.96	296	8.56	558	7.72

Motor Vehicle Occupants. The descriptive statistics for MVO injury severity, as presented in Table A.34, highlight a clear distinction between pre-COVID and post-COVID periods. Among the 348,652 crashes analyzed, most resulted in minor or possible injuries (91%), while KA injuries accounted for 9%. The proportion of KA injuries increased slightly post-COVID, rising from 8% pre-COVID to 10% post-COVID. Age distribution indicates that occupants aged 19–34 years represented the largest share (44%) of crashes, followed by those aged 35–54 years (29.3%), with a smaller proportion for occupants aged ≤18 (6.7%) and ≥55 (20.1%). Males were slightly more represented (51.9%) compared to females (48.2%), and White (40.6%), Hispanic (34.3%), and Black occupants (20.5%) had the largest portions of the cases. Most crashes occurred in clear weather (74.2%) and during daylight conditions (64.4%), with a higher proportion of crashes on weekends post-COVID (33.2%). Most crashes occurred on roads with speed limits ≥45 mph (56.8%), and a significant portion (89.6%) took place on straight road segments. Passenger cars and motorcycles (54.5%) and older vehicles (73.3%) were the most commonly involved. Hit-and-run incidents were relatively rare (1.1%), while crashes predominantly occurred in urban areas (54.8%), followed by rural locales (23.2%). These findings underscore the consistent role of high-speed roads, urban environments, and vehicle characteristics in MVO injury outcomes.

Table A.34. Descriptive Statistics for MVO Injury Crashes and Related Variables in Texas

Variable	Category	Count	%	Count	%	Count	%
		Pre-COVID		Post-COVID		Total	
		174,167		174,485		348,652	
Injury Severity	Minor or Possible Injury	160,318	92.05	156,976	89.97	317,294	91.01
	Fatal or Serious Injury	13,849	7.95	17,509	10.03	31,358	8.99
Age (years)	<=18	11,508	6.61	11,737	6.73	23,245	6.67
	19–34	76,109	43.70	77,281	44.29	153,390	44.00
	35–54	51,375	29.50	50,692	29.05	102,067	29.27
	>=55	35,175	20.20	34,775	19.93	69,950	20.06
Gender	Female	86,078	49.42	81,802	46.88	167,880	48.15
	Male	88,089	50.58	92,683	53.12	180,772	51.85
Race/Ethnicity	White	73,510	42.21	67,859	38.89	141,369	40.55
	Hispanic	56,950	32.70	62,639	35.90	119,589	34.30
	Black	34,211	19.64	37,278	21.36	71,489	20.50
	Asian	4,959	2.85	5,155	2.95	10,114	2.90
	Other	4,167	2.39	895	0.51	5,062	1.45
	AIAN	370	0.21	659	0.38	1,029	0.30
Alcohol/Drug Related	No	168,058	96.49	168,321	96.47	336,379	96.48
	Yes	6,109	3.51	6,164	3.53	12,273	3.52
Weather Condition	Clear	124,651	71.57	134,168	76.89	258,819	74.23
	Adverse	49,516	28.43	40,317	23.11	89,833	25.77
Lighting Condition	Daylight	113,847	65.37	110,614	63.39	224,461	64.38
	Dark–Lighted	35,529	20.40	38,759	22.21	74,288	21.31
	Dark–Not Lighted	20,719	11.90	21,134	12.11	41,853	12.00
	Dawn/Dusk	4,072	2.34	3,978	2.28	8,050	2.31
Weekend	No	119,529	68.63	116,507	66.77	236,036	67.70
	Yes	54,638	31.37	57,978	33.23	112,616	32.30
Speed Limit (mph)	<=25	1,791	1.03	2,041	1.17	3,832	1.10
	30–40	75,339	43.26	71,540	41.00	146,879	42.13
	>= 45	97,037	55.71	100,904	57.83	197,941	56.77
Horizontal Curve	No	155,329	89.18	155,538	89.14	310,867	89.16
	Yes	18,838	10.82	18,947	10.86	37,785	10.84
Vehicle Body Size	Light trucks, SUV, Van	75,095	43.12	78,204	44.82	153,299	43.97
	Passenger cars, Motorcycles	96,327	55.31	93,819	53.77	190,146	54.54
	Heavy trucks and Buses	2,745	1.58	2,462	1.41	5,207	1.49
Vehicle Age	Old	140,926	80.91	114,511	65.63	255,437	73.26
	New	33,241	19.09	59,974	34.37	93,215	26.74
Hit and Run	No	172,361	98.96	172,619	98.93	344,980	98.95
	Yes	1,806	1.04	1,866	1.07	3,672	1.05
Area Type	City	96,829	55.60	94,355	54.08	191,184	54.84
	Suburban	29,317	16.83	30,331	17.38	59,648	17.11
	Town	8,042	4.62	8,795	5.04	16,837	4.83
	Rural	39,979	22.95	41,004	23.50	80,983	23.23

A.4.2 Random Parameter Binary Logit Model

A random parameter (RP) binary logit model (Anastasopoulos & Mannering, 2011; Longford, 1994; Waseem et al., 2019; Zeng, 2011) was used to estimate the likelihood of crash injury severity as a function of several explanatory factors across different racial/ethnic groups. The likelihood of severe injury outcomes was predicted as a binary outcome, either 1 for KA crashes—fatal and incapacitating injuries; and 0 for less severe injury outcomes, including BC crashes—non-incapacitating and possible injuries. Given the complex, heterogeneous influences of socioeconomic and sociodemographic factors on injury severity (Pirdavani et al., 2017). An RP approach allowed for the capture of both fixed and varying effects across racial/ethnic groups, thereby addressing potential disparities in injury risk.

The choice of an RP binary logit model stems from two primary considerations: the heterogeneous nature of crash injury severity factors across racial/ethnic groups and the role of socioeconomic influences on injury severity in traffic safety. Due to data limitations and the unavailability of comprehensive economic information, race and ethnicity were used as a proxy for socioeconomic conditions. This approach reflects the strong correlation between an individual's socioeconomic status and their racial or ethnic background, as many aspects of economic opportunity are historically and structurally tied to these factors (Noël, 2018). Thus, structural inequities tied to race/ethnicity may indirectly affect crash outcomes (Haskins et al., 2013; Roll & McNeil, 2022; Zhu et al., 2024). This approach enables an analysis of disparities in how various factors impact injury severity across racial groups, with the goal of identifying systemic inequities in road safety.

The model allows certain parameters to vary randomly, capturing potential differences among groups. At the same time, it preserves fixed coefficients for factors with stable effects across racial/ethnic groups. This distinction enhances the model's flexibility, enabling more accurate and meaningful insights into disparities across race/ethnicity groups.

The RP binary logit model estimates the ratio of probability $P(Y=1|X, Z)$ that a crash results in a KA injury (outcome 1), given the explanatory factors X and Z, to the probability $P(Y=0|X, Z)$ that a BC injury (outcome 0), defined by the logistic function (Longford, 1994):

$$\frac{P(Y=1|X,Z)}{P(Y=0|X,Z)} = \exp\left(\beta_0 + \beta'X + \theta'Z\right) \tag{A-3}$$

The linear form of the RP binary logit model equation for the probability that a crash results in a KA injury (1) rather than a BC injury (0) is expressed as follows:

$$\text{Logit}\left(\frac{P(Y=1|X,Z)}{P(Y=0|X,Z)}\right) = \ln\left(\frac{P(Y=1|X,Z)}{P(Y=0|X,Z)}\right) = \beta_0 + \beta'X + \theta'Z \tag{A-4}$$

where

- $\text{Logit}(\frac{P(Y=1|X,Z)}{P(Y=0|X,Z)})$ represents the log odds of a severe crash outcome.
- β_0 is the intercept term, which may include both fixed and group-specific intercepts to account for racial/ethnic variability.
- $\beta'X$ is the linear predictor for explanatory variables with fixed effects across groups, where β' represents a vector of fixed coefficients.
- $\theta'Z$ is the linear predictor for explanatory variables with random effects, where θ' is modeled as a group-specific (race/ethnicity) parameter with $\theta' \sim N(\theta_g, \sigma_\theta)$. The random coefficients, θ' represent the deviation of group-specific effects from the fixed effects (Baayen et al., 2008).

The RP logit model was estimated using the maximum likelihood estimation technique (Baayen et al., 2008; Zeng, 2011). RPs for variables in Z are estimated with an assumed normal distribution (Jalayer et al., 2018), capturing variations in how racial/ethnic groups are impacted by each predictor. This flexible structure enables the model to reveal whether specific factors contribute to crash severity differently among racial/ethnic groups, indicating potential disparities in traffic safety outcomes.

A series of model fit checks, including the likelihood ratio test and comparison of log-likelihood values between the random and fixed parameter models (Cousineau & Allan, 2015) were performed to ensure that the RP model adequately captures the variability in crash severity outcomes. These tests verify whether allowing for RPs significantly improves model performance, thus justifying the complexity added by including random effects (Cousineau & Allan, 2015). A better fit of the RP model compared to the fixed parameter model would indicate that heterogeneity across racial/ethnic groups in the effects of certain predictors is indeed present.

In interpreting the RP binary logit model results, the coefficients for each predictor indicate the change in log odds of a fatal or severe crash outcome (KA injury) given a unit change in the predictor while accounting for variation across racial/ethnic groups. For fixed parameters, the odds ratios (OR) (Norton & Dowd, 2018; Sroka & Nagaraja, 2018) can be interpreted uniformly across groups, whereas for RPs, the variability captured by each group's mean and standard deviation highlights disparities in factor influence. Thus, if an RP is estimated for a particular variable, the model may reveal that the variable has a significantly stronger association with severe crashes for one racial/ethnic group than others, suggesting systemic safety disparities tied to socioeconomic factors. Through this modeling approach, critical insights into how the factors affecting crash severity differ across racial/ethnic groups are uncovered, providing evidence for targeted interventions to improve traffic safety equity.

A.4.3 Random Parameter Model Result of Texas

Table A.35. RP Model for Pedestrians (Pre-COVID in Texas)

Variable	Category	Fixed Effect			Random Coefficients					
		Coefficient	Std. Error	p.value	Whites	Hispanics	Black	Asian	Other	AIAN
Intercept		−2.6118	0.4111	0.0000	0.4991	0.2204	0.5899	0.0364	−0.9988	−0.3491
Intersection Related	No	Base								
	Yes	**−0.5443**	**0.0533**	**0.0000**	–	–	–	–	–	–
Vehicle Body Size	Light trucks, SUV, Van	Base								
	Passenger cars, Motorcycles	−0.0364	0.0477	0.4454	–	–	–	–	–	–
	Heavy trucks and Buses	**0.6004**	**0.1517**	**0.0001**	–	–	–	–	–	–
Pedestrian Age (years)	<=18	Base								
	19−34	0.3219	0.2050	0.1163	−0.1185	−0.0917	−0.4172	−0.0150	0.4698	0.1739
	35−54	**0.5610**	**0.2514**	**0.0256**	**−0.2143**	**−0.1325**	**−0.5203**	**−0.0217**	**0.6530**	**0.2376**
	>=55	**0.6574**	**0.2139**	**0.0021**	**−0.0227**	**−0.0641**	**−0.4515**	**−0.0113**	**0.3969**	**0.1540**
Pedestrian Gender	Female	Base								
	Male	**0.3763**	**0.1408**	**0.0075**	**−0.1226**	**−0.0723**	**−0.2910**	**−0.0123**	**0.3660**	**0.1332**
Alcohol/Drug Related	No	Base								
	Yes	0.0811	0.6662	0.9031	0.6547	0.5785	0.5346	0.0419	−1.3648	−0.4469
Speed Limit (mph)	<=25	Base								
	30−40	**0.7702**	**0.3375**	**0.0225**	**−0.4554**	**−0.1708**	**−0.2177**	**−0.0259**	**0.6543**	**0.2164**
	>= 45	**1.5428**	**0.3403**	**0.0000**	**−0.4119**	**−0.1851**	**−0.3197**	**−0.0262**	**0.7053**	**0.2388**
Area Type	City	Base								
	Suburban	0.2084	0.1384	0.1320	0.0648	0.0089	−0.2282	−0.0022	0.1075	0.0498
	Town	**0.7048**	**0.3275**	**0.0314**	**−0.1721**	**−0.0780**	**−0.5156**	**−0.0197**	**0.5730**	**0.2140**
	Rural	0.5190	0.2916	0.0752	−0.0395	−0.1459	−0.1876	−0.0059	0.2830	0.0965
Lighting Condition	Daylight	Base								
	Dark−Lighted	**0.7102**	**0.1215**	**0.0000**	**0.0883**	**0.0467**	**0.1393**	**0.0072**	**−0.2082**	**−0.0738**
	Dark−Not Lighted	**0.8113**	**0.1762**	**0.0000**	**0.0534**	**0.0852**	**0.3524**	**0.0104**	**−0.3659**	**−0.1366**
	Dawn/Dusk	0.2267	0.4574	0.6201	0.3088	0.1651	0.8838	0.0343	−1.0180	−0.3770
Hit and Run	No	Base								
	Yes	0.0881	0.2217	0.6911	0.0775	0.0285	0.2579	0.0095	−0.2715	−0.1027

***Note**: Std = Standard; Variables in bold are significant at a 95% confidence level.*

Table A.36. RP Model for Pedestrians (Post-COVID in Texas)

Variable	Category	Fixed Effect			Random Coefficients					
		Coefficient	Std. Error	p.value	Whites	Hispanics	Black	Asian	Other	AIAN
Intercept		−2.5361	0.5366	0.0000	0.5262	0.2158	0.3218	0.0551	−0.7659	−0.3498
Intersection Related	No	Base								
	Yes	**−0.6090**	**0.0546**	**0.0000**	–	–	–	–	–	–
Vehicle Body Size	Light trucks, SUV, Van	Base								
	Passenger cars, Motorcycles	−0.0714	0.0484	0.1400	–	–	–	–	–	–
	Heavy trucks and Buses	0.2127	0.1549	0.1697	–	–	–	–	–	–
Pedestrian Age (years)	<=18	Base								
	19−34	−0.1000	0.3360	0.7659	0.5536	0.5042	0.1374	0.0053	−0.7926	−0.4034
	35−54	−0.0199	0.4168	0.9619	0.7678	0.4884	0.4763	0.0195	−1.1787	−0.5671
	>=55	0.0760	0.5224	0.8843	0.9599	0.6520	0.4967	0.0310	−1.4356	−0.6963
Pedestrian Gender	Female	Base								
	Male	0.2574	0.2072	0.2141	−0.3027	−0.1473	−0.2571	−0.0086	0.4859	0.2273
Alcohol/Drug Related	No	Base								
	Yes	0.6068	0.8540	0.4774	−0.4067	−0.4556	−0.0340	0.0113	0.5755	0.3058
Speed Limit (mph)	<=25	Base								
	30−40	1.3037	0.6392	0.0414	−0.9606	−0.4881	−0.5798	−0.0699	1.4253	0.6664
	>= 45	**1.9556**	**0.5930**	**0.0010**	**−0.8206**	**−0.3335**	**−0.4810**	**−0.0914**	**1.1823**	**0.5391**
Area Type	City	Base								
	Suburban	0.1706	0.2335	0.4649	−0.1581	0.1065	−0.1008	−0.0745	0.1753	0.0520
	Town	0.4153	0.5340	0.4368	−0.0799	0.4464	−0.4210	−0.0944	0.1517	−0.0016
	Rural	**0.5331**	**0.3121**	**0.0877**	**0.1744**	**−0.1795**	**0.1018**	**0.1054**	**−0.1678**	**−0.0353**
Lighting Condition	Daylight	Base								
	Dark−Lighted	**0.8374**	**0.1841**	**0.0000**	**0.0056**	**−0.0282**	**0.2330**	**−0.0372**	**−0.1182**	**−0.0538**
	Dark−Not Lighted	**1.2659**	**0.2171**	**0.0000**	**−0.1742**	**−0.2069**	**−0.0942**	**0.0256**	**0.2921**	**0.1554**
	Dawn/Dusk	0.6442	0.5032	0.2005	−0.0272	−0.1556	0.1709	0.0072	−0.0105	0.0150
Hit and Run	No	Base								
	Yes	0.6070	0.3462	0.0795	−0.1460	−0.0083	−0.3106	0.0136	0.3112	0.1383

***Note**: Std = Standard; Variables in bold are significant at a 95% confidence level.*

Table A.37. RP Model for Bicyclists (Pre-COVID in Texas)

Variable	Category	Fixed Effect			Random Effect					
		Coefficient	Std. Error	p.value	Whites	Hispanics	Black	Asian	Other	AIAN
Intercept		−2.4803	0.5050	0.0000	−0.5727	−0.2636	−0.2857	0.7889	0.3180	0.0108
Bicyclist Age (years)	<=18	Base								
	19−34	0.0030	0.2142	0.9890	0.2951	0.1355	−0.1182	−0.2401	−0.1321	0.0644
	35−54	−0.0777	0.3197	0.8079	0.3361	0.4724	0.0750	−0.6455	−0.2883	0.0645
	>=55	**0.6367**	**0.2036**	**0.0018**	**0.1467**	**0.0438**	**−0.1857**	**−0.0221**	**−0.0422**	**0.0621**
Bicyclist Gender	Female	Base								
	Male	0.1737	0.2166	0.4226	−0.0979	−0.1001	0.4450	−0.1326	0.0151	−0.1365
Intersection Related	No	Base								
	Yes	**−0.4766**	**0.1660**	**0.0041**	**0.0376**	**−0.1095**	**−0.0321**	**0.0761**	**0.0302**	**−0.0058**
Vehicle Body Size	Light trucks, SUV, Van	Base								
	Passenger cars, Motorcycles	−0.0244	0.0774	0.7526	−	−	−	−	−	−
	Heavy trucks and Buses	**0.9024**	**0.2711**	**0.0009**	−	−	−	−	−	−
Alcohol/Drug Related	No	Base								
	Yes	0.7951	1.0549	0.4510	0.6609	0.1097	0.5774	−0.9184	−0.3274	−0.1063
Traffic Control Type	Traffic Signal	Base								
	Human control	−2.1572	4.8862	0.6589	−1.6608	2.3741	0.8535	−1.1406	−0.3918	0.0458
	Traffic Sign	−0.1837	0.2654	0.4887	0.3323	0.0617	0.2392	−0.4347	−0.1609	−0.0390
	No Traffic Control	−0.2225	0.2491	0.3717	0.2494	−0.1658	−0.4406	0.2225	0.0283	0.1034
	Other Controls	−0.1059	0.6781	0.8759	−1.2928	−0.3048	0.1142	1.0861	0.5245	−0.1335
Speed Limit (mph)	<=25	Base								
	30−40	0.3500	0.3827	0.3604	0.2983	0.3693	0.1469	−0.5854	−0.2477	0.0288
	>= 45	**0.8622**	**0.3511**	**0.0141**	**0.3654**	**−0.1223**	**0.0642**	**−0.2095**	**−0.0858**	**−0.0181**
Area Type	City	Base								
	Suburban	0.2335	0.1987	0.2401	0.0843	0.0717	−0.4012	0.1365	−0.0057	0.1202
	Town	0.5558	0.3813	0.1449	0.3058	0.2957	−0.5915	−0.0728	−0.1363	0.2132
	Rural	0.4937	0.3917	0.2075	0.4824	0.3800	−0.6870	−0.2035	−0.2136	0.2588
Lighting Condition	Daylight	Base								
	Dark−Lighted	**0.6040**	**0.1980**	**0.0023**	**−0.1867**	**0.1112**	**−0.1691**	**0.1555**	**0.0427**	**0.0524**
	Dark−Not Lighted	**0.8594**	**0.2273**	**0.0002**	**−0.0010**	**−0.2242**	**0.2708**	**0.0009**	**0.0477**	**−0.1042**
	Dawn/Dusk	0.0030	0.5060	0.9953	−0.3118	0.2149	0.9287	−0.5206	−0.0831	−0.2279

Note*: Std = Standard; Variables in bold are significant at a 95% confidence level.*

Table A.38. RP Model for Bicyclists (Post-COVID in Texas)

Variable	Category	Fixed Effect			Random Effect					
		Coefficient	Std. Error	p.value	Whites	Hispanics	Black	Asian	Other	AIAN
Intercept		−2.6179	0.7734	0.0007	0.2035	0.2693	0.6115	−1.2805	0.4257	−0.2289
Bicyclist Age (years)	<=18	Base								
	19–34	**0.4751**	**0.2204**	**0.0311**	**−0.0468**	**−0.0030**	**−0.1119**	**0.1893**	**−0.0665**	**0.0393**
	35–54	**0.5202**	**0.2017**	**0.0099**	**−0.0468**	**−0.1468**	**−0.2154**	**0.4801**	**−0.1518**	**0.0796**
	>=55	**1.0241**	**0.2922**	**0.0005**	**−0.0976**	**−0.1726**	**−0.3351**	**0.7128**	**−0.2327**	**0.1244**
Bicyclist Gender	Female	Base								
	Male	−0.0112	0.2539	0.9648	−0.1469	−0.1873	−0.4176	0.8908	−0.2982	0.1589
Intersection Related	No	Base								
	Yes	**−0.4617**	**0.1733**	**0.0077**	**−0.0152**	**−0.0333**	**−0.0897**	**0.1580**	**−0.0488**	**0.0288**
Vehicle Body Size	Light trucks, SUV, Van	Base								
	Passenger cars, Motorcycles	**−0.2922**	**0.0946**	**0.0020**	–	–	–	–	–	–
	Heavy trucks and Buses	0.4215	0.3435	0.2197	–	–	–	–	–	–
Alcohol/Drug Related	No	Base								
	Yes	1.6833	1.2260	0.1698	0.0122	−0.0019	−0.0242	0.0089	0.0022	0.0024
Traffic Control Type	Traffic Signal	Base								
	Human control	0.7882	3.3352	0.8132	−0.0006	−0.0008	−0.0019	0.0040	−0.0013	0.0007
	Traffic Sign	0.2713	0.2681	0.3115	0.0097	0.0138	0.0312	−0.0647	0.0214	−0.0114
	No Traffic Control	−0.4201	0.2909	0.1487	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Other Controls	0.0563	0.8247	0.9456	−0.0192	−0.0254	−0.0578	0.1209	−0.0402	0.0216
Speed Limit (mph)	<=25	Base								
	30–40	0.5859	0.6505	0.3678	−0.0377	−0.0499	−0.1134	0.2375	−0.0789	0.0425
	>= 45	1.0646	0.6331	0.0927	−0.0268	−0.0355	−0.0806	0.1687	−0.0561	0.0302
Area Type	City	Base								
	Suburban	0.1105	0.2199	0.6151	−0.0625	−0.0828	−0.1880	0.3936	−0.1308	0.0704
	Town	0.7261	0.3946	0.0658	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Rural	0.6029	0.3451	0.0807	−0.0661	−0.0875	−0.1987	0.4160	−0.1383	0.0744
Lighting Condition	Daylight	Base								
	Dark–Lighted	0.4337	0.3535	0.2200	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Dark–Not Lighted	0.6956	0.6291	0.2688	0.1549	0.2050	0.4655	−0.9747	0.3241	−0.1742
	Dawn/Dusk	−0.1755	0.5379	0.7442	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

***Note**: Std = Standard; Variables in bold are significant at a 95% confidence level.*

Table A.39. RP Model for MVOs (Pre-COVID in Texas)

Variable	Category	Fixed Effect			Random Coefficients					
		Coefficient	Std. Error	p.value	Whites	Hispanics	Black	Asian	Other	AIAN
Intercept		−3.6966	0.2022	0.0000	−0.1426	0.0133	−0.0057	0.0945	0.0590	−0.0184
Intersection Related	No	Base								
	Yes	**−0.3025**	**0.0219**	**0.0000**	–	–	–	–	–	–
Vehicle Body Size	Light trucks, SUV, Van	Base								
	Passenger cars, Motorcycles	**−0.0410**	**0.0193**	**0.0338**	–	–	–	–	–	–
	Heavy trucks and Buses	0.0541	0.0573	0.3452	–	–	–	–	–	–
Weather Condition	Clear	Base								
	Adverse	**−0.1242**	**0.0205**	**0.0000**	–	–	–	–	–	–
Horizontal Curve	No	Base								
	Yes	**0.3717**	**0.0245**	**0.0000**	–	–	–	–	–	–
MVO Age (years)	<=18	Base								
	19–34	0.0906	0.0941	0.3357	0.2004	−0.0186	0.0080	−0.1328	−0.0829	0.0259
	35–54	0.0811	0.1112	0.4654	0.2546	−0.0800	0.0999	−0.2315	−0.0638	0.0208
	>=55	0.1770	0.1257	0.1592	0.3401	−0.1788	−0.0380	0.0692	−0.1962	0.0038
MVO Gender	Female	Base								
	Male	**0.4566**	**0.0196**	**0.0000**	–	–	–	–	–	–
Speed Limit (mph)	<=25	Base								
	30–40	0.0798	0.2019	0.6926	−0.0216	0.0531	0.1635	−0.3228	0.1122	0.0156
	>= 45	0.3308	0.2001	0.0984	0.0592	0.1221	0.0549	−0.3070	0.0282	0.0427
Alcohol/Drug Related	No	Base								
	Yes	**0.6211**	**0.1163**	**0.0000**	**−0.0167**	**−0.1386**	**0.2556**	**−0.1981**	**0.1290**	**−0.0311**
Weekend	No	Base								
	Yes	**0.1830**	**0.0195**	**0.0000**	–	–	–	–	–	–
Hit and Run	No	Base								
	Yes	**−0.4951**	**0.1069**	**0.0000**	–	–	–	–	–	–
Lighting Condition	Daylight	Base								
	Dark–Lighted	**0.5275**	**0.0705**	**0.0000**	**−0.2070**	**0.0194**	**−0.0350**	**0.1798**	**0.0703**	**−0.0275**
	Dark–Not Lighted	**0.3818**	**0.0702**	**0.0000**	**−0.0147**	**0.1657**	**−0.0871**	**−0.0880**	**−0.0145**	**0.0385**
	Dawn/Dusk	**0.2576**	**0.1242**	**0.0381**	**−0.1488**	**0.1325**	**0.0448**	**−0.1535**	**0.1116**	**0.0134**
Vehicle Age	Old	Base								
	New	**−0.2336**	**0.0642**	**0.0003**	**−0.0927**	**−0.1186**	**0.0178**	**0.2100**	**0.0282**	**−0.0447**
Area Type	City	Base								
	Suburban	**0.2905**	**0.0662**	**0.0000**	**0.1395**	**0.0928**	**−0.0386**	**−0.1737**	**−0.0644**	**0.0444**
	Town	**0.4359**	**0.2026**	**0.0314**	**0.3326**	**0.1843**	**0.1107**	**−0.6861**	**−0.0438**	**0.1023**
	Rural	**0.9863**	**0.0673**	**0.0000**	**0.0715**	**0.0426**	**−0.1500**	**0.1269**	**−0.1085**	**0.0175**

***Note**: Std = Standard; Variables in bold are significant at a 95% confidence level.*

Table A.40. RP Model for MVOs (Post-COVID in Texas)

Variable	Category	Fixed Effect			Random Coefficients					
		Coefficient	Std. Error	p.value	Whites	Hispanics	Black	Asian	Other	AIAN
Intercept		−3.4828	0.1773	0.0000	−0.2208	−0.0127	0.1893	−0.0304	0.2532	−0.1790
Intersection Related	No	Base								
	Yes	**−0.3091**	**0.0191**	**0.0000**	–	–	–	–	–	–
Vehicle Body Size	Light trucks, SUV, Van	Base								
	Passenger cars, Motorcycles	−0.0339	0.0174	0.0505	–	–	–	–	–	–
	Heavy trucks and Buses	0.0427	0.0564	0.4488	–	–	–	–	–	–
Weather Condition	Clear	Base								
	Adverse	**−0.1143**	**0.0198**	**0.0000**	–	–	–	–	–	–
Road Alignment	No	Base								
	Yes	**0.3478**	**0.0226**	**0.0000**	–	–	–	–	–	–
MVO Age (years)	<=18	Base								
	19−34	**0.1554**	**0.0595**	**0.0090**	**0.0179**	**0.0565**	**−0.0604**	**0.0058**	**−0.0555**	**0.0359**
	35−54	**0.1657**	**0.0778**	**0.0332**	**0.1239**	**−0.0363**	**−0.0709**	**0.0144**	**−0.1146**	**0.0837**
	>=55	**0.1924**	**0.0776**	**0.0132**	**0.1639**	**−0.1173**	**−0.0399**	**0.0182**	**−0.1108**	**0.0862**
MVO Gender	Female	Base								
	Male	**0.4610**	**0.0177**	**0.0000**	–	–	–	–	–	–
Speed Limit (mph)	<=25	Base								
	30−40	0.0615	0.1806	0.7334	0.2535	0.1032	0.1254	−0.4965	0.1385	−0.1232
	>= 45	**0.3832**	**0.1557**	**0.0139**	**0.2596**	**0.0477**	**−0.0183**	**−0.2611**	**−0.0483**	**0.0211**
Alcohol/Drug Related	No	Base								
	Yes	**0.5676**	**0.1419**	**0.0001**	**0.0248**	**0.0788**	**0.2285**	**−0.3966**	**0.2885**	**−0.2237**
Weekend	No	Base								
	Yes	**0.1702**	**0.0176**	**0.0000**	–	–	–	–	–	–
Hit and Run	No	Base								
	Yes	**−0.3870**	**0.0911**	**0.0000**	–	–	–	–	–	–
Lighting Condition	Daylight	Base								
	Dark−Lighted	**0.4663**	**0.0591**	**0.0000**	**−0.1562**	**0.0670**	**−0.0116**	**0.0914**	**0.0332**	**−0.0241**
	Dark−Not Lighted	**0.4406**	**0.0776**	**0.0000**	**−0.1281**	**0.0205**	**0.1338**	**−0.0764**	**0.1839**	**−0.1340**
	Dawn/Dusk	**0.3525**	**0.1504**	**0.0191**	**−0.1386**	**−0.1229**	**−0.2005**	**0.5082**	**−0.2513**	**0.2045**
Vehicle Age	Old	Base								
	New	**−0.2623**	**0.0411**	**0.0000**	**−0.0045**	**−0.0704**	**−0.0088**	**0.0854**	**−0.0321**	**0.0303**
Area Type	City	Base								
	Suburban	**0.3242**	**0.0520**	**0.0000**	**0.0606**	**0.0106**	**−0.0781**	**0.0351**	**−0.0979**	**0.0697**
	Town	**0.5514**	**0.1345**	**0.0000**	**0.1627**	**−0.0014**	**−0.2256**	**0.1446**	**−0.2908**	**0.2108**
	Rural	**0.9777**	**0.1019**	**0.0000**	**0.0785**	**−0.0066**	**−0.2244**	**0.2252**	**−0.2773**	**0.2047**

Note*: std = Standard; Variables in bold are significant at a 95% confidence level.*

APPENDIX B: NEIGHBORHOOD ANALYSIS APPENDICES

Appendix B.1: Spatial Distributions of KA Injury Rates

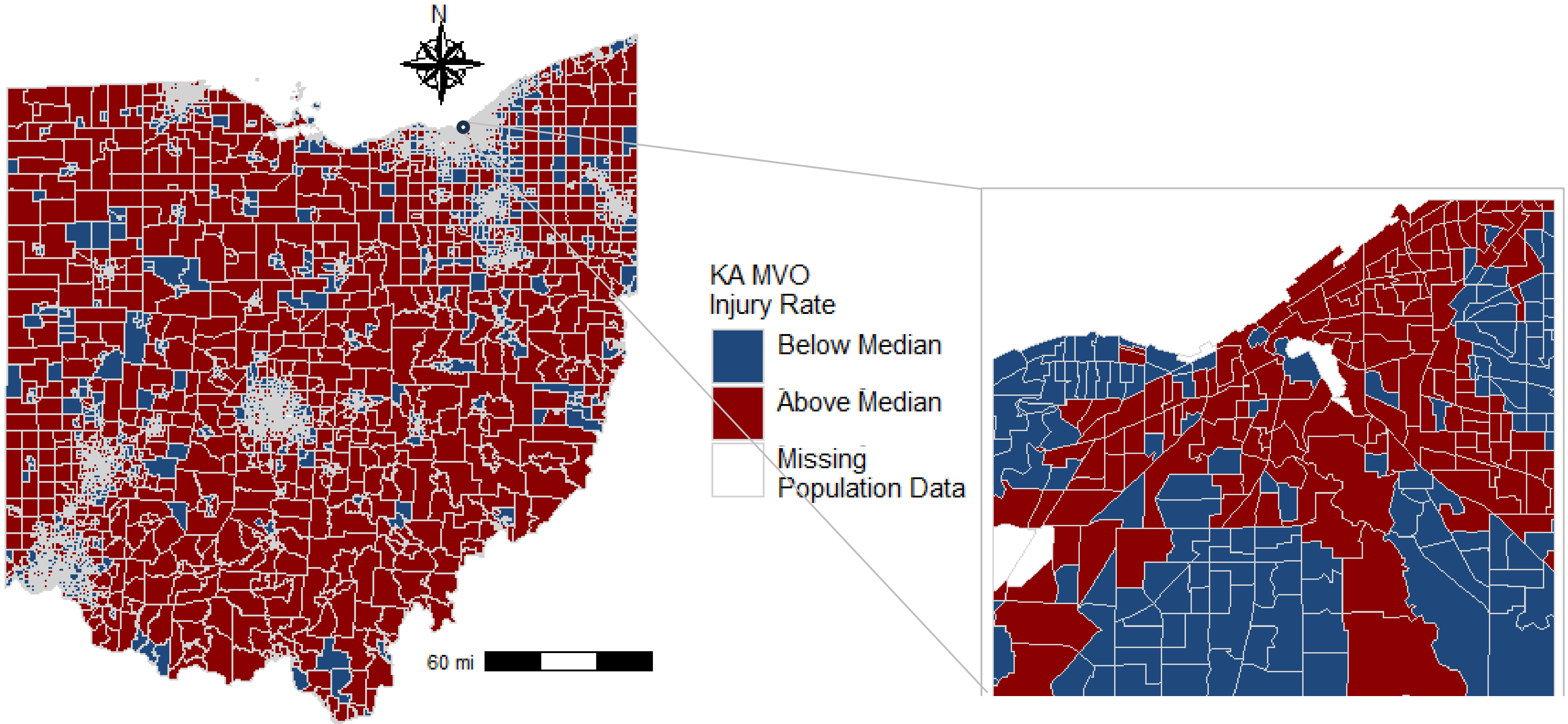


Figure B.1. KA MVO Injuries per 1,000 Population across Census Tracts in Ohio

Figure B.1 depicts the spatial distribution of KA injury rates of MVOs, using the median rate of 2.2 as the threshold. Approximately 50.0% of census tracts (1,578 tracts) have rates below the median, while 50.0% (1,577 tracts) are above the median. While the number of tracts above and below the median is nearly equal, the visual dominance of red tracts highlights a spatial concentration of higher KA injury rates in larger geographic areas (generally, non-urban tracts).

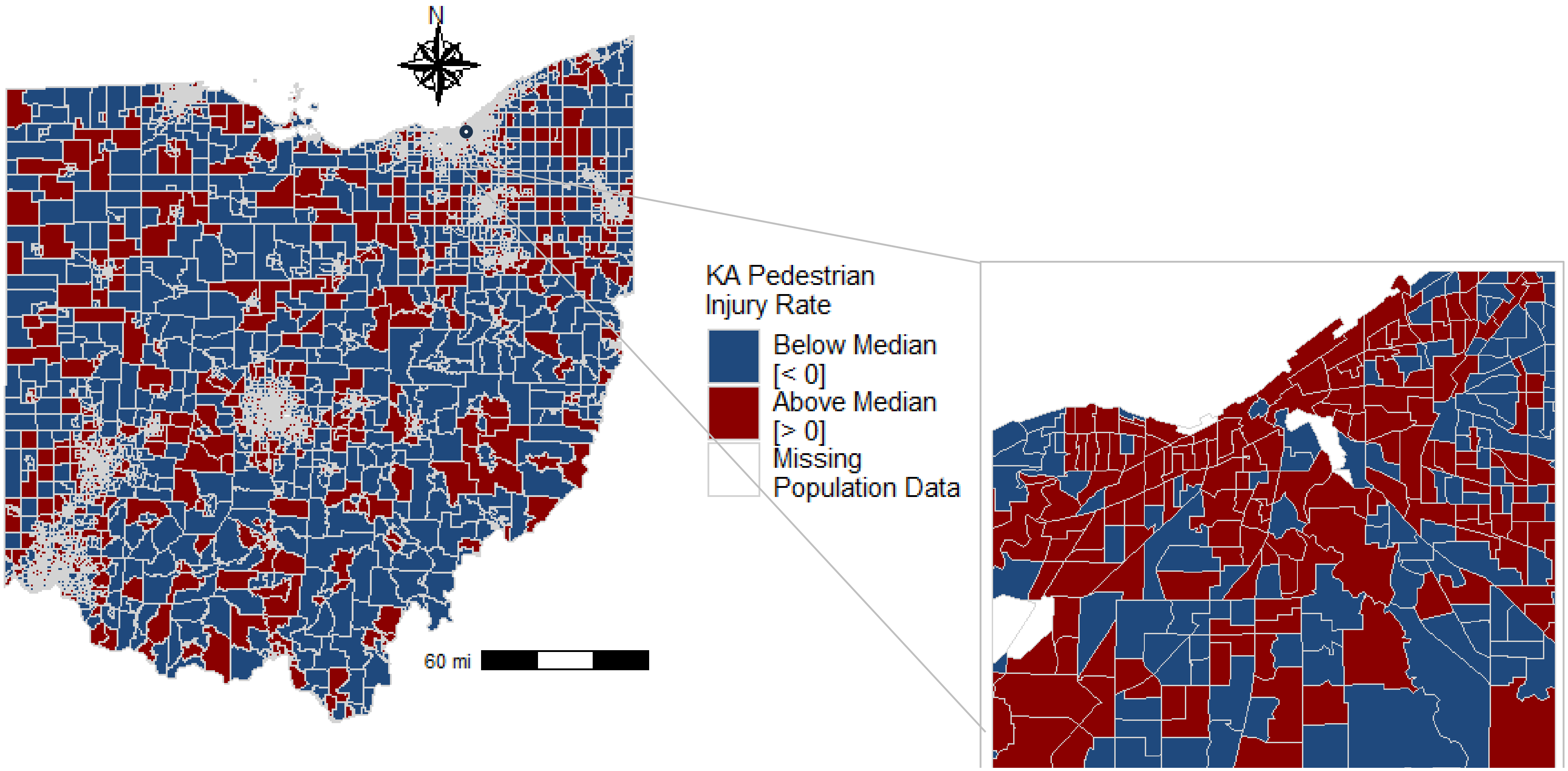


Figure B.2. KA Pedestrian Injuries per 1,000 Population across Census Tracts in Ohio

Figure B.2 presents the spatial distribution of the rates of KA injuries sustained by pedestrians, with the median rate of 0 as the threshold. Most tracts, 59.0% (1,861 tracts), fall below the median, while 41.0% (1,294 tracts) have rates exceeding the median. The map shows both red and blue tracts spread out across Ohio.

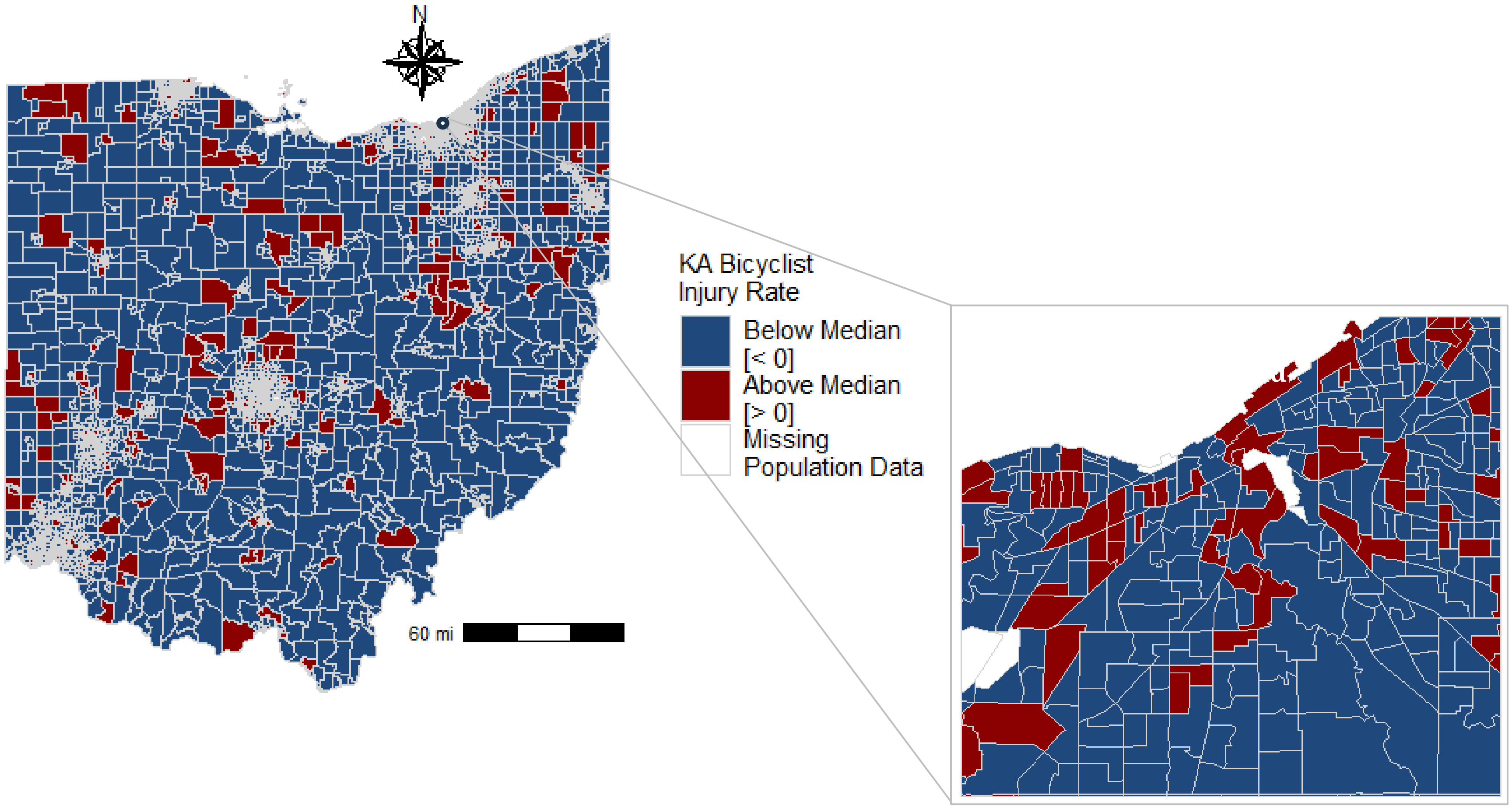


Figure B.3. KA Bicyclist Injuries per 1,000 Population across Census Tracts in Ohio

Figure B.3 shows the spatial distribution of the rates of KA injuries sustained by bicyclists using the median (0) as the threshold. About 83.9% of tracts (2,646 tracts) have rates below the median, while 16.1% (509 tracts) are above the median. The map shows a sparse distribution of bicyclist KA injury rates, with values above the median concentrated in a small number of tracts, often clustered in specific areas or isolated as outliers.

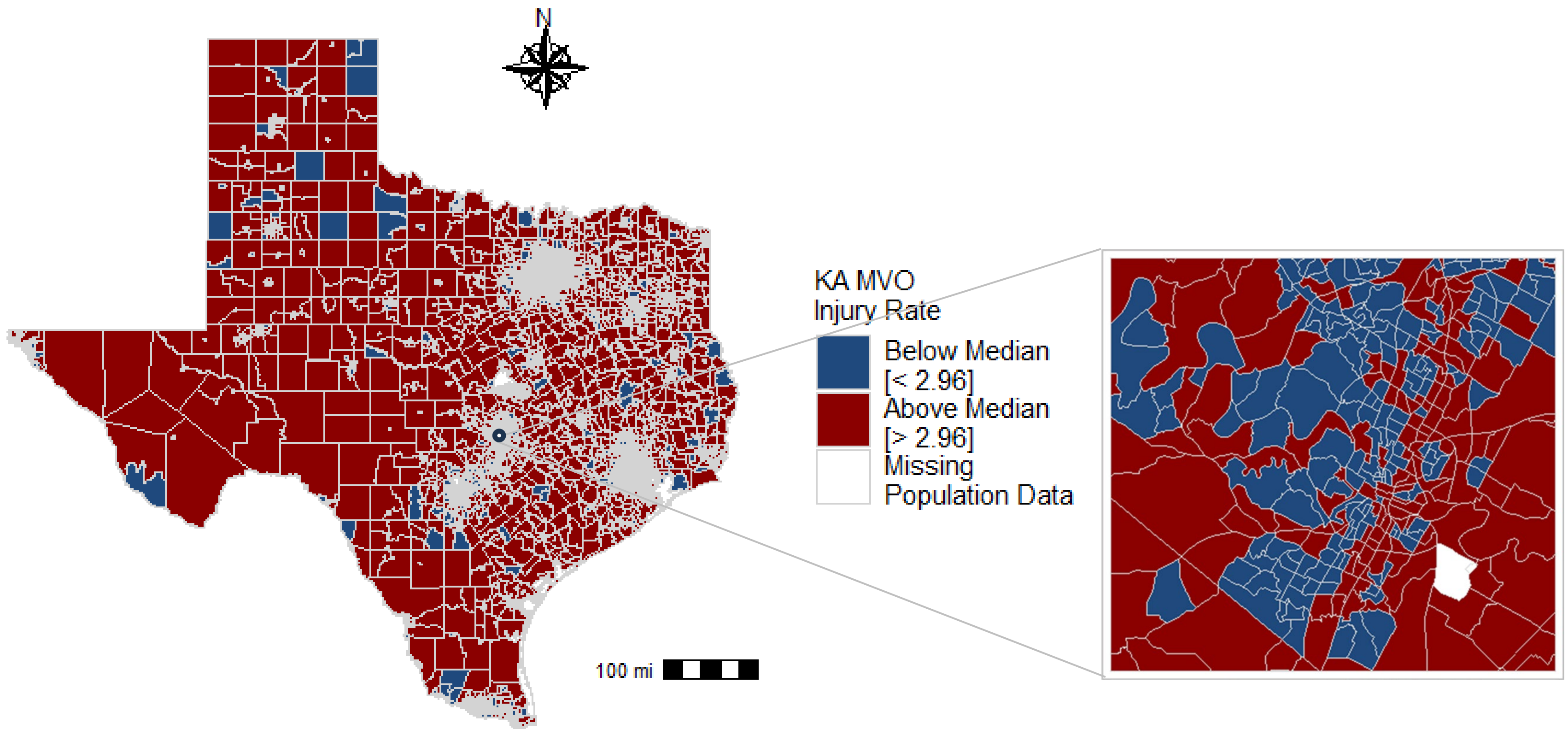


Figure B.4. KA MVO Injuries per 1,000 Population across Census Tracts in Texas

Figure B.4 shows the spatial distribution of KA injury rates of MVOs, with the median rate of 3.0 serving as the threshold. Half of the census tracts (3,415) have rates below the median, while the other half (3,415 tracts) have rates above it. Despite the equal number of tracts in each category, red tracts visually dominate the map due to the smaller geographic size of many blue tracts. This visual pattern highlights a spatial concentration of higher KA injury rates in larger tracts, generally non-urban areas.

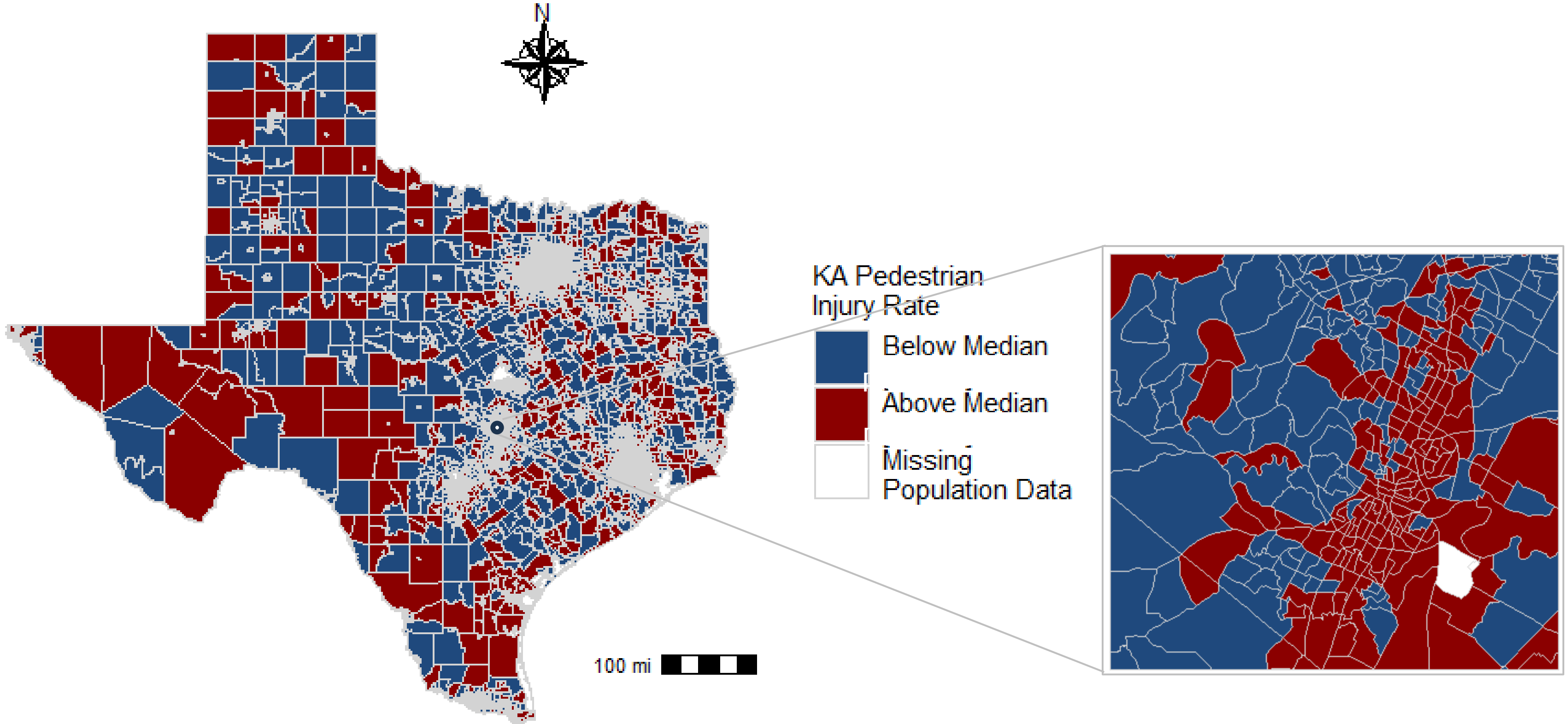


Figure B.5. KA Pedestrian Injuries per 1,000 Population across Census Tracts in Texas

Figure B.5 illustrates the spatial distribution of KA injury rates of pedestrians in Texas. The tracts are evenly divided, with 50.0% having rates below the median and the remaining 50.0% (3,415 tracts) exceeding the median. The map highlights a balanced distribution of tracts based on the median threshold of 0.3.

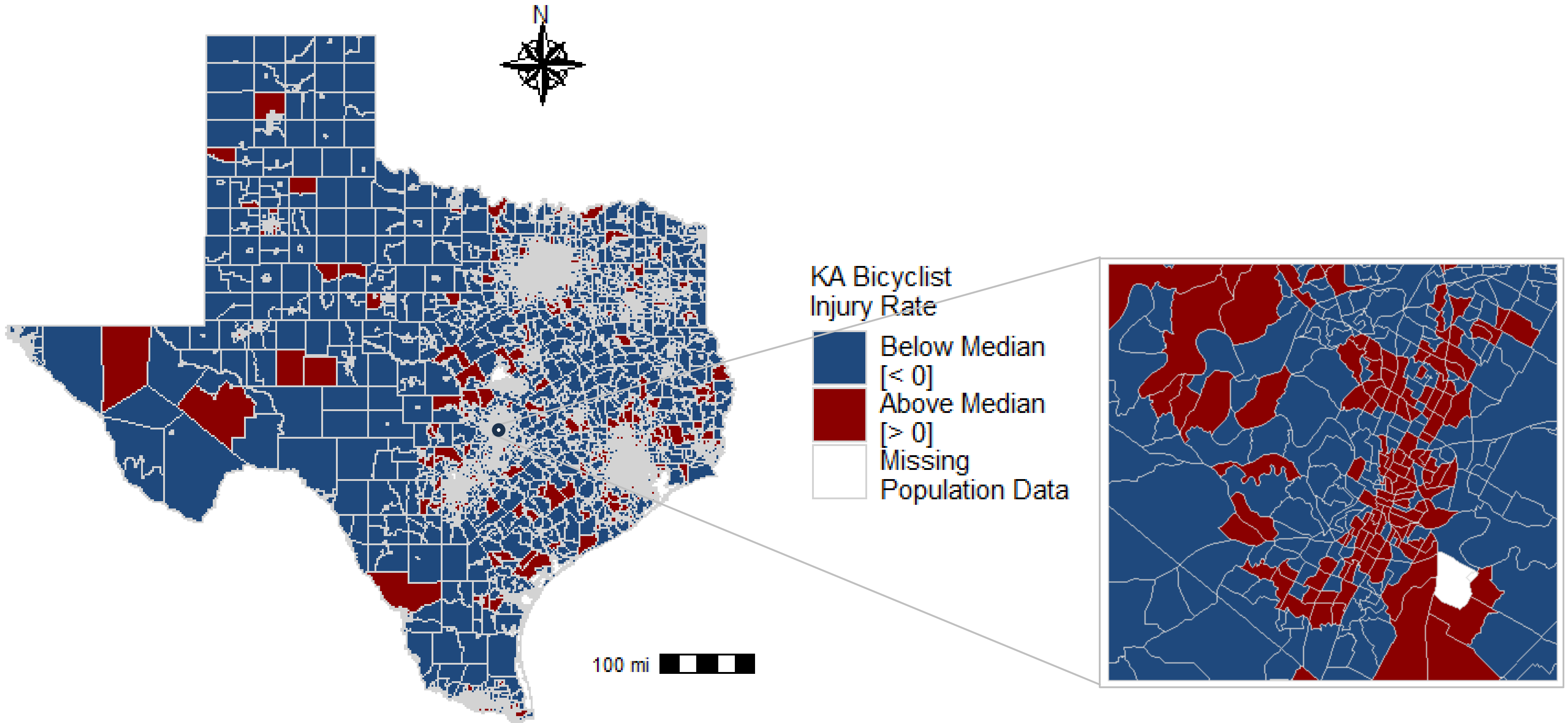


Figure B.6. KA Bicyclist Injuries per 1,000 Population across Census Tracts in Texas

Figure B.6 illustrates the spatial distribution of KA injury rates of bicyclists, with a median rate of 0 serving as the threshold. Approximately 74.3% of tracts (5,072 tracts) have rates below the median, while 25.7% (1,758 tracts) exceed it. The map shows that tracts with rates above the median are primarily clustered in smaller geographic areas, predominantly urban areas near major cities such as Dallas, Austin, Houston, and San Antonio. This clustering suggests that higher bicyclist injury rates are associated with tracts of higher population densities and increased cycling activities typically found in urban settings.

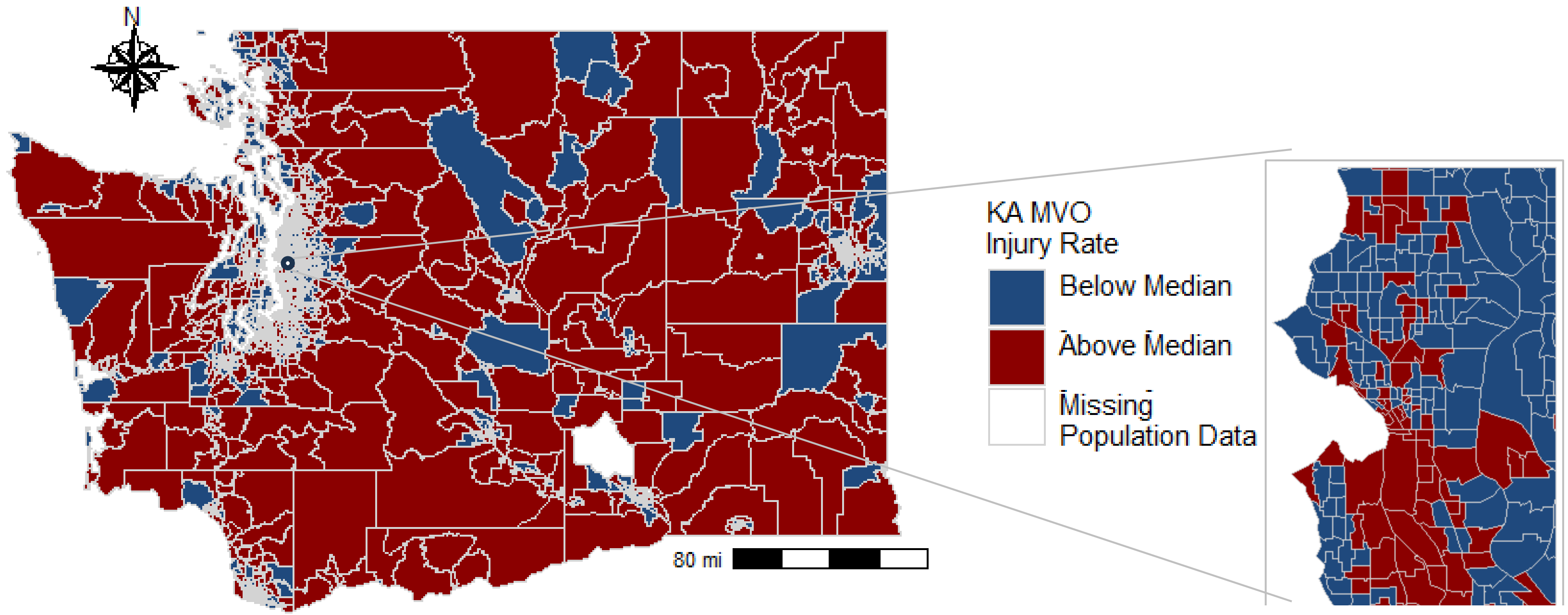


Figure B.7. KA MVO Injuries per 1,000 Population across Census Tracts in Washington

Figure B.7 illustrates the spatial distribution of the rates of KA injuries sustained by MVOs, using a median rate of 6.9 as the threshold. Approximately 50.1% of census tracts (886) have rates below the median, while 49.9% (884 tracts) exceed it. Similar to observations in Ohio and Texas, higher MVO injury rates (above the median) in Washington are primarily concentrated in smaller tracts, which are mainly urbanized areas.

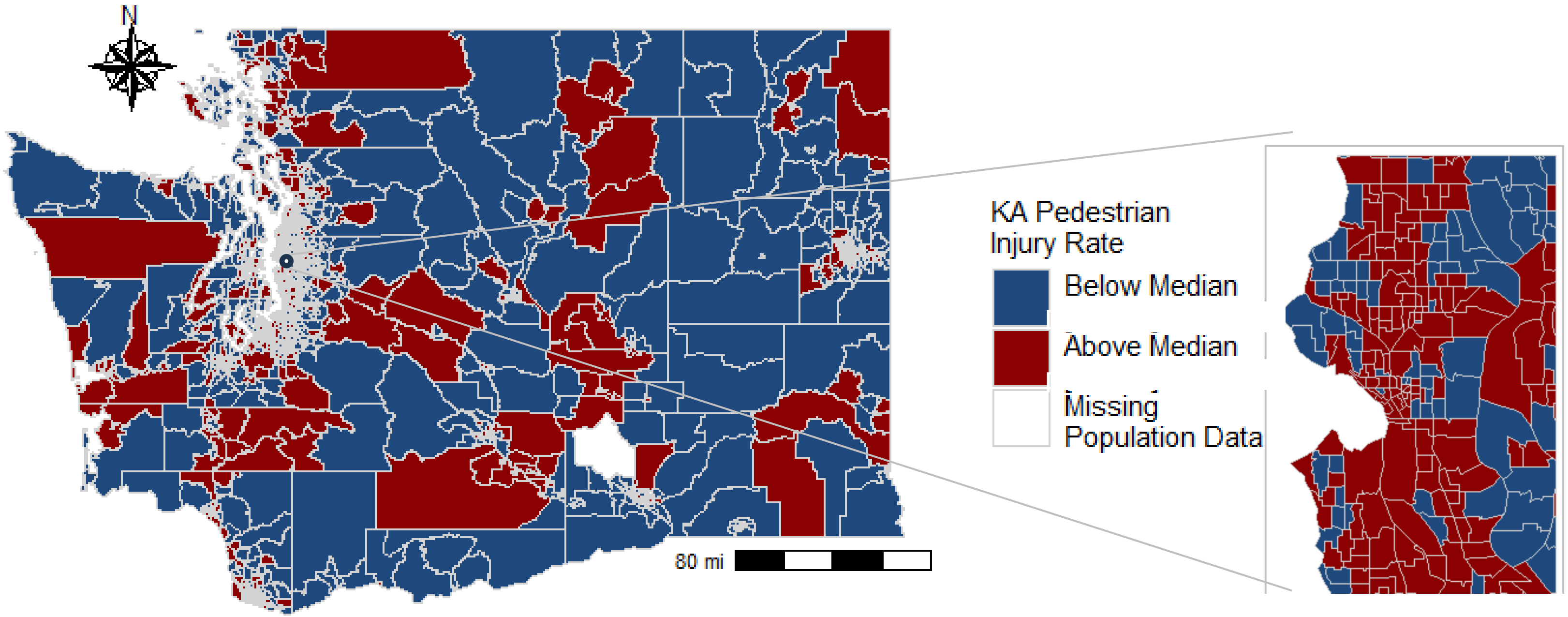


Figure B.8. KA Pedestrian Injuries per 1,000 Population across Census Tracts in Washington

Figure B.8 shows the spatial distribution of KA injury rates for pedestrians. The tracts are evenly split, with 50.0% (885 tracts) having rates below the median (0.2), and the other 50.0% surpassing the median. Tracts with higher KA pedestrian injury rates (above the median) are mostly smaller in size compared to those with rates below the median.

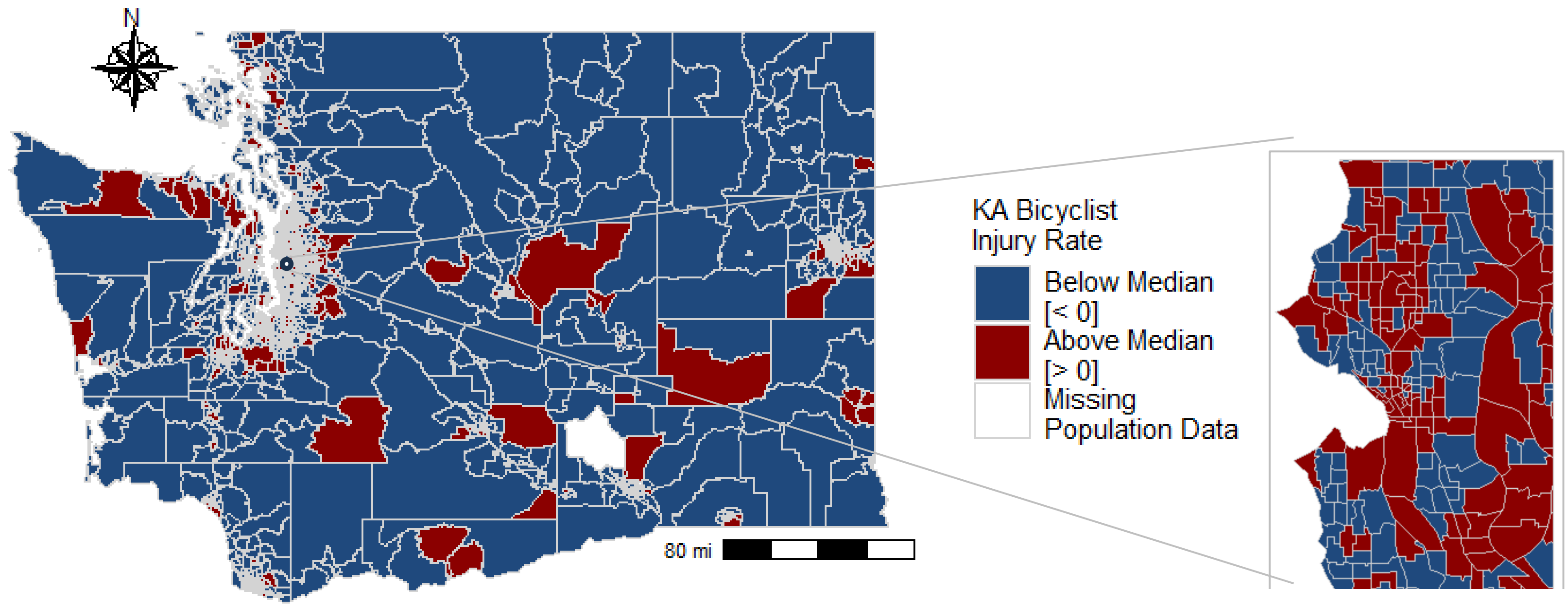


Figure B.9. KA Bicyclist Injuries per 1,000 Population across Census Tracts in Washington

Figure B.9 displays the spatial distribution of KA injury rates for bicyclists, using the median rate of 0 as the threshold. About 68.5% of tracts (1,212 tracts) have rates below the median, while 31.5% (558 tracts) exceed it. The map highlights that KA bicyclist injuries are concentrated in different regions of Washington, with the exception of the northern part of the state. Moreover, similar to KA pedestrian injury rates, KA bicyclist injury rates are predominantly concentrated in smaller tracts.

Appendix B.2: Descriptive Statistics

Table B.1. Tract-level Data Summary–Ohio

Variable	Description	Mean	Median	Std. Dev.
Area/Population				
Tract_Area	Tract area in square miles	12.96	2.05	25.76
Area_Type	Area type Area type (city = 1, suburban = 2, town = 3, and rural = 4 ordered from a population density perspective)	2.42	2.00	1.20
Total_Population	Population	3733.78	3575.00	1547.36
Race/Ethnicity				
Pct_White	Percentage of White American, not Hispanic or Latino persons	74.24	84.80	25.68
Pct_Hispanic	Percentage of Hispanic or Latino persons	4.43	2.50	6.03
Pct_Black	Percentage of Black/African American, not Hispanic or Latino persons	15.09	3.80	23.52
Pct_Asian	Percentage of Asian, not Hispanic or Latino persons	2.09	0.50	3.88
Pct_AIAN	Percentage of American Indian or Alaska Native, not Hispanic or Latino persons	0.08	0.00	0.25
Pct_NHPI	Percentage of Native Hawaiian or Other Pacific Islander, not Hispanic or Latino persons	0.03	0.00	0.21
Pct_MultiRace	Percentage of two or more races, not Hispanic or Latino persons	3.70	2.90	3.20
Pct_OtherRace	Percentage of some other race, not Hispanic or Latino persons	0.34	0.00	0.94
Other sociodemographics and economics				
Pct_Age_17_Under	Percentage of persons aged 17 years and younger	21.64	21.70	6.66
Pct_Age_65_Over	Percentage of persons aged 65 years and older	17.68	17.50	6.84
Pct_Below_Poverty	Percentage of persons below 150% poverty estimate	23.86	19.70	16.67
Unemployment_Rate	Unemployment rate	5.85	4.20	5.64
Pct_Cost_Burdened	Percentage of housing cost-burdened occupied housing units with annual income less than $75,000 (30%+ of income spent on housing costs)	24.72	22.80	11.41
Pct_No_HS_Diploma	Percentage of persons with no high school diploma (age 25+)	9.49	7.70	7.50
Pct_Uninsured	Percentage uninsured in the total civilian noninstitutionalized population	6.64	5.40	5.54
Pct_Disability	Percentage of civilian noninstitutionalized population with a disability	15.01	14.20	6.45
Pct_Single_Parent	Percentage of single-parent households with children under 18	7.07	5.20	6.68
Pct_Limited_English	Percentage of persons (age 5+) who speak English less than well	1.06	0.30	2.04
Pct_Mobile_Homes	Percentage of mobile homes	3.47	0.00	7.12
Pct_Crowded_Housing	Percentage of occupied housing units with more people than rooms estimate	1.45	0.70	2.17
Pct_No_Vehicle	Percentage of households with no vehicle available	8.41	5.40	9.38
Retail_Jobs	Retail jobs within a 5-tier employment classification scheme	178.94	66.91	346.57
Office_Jobs	Office jobs within a 5-tier employment classification scheme	213.34	48.97	897.14
Industrial_Jobs	Industrial jobs within a 5-tier employment classification scheme	437.23	138.15	884.18

Variable	Description	Mean	Median	Std. Dev.
Service_Jobs	Service jobs within a 5-tier employment classification scheme	646.08	311.09	1433.06
Entertainmemt_Jobs	Entertainment jobs within a 5-tier employment classification scheme	176.32	77.58	345.48
Roadway-related				
Bicycle_Lane_Density	Density of bicycle lanes (miles of bicycle lanes per square mile)	0.23	0.00	0.65
Crosswalk_Density	Density of crosswalk locations (number of crosswalks per square mile)	0.44	0.00	2.65
Shoulder_Density	Density of shoulders on all state-maintained roads (miles of shoulders per square mile)	0.67	0.49	0.86
Shouder_PedBike_Density	Density of shoulders on all state-maintained roads except interstates and other freeways and expressways (miles of shoulders per square mile)	0.34	0.16	0.45
Avg_Through_Lanes	Average number of through-road lanes	2.06	2.04	0.22
Avg_Through_Lanes_PedBike	Average number of through-road lanes excluding interstates and other freeways and expressways	2.11	2.07	0.23
Exposure/Proxy				
Road_Density_Speed25_Less	Density of all roads with ≤25 mph as speed limit (miles per square mile)	9.39	8.29	7.92
Road_Density_Speed25_Less_PedBike	Density of roads (except interstates and other freeways and expressways) with ≤25 mph as speed limit (miles per square mile)	8.72	7.51	7.46
Road_Density_Speed30_40	Density of roads with 30 mph to 40 mph as speed limit (miles per square mile)	1.02	0.36	1.61
Road_Density_Speed30_40_PedBike	Density of roads (excluding interstates and other freeways and expressways) with 30 mph to 40 mph as speed limits (miles per square mile)	1.02	0.36	1.61
Road_Density_Speed45_55	Density of roads with 45 to 55 mph as speed limit (miles per square mile)	1.13	0.57	1.65
Road_Density_Speed45_55_PedBike	Density of roads (excluding interstates and other freeways and expressways) with 45 to 55 mph as speed limits (miles per square mile)	1.07	0.42	1.64
Road_Density_Speed60_More	Density of roads with ≥60 mph as speed limit (miles per square mile)	0.20	0.00	0.45
Mean_AADT_Overall	Mean of AADT for both the pre-and post-COVID periods	16909.00	14897.19	5777.76
Mean_AADT_PedBike_Overall	Mean of AADT (excluding interstates and other freeways and expressways) for both the pre-and post-COVID periods	13607.26	13625.98	2477.09
Intermodal_Facility_Density	Density of intermodal facilities per square mile	0.07	0.00	0.58
School_Density	Density of public schools (including postsecondary schools) per square mile	0.29	0.00	0.87
Highway_Lighted_Density	Density of lighted highways	9.17	0.00	26.53
Serious and fatal injury (KA) count				
MVO_Count_PreCOVID	Count of MVOs for the pre-COVID period	6.39	4.00	15.94
MVO_Count_PostCOVID	Count of MVOs for the post-COVID period	5.89	3.00	7.80
Pedestrian_Count_PreCOVID	Count of pedestrians for the pre-COVID period	0.38	0.00	0.85
Pedestrian_Count_PostCOVID	Count of pedestrians for the post-COVID period	0.32	0.00	0.71
Bicyclist_Count_PreCOVID	Count of bicyclists for the pre-COVID period	0.09	0.00	0.33
Bicyclist_Count_PostCOVID	Count of bicyclists for the post-COVID period	0.11	0.00	0.37
Bicyclist_Count_Overall	Count of bicyclists for both pre-and post-COVID periods	0.20	0.00	0.52

Table B.2. Tract-level Data Summary–Texas

Variable	Description	Mean	Median	Std. Dev.
Area/Population				
Tract_Area	Tract area in square miles	38.18	1.55	184.38
Area_Type	Area type Area type (city = 1, suburban = 2, town = 3, and rural = 4 ordered from a population density perspective)	2.22	2	1.28
Total_Population	Population	4272.51	3977.00	2062.18
Race/Ethnicity				
Pct_White	Percentage of White American, not Hispanic or Latino persons	40.98	41.00	27.07
Pct_Hispanic	Percentage of Hispanic or Latino persons	39.70	31.40	28.20
Pct_Black	Percentage of Black/African American, not Hispanic or Latino persons	11.65	5.90	15.22
Pct_Asian	Percentage of Asian, not Hispanic or Latino persons	4.64	1.30	8.42
Pct_AIAN	Percentage of American Indian or Alaska Native, not Hispanic or Latino persons	0.17	0.00	0.52
Pct_NHPI	Percentage of Native Hawaiian or Other Pacific Islander, not Hispanic or Latino persons	0.08	0.00	0.46
Pct_MultiRace	Percentage of two or more races, not Hispanic or Latino persons	2.50	1.90	2.69
Pct_OtherRace	Percentage of some other race, not Hispanic or Latino persons	0.28	0.00	0.95
Other sociodemographics and economics				
Pct_Age_17_Under	Percentage of persons aged 17 years and younger	24.37	24.70	7.68
Pct_Age_65_Over	Percentage of persons aged 65 years and older	13.85	12.90	7.75
Pct_Below_Poverty	Percentage of persons below 150% poverty estimate	24.60	21.80	16.16
Unemployment_Rate	Unemployment rate	5.36	4.40	4.22
Pct_Cost_Burdened	Percentage of housing cost-burdened occupied housing units with annual income less than $75,000 (30%+ of income spent on housing costs)	27.34	25.60	12.86
Pct_No_HS_Diploma	Percentage of persons with no high school diploma (age 25+)	15.97	11.90	13.65
Pct_Uninsured	Percentage uninsured in the total civilian noninstitutionalized population	18.08	16.30	11.01
Pct_Disability	Percentage of civilian noninstitutionalized population with a disability	12.36	11.50	5.97
Pct_Single_Parent	Percentage of single-parent households with children under 18	7.50	6.20	6.14
Pct_Limited_English	Percentage of persons (age 5+) who speak English less than well	6.98	3.60	8.76
Pct_Mobile_Homes	Percentage of mobile homes	7.21	0.90	12.04
Pct_Crowded_Housing	Percentage of occupied housing units with more people than rooms estimate	5.12	3.40	5.78
Pct_No_Vehicle	Percentage of households with no vehicle available	5.61	3.60	6.37
Retail_Jobs	Retail jobs within a 5-tier employment classification scheme	193.65	78.97	346.80
Office_Jobs	Office jobs within a 5-tier employment classification scheme	207.39	46.51	937.51
Industrial_Jobs	Industrial jobs within a 5-tier employment classification scheme	428.11	131.69	1115.00
Service_Jobs	Service jobs within a 5-tier employment classification scheme	686.94	231.15	1868.25
Entertainmemt_Jobs	Entertainment jobs within a 5-tier employment classification scheme	190.71	82.08	377.48

Variable	Description	Mean	Median	Std. Dev.
Roadway-related				
Shoulder_Density	Density of shoulders on all state-maintained roads (miles of shoulders per square mile)	1.28	0.55	1.89
Shoulder_PedBike_Density	Density of shoulders on all state-maintained roads except interstates and other freeways and expressways (miles of shoulders per square mile)	0.57	0.26	0.86
Avg_Through_Lanes	Average number of through-road lanes	2.37	2.26	0.37
Avg_Through_Lanes_PedBike	Average number of through-road excluding interstates and other freeways and expressways	2.29	2.22	0.30
Exposure/Proxy				
Road_Density_Speed25_Less	Density of all roads with ≤25 mph as speed limit (miles per square mile)	10.05	9.79	6.91
Road_Density_Speed25_Less_PedBike	Density of roads (excluding limited access facilities) with ≤25 mph as speed limit (miles per square mile)	9.95	9.64	6.87
Road_Density_Speed30_40	Density of roads with 30 mph to 40 mph as speed limit (miles per square mile)	0.27	0.00	0.74
Road_Density_Speed30_40_PedBike	Density of roads (excluding limited access facilities) with 30 mph to 40 mph as speed limits (miles per square mile)	0.27	0.00	0.74
Road_Density_Speed45_55	Density of roads with 45 to 55 mph as speed limit (miles per square mile)	0.87	0.39	1.28
Road_Density_Speed45_55_PedBike	Density of roads (excluding interstates and other freeways and expressways) with 45 to 55 mph as speed limits (miles per square mile)	0.78	0.36	1.08
Road_Density_Speed60_More	Density of roads with ≥60 mph as speed limit (miles per square mile)	0.80	0.16	1.60
Mean_AADT_Overall	Mean of AADT for both pre-and post-COVID periods	9697.01	4242.78	14102.53
Mean_AADT_PedBike_Overall	Mean of AADT (excluding interstates and other freeways and expressways) for both pre-and post-COVID periods	3902.19	2828.03	3583.97
School_Density	Density of public schools (including postsecondary schools) per square mile	0.95	0.31	1.60
Serious and fatal injury (KA) count				
MVO_Count_PreCOVID	Count of MVOs for the pre-COVID period	8.22	5.00	12.50
MVO_Count_PostCOVID	Count of MVOs for the post-COVID period	10.90	6.00	17.12
Pedestrian_Count_PreCOVID	Count of pedestrians for the pre-COVID period	0.85	0.00	1.50
Pedestrian_Count_PostCOVID	Count of pedestrians for the post-COVID period	1.06	0.00	2.03
Bicyclist_Count_PreCOVID	Count of bicyclists for the pre-COVID period	0.15	0.00	0.44
Bicyclist_Count_PostCOVID	Count of bicyclists for the post-COVID period	0.20	0.00	0.79

Table B.3. Tract-level Data Summary–Washington

Variable	Description	Mean	Median	Std. Dev.
Area/Population				
Tract_Area	Tract area in square miles	37.32	1.57	141.81
Area_Type	Area type Area type (city = 1, suburban = 2, town = 3, and rural = 4 ordered from a population density perspective)	2.28	2.00	1.23
Total_Population	Population	4345.06	4263.00	1489.09
Race/Ethnicity				
Pct_White	Percentage of White American, not Hispanic or Latino persons	66.47	71.00	19.12
Pct_Hispanic	Percentage of Hispanic or Latino persons	13.22	8.90	14.61
Pct_Black	Percentage of Black/African American, not Hispanic or Latino persons	3.59	1.40	5.61
Pct_Asian	Percentage of Asian, not Hispanic or Latino persons	8.61	4.50	10.78
Pct_AIAN	Percentage of American Indian or Alaska Native, not Hispanic or Latino persons	1.08	0.20	4.40
Pct_NHPI	Percentage of Native Hawaiian or Other Pacific Islander, not Hispanic or Latino persons	0.64	0.00	1.61
Pct_MultiRace	Percentage of two or more races, not Hispanic or Latino persons	5.93	5.40	3.42
Pct_OtherRace	Percentage of some other race, not Hispanic or Latino persons	0.45	0.00	0.98
Other sociodemographics and economics				
Pct_Age_17_Under	Percentage of persons aged 17 and younger	20.97	21.20	7.04
Pct_Age_65_Over	Percentage of persons aged 65 and older	16.73	15.70	8.09
Pct_Below_Poverty	Percentage of persons below 150% poverty estimate	16.96	14.30	11.36
Unemployment_Rate	Unemployment rate	5.11	4.40	3.32
Pct_Cost_Burdened	Percentage of housing cost-burdened occupied housing units with annual income less than $75,000 (30%+ of income spent on housing costs)	25.22	23.30	11.44
Pct_No_HS_Diploma	Percentage of persons with no high school diploma (age 25+)	8.37	6.30	8.22
Pct_Uninsured	Percentage uninsured in the total civilian noninstitutionalized population	6.50	5.30	4.89
Pct_Disability	Percentage of civilian noninstitutionalized population with a disability	13.46	12.70	5.83
Pct_Single_Parent	Percentage of single-parent households with children under 18	5.15	4.20	4.15
Pct_Limited_English	Percentage of persons (age 5+) who speak English less than well	3.50	1.70	4.98
Pct_Mobile_Homes	Percentage of mobile homes	6.30	1.90	9.23
Pct_Crowded_Housing	Percentage of occupied housing units with more people than rooms estimate	3.61	2.40	4.07
Pct_No_Vehicle	Percentage of households with no vehicle available	6.49	3.80	8.65
Retail_Jobs	Retail jobs within a 5-tier employment classification scheme	206.33	60.53	821.15
Office_Jobs	Office jobs within a 5-tier employment classification scheme	259.23	44.19	1338.16
Industrial_Jobs	Industrial jobs within a 5-tier employment classification scheme	457.71	130.89	1388.43
Service_Jobs	Service jobs within a 5-tier employment classification scheme	648.46	225.21	1484.68
Entertainmemt_Jobs	Entertainment jobs within a 5-tier employment classification scheme	185.51	74.65	371.81
Roadway-related				
Bicycle_Lane_Density	Density of bicycle lanes (miles of bicycle lanes per square mile)	0.14	0.00	0.45
Crosswalk_Density	Density of crosswalks (miles of crosswalks per square mile)	0.09	0.01	0.19

Variable	Description	Mean	Median	Std. Dev.
Unmarked_Crosswalk_Density	Density of unmarked crosswalks (miles of unmarked crosswalks per square mile)	0.04	0.00	0.10
Marked_Crosswalk_Density	Density of marked crosswalks (miles of marked crosswalks per square mile)	0.01	0.00	0.04
Sidewalk_Density	Density of sidewalks (miles of sidewalks per square mile)	0.32	0.00	0.74
Shoulder_Density	Density of shoulders (miles of shoulders per square mile)	2.83	1.02	4.64
Shoulder_PedBike_Density	Density of shoulders excluding those on interstates and other freeways and expressways (miles of shoulders per square mile)	0.62	0.00	1.40
Avg_Through_Lanes	Average number of through-road lanes	2.75	2.4	0.91
Avg_Through_Lanes_PedBike	Average number of through-road lanes, excluding interstates and other freeways and expressways	2.79	2.00	1.18
Exposure/Proxy				
Road_Density_Speed25_Less	Density of roads with ≤25 mph as speed limit (miles per square mile)	0.03	0.00	0.24
Road_Density_Speed25_Less_PedBike	Density of roads (excluding interstates and other freeways and expressways) with ≤25 mph as speed limit (miles per square mile)	0.43E-04	0.00	0.47-E02
Road_Density_Speed30_40	Density of roads with 30 mph to 40 mph as speed limit (miles per square mile)	0.34	0.00	0.81
Road_Density_Speed30_40_PedBike	Density of roads (excluding interstates and other freeways and expressways) with 30 mph to 40 mph as speed limits (miles per square mile)	0.09	0.00	0.32
Road_Density_Speed45_55	Density of roads with 45 to 55 mph as speed limit (miles per square mile)	0.23	0.00	0.60
Road_Density_Speed45_55_PedBike	Density of roads (excluding interstates and other freeways and expressways) with 45 to 55 mph as speed limits (miles per square mile)	0.10	0.00	0.43
Road_Density_Speed60_More	Density of roads with ≥60 mph as speed limit (miles per square mile)	0.40	0.00	0.99
Mean_AADT_PreCOVID	Mean of AADT for the pre-COVID period	31302.42	14418.75	36885.16
Mean_AADT_PostCOVID	Mean of AADT for the post-COVID period	30152.31	16531.82	33427.68
Mean_AADT_PreCOVID_PedBike	Mean of AADT (excluding interstates and other freeways and expressways) for the pre-COVID period	19770.33	18300.00	14338.69
Mean_AADT_PostCOVID_PedBike	Mean of AADT (excluding interstates and other freeways and expressways) for the post-COVID period	16426.98	9936.43	15536.27
Mean_AADT_Overall_PedBike	Mean of AADT (excluding interstates and other freeways and expressways) for both pre-and post-COVID periods	18098.65	13959.29	14363.85
Transit_Stop_Density	Density of transit stops per square mile	18.44	8.68	29.46
School_Density	Density of public schools (including postsecondary schools) per square mile	1.03	0.31	1.87
Serious and fatal injury (KA) count				
MVO_Count_PreCOVID	Count of MVOs for the pre-COVID period	26.76	10.00	105.68
MVO_Count_PostCOVID	Count of MVOs for the post-COVID period	28.76	14.00	50.43
Pedestrian_Count_PreCOVID	Count of pedestrians for the pre-COVID period	0.97	0.00	3.32
Pedestrian_Count_PostCOVID	Count of pedestrians for the post-COVID period	0.98	0.00	1.78
Pedestrian_Count_Overall	Count of pedestrians for both pre-and post-COVID periods	1.95	1.00	4.07
Bicyclist_Count_PreCOVID	Count of bicyclists for the pre-COVID period	0.23	0.00	0.60
Bicyclist_Count_PostCOVID	Count of bicyclists for the post-COVID period	0.28	0.00	0.90
Bicyclist_Count_Overall	Count of bicyclists for both pre-and post-COVID periods	0.51	0.00	1.15

Appendix B.3: Neighborhood Analysis Methodology

Figure B.10 provides a graphical summary of the methodological approach adopted in this project. The models were fitted using Bayesian inference through the Integrated Nested Laplace Approximation (INLA) algorithm proposed by Rue and colleagues (2009). The INLA approach has been widely used in many safety-related studies (Cui & Xie, 2021; Saha et al., 2018; Zhai et al., 2023) due to its ability to provide accurate approximations of posterior marginals for parameters of latent Gaussian models (Serhiyenko et al., 2016). A threshold of 65% or higher for excess zero KA counts was set to justify the use of zero-inflated NB models (Dong et al., 2014). If spatial autocorrelation was detected (using Moran's I test), the Besag model was applied. This model accounts for the value (KA injury counts) of a neighborhood (census tract) by considering the values of neighboring regions, thereby modeling regional differences through a spatial random effect that smooths spatial variability. Conversely, the Independent and Identically Distributed (IID) model was used when no evidence of spatial dependence was found. The IID model represents a simple random effect where each KA injury count is independent and follows the same distribution. Nevertheless, it captures unstructured variability or noise in the data.

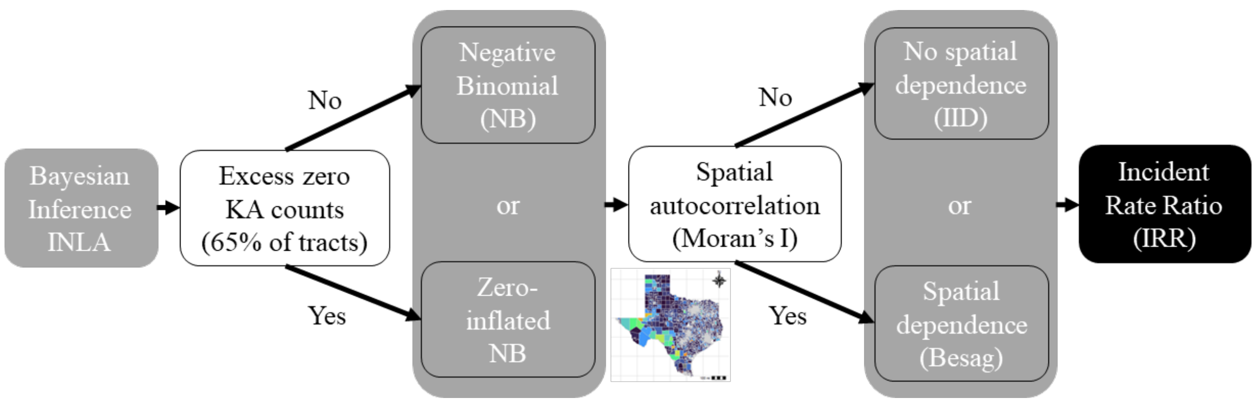


Figure B.10. Bayesian Spatial Data Analysis Approach using INLA Algorithm

Non-parametric tests were used to assess if significant differences exist in KA injury counts across census tracts between pre-COVID (2018–2019) and post-COVID (2021–2022) periods in order to determine whether separate models are required for each period. Results from these analyses indicated that separate model should be employed for MVO crashes in all three states, for pedestrian crashes in OH and TX, and for bicyclist crashes in OH and WA. In other cases, a combined model (pre- and post-COVID) was appropriate.

Appendix B.4: Standard Bayesian Model Results

***Note**. In following tables, 2.5% HDI and 97.5% HDI are the lower and the upper bounds, respectively, of the highest density interval (credible interval) of an estimate; Variables in bold are significant at a 95% HDI; IRR stands for the incident rate ratio of the mean estimate.*

B.4.1 Ohio

Table B.4. Bayesian Model Results for Pedestrians in Ohio

Variable	Pre-COVID			Post-COVID		
	2.5% HDI	97.5% HDI	IRR	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)						
Area_Type [Rural]	−0.379	1.035	1.39	−0.954	0.515	0.8
Area_Type [Suburban]	−0.354	0.548	1.1	−1.08	−0.066	**0.56**
Area_Type [Town]	−0.709	0.71	1	−2.078	−0.316	**0.3**
Race/Ethnicity						
Pct_Hispanic	0.004	0.059	**1.03**	−0.021	0.038	1.01
Pct_Black	0.003	0.019	**1.01**	−0.006	0.013	1
Pct_Asian	−0.033	0.041	1	**−0.143**	**−0.025**	**0.92**
Pct_AIAN	−0.274	0.861	1.34	−0.124	1.006	1.55
Pct_NHPI	−0.315	0.767	1.25	−0.741	0.482	0.88
Pct_MultiRace	−0.037	0.053	1.01	−0.038	0.07	1.02
Pct_OtherRace	−0.114	0.201	1.04	−0.093	0.183	1.05
Other sociodemographics and economics						
Pct_Age_17_Under	−0.052	−0.002	**0.97**	−0.075	−0.018	**0.95**
Pct_Age_65_Over	−0.011	0.045	1.02	−0.01	0.049	1.02
Unemployment_Rate	−0.038	0.024	0.99	−0.047	0.024	0.99
Pct_Uninsured	−0.004	0.053	1.02	0.034	0.106	**1.07**
Pct_Disability	−0.014	0.047	1.02	−0.027	0.038	1.01
Pct_Single_Parent	−0.021	0.034	1.01	−0.022	0.031	1
Pct_Mobile_Homes	−0.032	0.032	1	−0.045	0.019	0.99
Pct_Limited_English	−0.076	0.065	0.99	−0.09	0.081	1
Pct_No_Vehicle	0.007	0.041	**1.02**	−0.027	0.019	1
Retail_Jobs [log]	−0.098	0.115	1.01	−0.091	0.153	1.03
Office_Jobs [log]	−0.035	0.132	1.05	−0.104	0.083	0.99
Service_Jobs [log]	−0.128	0.14	1.01	−0.166	0.147	0.99
Roadway-related						
Crosswalk_Density	−0.034	0.062	1.01	−0.072	0.028	0.98
Shouder_PedBike_Density	−0.217	0.48	1.14	−0.406	0.381	0.99
Avg_Through_Lanes_PedBike	0.247	1.93	**2.97**	−0.549	1.457	1.57
Exposure/Proxy						
Road_Density_Speed25_Less_PedBike	−0.022	0.037	1.01	−0.009	0.064	1.03
Road_Density_Speed30_40_PedBike	−0.09	0.075	0.99	−0.236	0.019	0.9
Road_Density_Speed45_55_PedBike	−0.084	0.111	1.01	0.067	0.269	**1.18**
Mean_AADT_PedBike_Overall	−1.465	0.002	0.48	−0.965	0.895	0.97
Intermodal_Facility_Density	−0.146	0.347	1.11	−0.077	0.739	1.39
School_Density	−0.08	0.184	1.05	−0.136	0.212	1.04

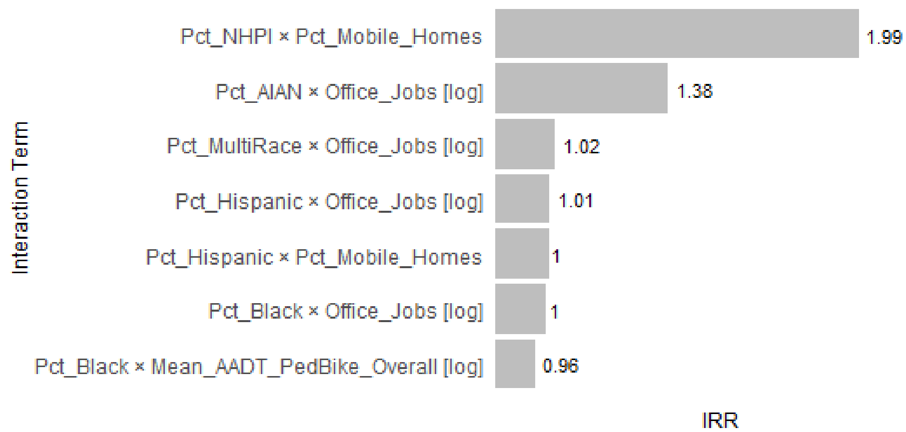


Figure B.11. Effects of Interacting Variables on KA Injury Rates of Pedestrians in Ohio

Table B.5. Bayesian Model Results for Bicyclists in Ohio

Variable	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)			
Area_Type [Rural]	−0.983	1.163	1.09
Area_Type [Suburban]	−0.996	0.500	0.78
Area_Type [Town]	−0.900	1.150	1.13
Race/Ethnicity			
Pct_Hispanic	−0.031	0.044	1.01
Pct_Black	−0.017	0.012	1.00
Pct_Asian	0.003	0.129	**1.07**
Pct_AIAN	−0.830	1.220	1.22
Pct_NHPI	−2.133	0.945	0.55
Pct_MultiRace	−0.012	0.103	1.05
Pct_OtherRace	−0.578	0.136	0.80
Other sociodemographics and economics			
Pct_Age_17_Under	−0.021	0.059	1.02
Pct_Age_65_Over	−0.025	0.059	1.02
Unemployment_Rate	−0.104	0.013	0.96
Pct_Uninsured	0.007	0.079	**1.04**
Pct_Disability	0.019	0.106	**1.06**
Pct_Single_Parent	−0.024	0.050	1.01
Pct_Mobile_Homes	−0.096	0.020	0.96
Pct_Limited_English	−0.138	0.091	0.98
Pct_No_Vehicle	−0.016	0.040	1.01
Retail_Jobs [log]	−0.163	0.209	1.02
Office_Jobs [log]	−0.215	0.052	0.92
Service_Jobs [log]	−0.056	0.409	1.19
Roadway-related			
Bicycle_Lane_Density	−0.369	0.293	0.96
Crosswalk_Density	−0.227	0.080	0.93
Shouder_PedBike_Density	−0.083	0.868	1.48
Avg_Through_Lanes_PedBike	0.132	2.782	**4.29**
Exposure/Proxy			
Road_Density_Speed25_Less_PedBike	−0.053	0.061	1.00
Road_Density_Speed30_40_PedBike	−0.277	0.109	0.92
Road_Density_Speed45_55_PedBike	−0.036	0.265	1.12
Mean_AADT_PedBike_Overall	−2.509	0.218	0.32
Intermodal_Facility_Density	−2.802	1.078	0.42
School_Density	−0.429	0.075	0.84

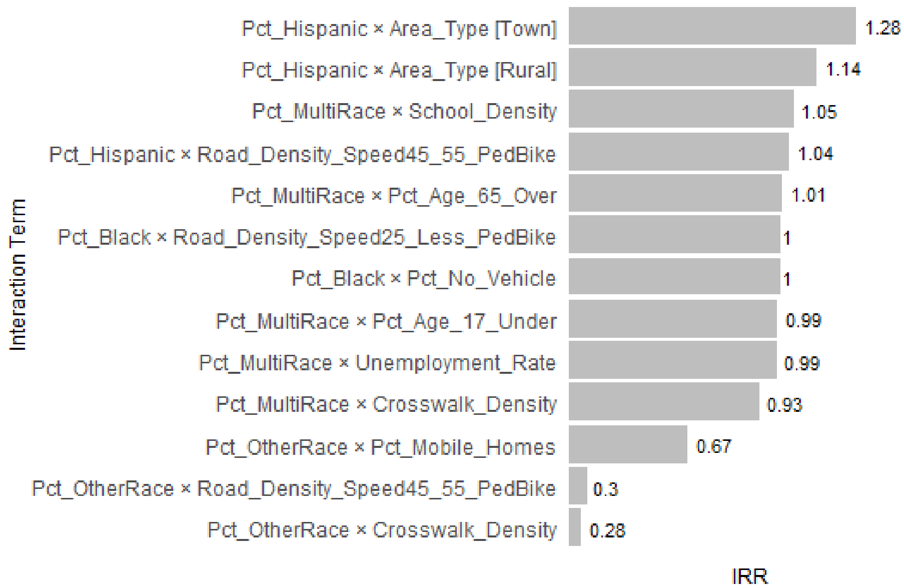


Figure B.12. Effects of Interacting Variables on KA Injury Rates of Bicyclists in Ohio.

Table B.6. Bayesian Model Results for MVOs in Ohio

Variable	Pre-COVID			Post-COVID		
	2.5% HDI	97.5% HDI	IRR	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)						
Area_Type [Rural]	0.365	0.772	**1.77**	0.764	1.194	**2.66**
Area_Type [Suburban]	−0.379	−0.068	**0.80**	−0.306	0.027	0.87
Area_Type [Town]	−1.150	−0.552	**0.43**	−0.608	0.014	0.74
Race/Ethnicity						
Pct_Hispanic	−0.010	0.008	1.00	−0.010	0.010	1.00
Pct_Black	0.002	0.009	**1.01**	0.006	0.013	**1.01**
Pct_Asian	−0.032	−0.007	**0.98**	−0.019	0.007	0.99
Pct_AIAN	−0.032	0.253	1.12	−0.087	0.217	1.07
Pct_NHPI	−0.149	0.189	1.02	−0.138	0.209	1.04
Pct_MultiRace	−0.014	0.010	1.00	−0.006	0.020	1.01
Pct_OtherRace	−0.001	0.075	1.04	−0.005	0.073	1.03
Other sociodemographics and economics						
Pct_Age_17_Under	−0.008	0.007	1.00	−0.009	0.006	1.00
Pct_Age_65_Over	−0.005	0.009	1.00	0.001	0.016	**1.01**
Unemployment_Rate	−0.007	0.010	1.00	−0.002	0.015	1.01
Pct_Uninsured	0.001	0.017	**1.01**	−0.001	0.016	1.01
Pct_Disability	−0.005	0.011	1.00	−0.007	0.011	1.00
Pct_Single_Parent	−0.017	0.000	0.99	−0.020	−0.003	**0.99**
Pct_Mobile_Homes	0.008	0.021	**1.01**	0.008	0.021	**1.01**
Pct_Limited_English	−0.032	0.017	0.99	−0.041	0.011	0.99
Pct_No_Vehicle	0.000	0.012	**1.01**	−0.006	0.007	1.00
Retail_Jobs [log]	0.023	0.076	**1.05**	0.001	0.056	**1.03**
Office_Jobs [log]	0.017	0.062	**1.04**	−0.015	0.031	1.01
Service_Jobs [log]	−0.026	0.045	1.01	−0.035	0.039	1.00
Roadway-related						
Avg_Through_Lanes	−0.098	0.371	1.15	−0.437	0.045	0.82
Exposure/Proxy						
Road_Density_Speed30_40	−0.044	0.027	0.99	−0.021	0.056	1.02
Road_Density_Speed45_55	0.009	0.067	**1.04**	0.041	0.101	**1.07**
Road_Density_Speed60_More	0.125	0.383	**1.29**	0.033	0.307	**1.19**
Mean_AADT_Overall [log]	0.176	0.523	**1.42**	0.212	0.576	**1.48**
Highway_Lighted_Density	0.001	0.004	**1.00**	0.002	0.006	**1.00**

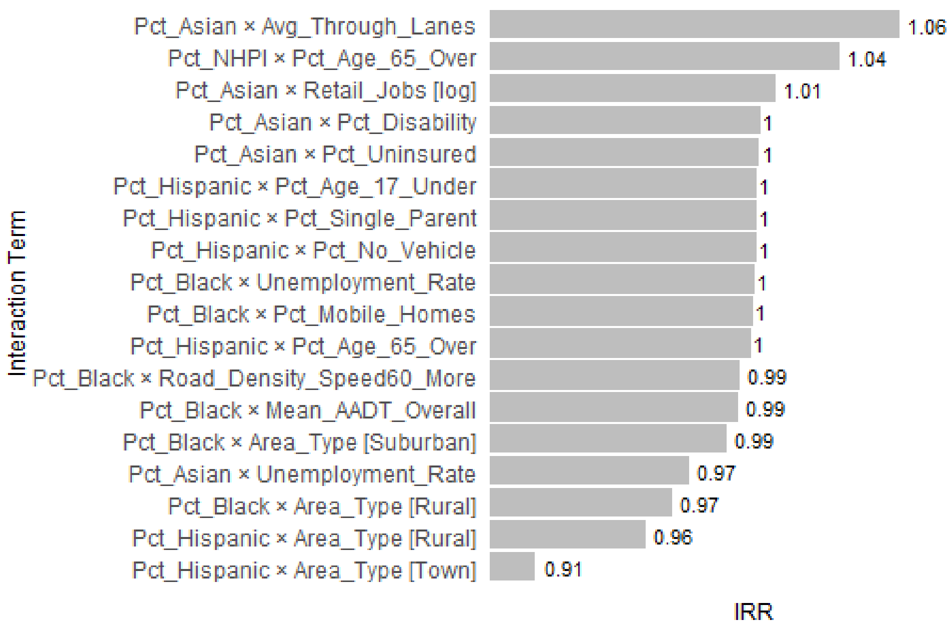


Figure B.13. Effects of Interacting Variables on KA Injury Rates of MVOs in Ohio (Note: Pct = Percentage)

B.4.2 Texas

Table B.7. Bayesian Model Results for Pedestrians in Texas

Variable	Pre-COVID			Post-COVID		
	2.5% HDI	97.5% HDI	IRR	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)						
Area_Type [Rural]	−0.225	0.072	0.93	−0.125	0.156	1.02
Area_Type [Suburban]	−0.306	−0.040	**0.84**	−0.249	0.005	0.89
Area_Type [Town]	−0.750	−0.171	**0.63**	−0.697	−0.147	**0.66**
Race/Ethnicity						
Pct_Hispanic	0.005	0.011	**1.01**	0.006	0.012	**1.01**
Pct_Black	0.007	0.014	**1.01**	0.004	0.011	**1.01**
Pct_Asian	−0.006	0.007	1.00	−0.009	0.003	1.00
Pct_AIAN	−0.089	0.046	0.98	−0.007	0.111	1.05
Pct_NHPI	−0.067	0.087	1.01	−0.097	0.057	0.98
Pct_MultiRace	−0.007	0.024	1.01	−0.008	0.020	1.01
Pct_OtherRace	−0.073	0.007	0.97	−0.056	0.017	0.98
Other sociodemographics and economics						
Pct_Age_17_Under	−0.020	−0.008	**0.99**	−0.020	−0.008	**0.99**
Pct_Age_65_Over	−0.002	0.012	1.01	0.005	0.018	**1.01**
Unemployment_Rate	−0.005	0.012	1.00	0.002	0.018	**1.01**
Retail_Jobs [log]	0.037	0.095	**1.07**	0.079	0.134	**1.11**
Office_Jobs [log]	−0.019	0.033	1.01	−0.034	0.015	0.99
Industrial_Jobs [log]	0.020	0.072	**1.05**	0.037	0.087	**1.06**
Service_Jobs [log]	0.024	0.090	**1.06**	0.008	0.070	**1.04**
Pct_Disability	0.009	0.026	**1.02**	0.001	0.017	**1.01**
Pct_No_Vehicle	0.011	0.024	**1.02**	0.002	0.014	**1.01**
Pct_Mobile_Homes	0.009	0.017	**1.01**	0.009	0.017	**1.01**
Pct_Single_Parent	−0.011	0.004	1.00	0.001	0.014	**1.01**
Exposure/Proxy						
Road_Density_Speed30_40_PedBike	0.039	0.136	**1.09**	0.100	0.191	**1.16**
Road_Density_Speed45_55_PedBike	0.011	0.083	**1.05**	0.035	0.104	**1.07**
School_Density	−0.016	0.023	1.00	−0.009	0.028	1.01
Mean_AADT_PedBike_Overall [log]	0.267	0.396	**1.39**	0.303	0.425	**1.44**

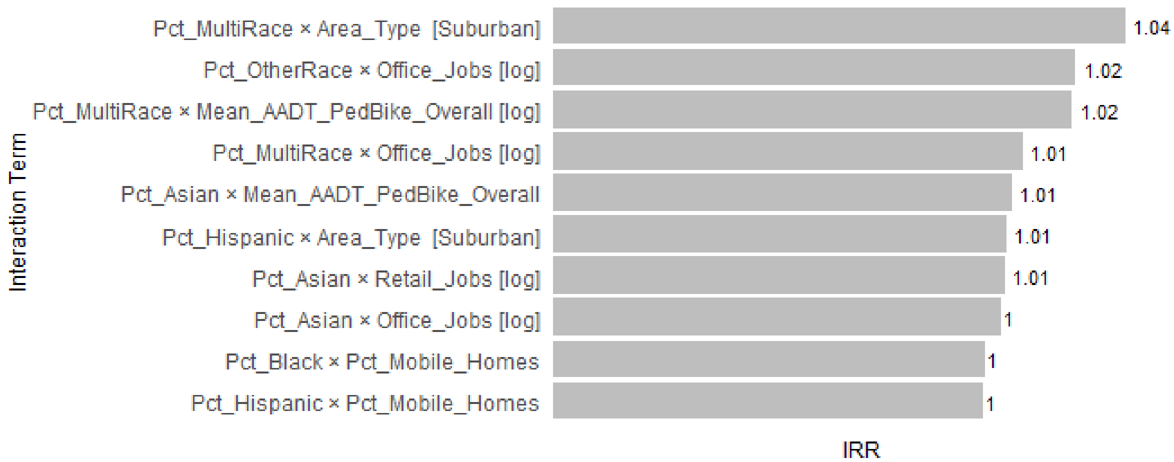


Figure B.14. Effects of Interacting Variables on KA Injury Rates of Pedestrians in Texas

Table B.8. Bayesian Model Results for Bicyclists in Texas

Variable	Pre-COVID			Post-COVID		
	2.5% HDI	97.5% HDI	IRR	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)						
Area_Type [Rural]	−0.530	0.669	1.07	−0.246	0.830	1.34
Area_Type [Suburban]	−1.213	−0.129	**0.51**	−0.523	0.484	0.98
Area_Type [Town]	−1.242	0.907	0.85	−1.214	0.838	0.83
Race/Ethnicity						
Pct_Hispanic	0.006	0.028	**1.02**	−0.015	0.005	1.00
Pct_Black	0.016	0.041	**1.03**	−0.012	0.014	1.00
Pct_Asian	−0.033	0.021	0.99	−0.064	0.005	0.97
Pct_AIAN	−0.890	0.218	0.72	−0.578	0.149	0.81
Pct_NHPI	−0.824	0.197	0.73	−0.628	0.293	0.85
Pct_MultiRace	−0.101	0.079	0.99	−0.296	−0.088	**0.83**
Pct_OtherRace	−0.335	0.143	0.91	−0.942	−0.114	**0.59**
Other sociodemographics and economics						
Pct_Age_17_Under	−0.058	−0.005	**0.97**	−0.098	−0.043	**0.93**
Pct_Age_65_Over	−0.032	0.031	1.00	−0.115	−0.047	**0.92**
Pct_Below_Poverty	−0.036	0.048	1.01	0.014	0.084	**1.05**
Retail_Jobs [log]	−0.244	0.065	0.92	−0.020	0.289	1.14
Office_Jobs [log]	−0.222	0.022	0.91	−0.090	0.189	1.05
Industrial_Jobs [log]	0.047	0.276	**1.18**	0.117	0.373	**1.28**
Service_Jobs [log]	0.076	0.391	**1.26**	−0.217	0.132	0.96
Pct_Disability	−0.058	0.020	0.98	0.014	0.077	**1.05**
Pct_No_Vehicle	−0.037	0.017	0.99	−0.010	0.049	1.02
Pct_Mobile_Homes	−0.037	0.011	0.99	0.001	0.034	**1.02**
Pct_Single_Parent	−0.060	0.010	0.98	−0.048	0.021	0.99
Exposure/Proxy						
Road_Density_Speed30_40_PedBike	−0.092	0.266	1.09	−0.074	0.316	1.13
Road_Density_Speed45_55_PedBike	−0.244	0.123	0.94	−0.127	0.206	1.04
School_Density	−0.116	0.095	0.99	−0.074	0.076	1.00
Mean_AADT_PedBike_Overall [log]	−0.132	0.535	1.22	−0.512	0.054	0.80

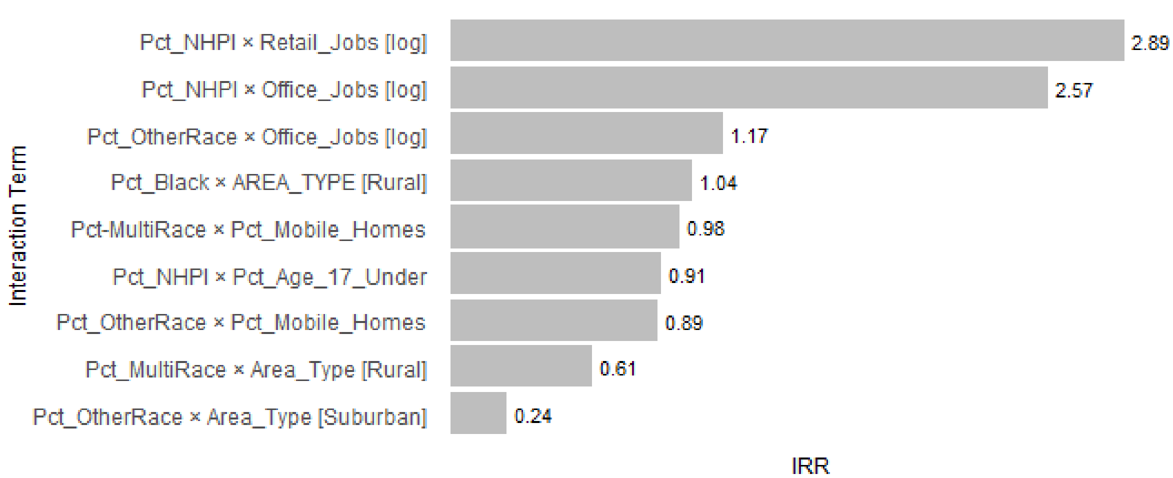


Figure B.15. Effects of Interacting Variables on KA Injury Rates of Bicyclists in Texas

Table B.9. Bayesian Model Results for MVOs in Texas

Variable	Pre-COVID			Post-COVID		
	2.5% HDI	97.5% HDI	IRR	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)						
Area_Type [Rural]	0.336	0.543	**1.55**	0.441	0.643	**1.72**
Area_Type [Suburban]	−0.190	0.004	0.91	−0.142	0.046	0.95
Area_Type [Town]	−0.877	−0.478	**0.51**	−0.619	−0.234	**0.65**
Race/Ethnicity						
Pct_Hispanic	−0.007	−0.003	**1.00**	−0.006	−0.001	**1.00**
Pct_Black	−0.004	0.002	1.00	−0.001	0.005	1.00
Pct_Asian	−0.010	−0.001	**0.99**	−0.010	−0.001	**0.99**
Pct_AIAN	−0.021	0.063	1.02	−0.030	0.054	1.01
Pct_NHPI	−0.053	0.046	1.00	−0.075	0.023	0.97
Pct_MultiRace	−0.020	−0.001	**0.99**	−0.019	0.000	0.99
Pct_OtherRace	−0.031	0.017	0.99	−0.025	0.020	1.00
Other sociodemographics and economics						
Pct_Age_17_Under	−0.008	0.001	1.00	−0.009	−0.001	**1.00**
Pct_Age_65_Over	0.011	0.020	**1.02**	0.013	0.022	**1.02**
Unemployment_Rate	−0.008	0.004	1.00	−0.009	0.003	1.00
Retail_Jobs [log]	0.033	0.069	**1.05**	0.004	0.040	**1.02**
Office_Jobs [log]	−0.050	−0.016	**0.97**	−0.020	0.013	1.00
Industrial_Jobs [log]	0.107	0.145	**1.13**	0.110	0.146	**1.14**
Service_Jobs [log]	−0.045	−0.002	**0.98**	−0.040	0.003	0.98
Pct_Uninsured	−0.001	0.006	1.00	0.003	0.009	**1.01**
Pct_Disability	0.006	0.018	**1.01**	0.003	0.014	**1.01**
Pct_No_Vehicle	−0.005	0.005	1.00	−0.011	−0.001	**0.99**
Pct_Mobile_Homes	0.009	0.015	**1.01**	0.010	0.015	**1.01**
Pct_Single_Parent	−0.005	0.004	1.00	−0.006	0.003	1.00
Roadway-related						
Avg_Through_Lanes	0.062	0.275	**1.18**	0.025	0.234	**1.14**
Exposure/Proxy						
Road_Density_Speed30_40	−0.026	0.052	1.01	−0.006	0.070	1.03
Road_Density_Speed45_55	0.020	0.065	**1.04**	0.031	0.074	**1.05**
Road_Density_Speed60_More	0.007	0.044	**1.03**	−0.006	0.029	1.01
Mean_AADT_Overall [log]	0.323	0.399	**1.43**	0.345	0.419	**1.47**

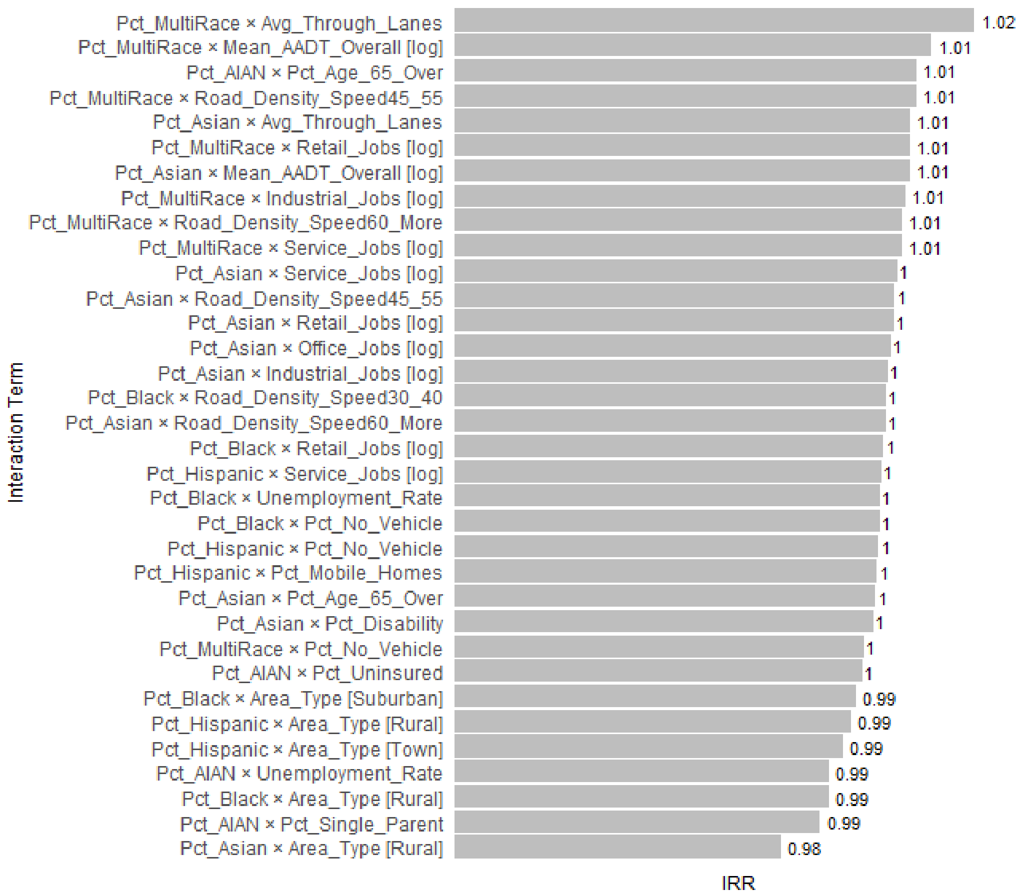


Figure B.16. Effects of Interacting Variables on KA Injury Rates of MVOs in Texas

B.4.3 Washington

Table B.10. Bayesian Model Results for Pedestrians in Washington

Variable	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)			
Area_Type [Rural]	−0.361	0.066	0.86
Area_Type [Suburban]	−0.402	−0.107	**0.78**
Area_Type [Town]	−0.798	−0.114	**0.63**
Race/Ethnicity			
Pct_Hispanic	−0.001	0.012	1.01
Pct_Black	0.016	0.037	**1.03**
Pct_Asian	−0.006	0.007	1
Pct_AIAN	0.009	0.039	**1.02**
Pct_NHPI	0.011	0.076	**1.04**
Pct_MultiRace	−0.012	0.025	1.01
Pct_OtherRace	−0.045	0.079	1.02
Other sociodemographics and economics			
Pct_Age_17_Under	−0.035	−0.011	**0.98**
Pct_Age_65_Over	−0.02	0.001	0.99
Unemployment_Rate	−0.005	0.032	1.01
Pct_Uninsured	−0.002	0.033	1.02
Pct_Disability	0.011	0.037	**1.02**
Pct_Single_Parent	−0.01	0.025	1.01
Pct_Mobile_Homes	−0.014	0.005	1
Pct_No_Vehicle	−0.003	0.016	1.01
Retail_Jobs [log]	0.094	0.179	**1.15**
Office_Jobs [log]	−0.011	0.08	1.04
Industrial_Jobs [log]	−0.017	0.084	1.03
Service_Jobs [log]	−0.015	0.117	1.05
Roadway-related			
Unmarked_Crosswalk_Density	0.465	1.647	**2.87**
Exposure/Proxy			
Road_Density_Speed25_Less_PedBike	−6.994	7.497	0
Road_Density_Speed30_40_PedBike	−0.058	0.281	1.12
Road_Density_Speed45_55_PedBike	−0.031	0.203	1.09
Mean_AADT_Overall_PedBike [log]	0.147	0.34	**1.28**
Transit_Stop_Density	−0.001	0.005	1
School_Density	−0.023	0.035	1.01

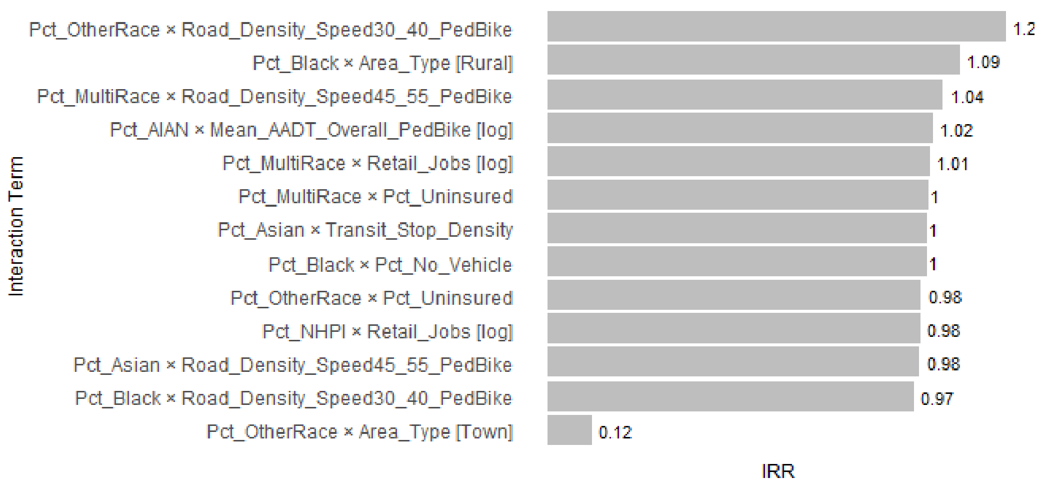


Figure B.17. Effects of Interacting Variables on KA Injury Rates of Pedestrians in Washington

Table B.11. Bayesian Model Results for Bicyclists in Washington

Variable	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)			
Area_Type [Rural]	−0.898	0.438	0.79
Area_Type [Suburban]	−0.903	0.033	0.65
Area_Type [Town]	−1.238	0.733	0.78
Race/Ethnicity			
Pct_Hispanic	−0.008	0.038	1.01
Pct_Black	−0.038	0.028	0.99
Pct_Asian	−0.021	0.015	1.00
Pct_AIAN	−0.233	0.082	0.93
Pct_NHPI	−0.201	0.065	0.93
Pct_MultiRace	−0.054	0.064	1.00
Pct_OtherRace	−0.307	0.141	0.92
Other sociodemographics and economics			
Pct_Age_17_Under	−0.023	0.044	1.01
Pct_Age_65_Over	0.008	0.068	**1.04**
Pct_Below_Poverty	0.003	0.045	**1.02**
Unemployment_Rate	−0.050	0.069	1.01
Pct_Uninsured	−0.075	0.036	0.98
Pct_Disability	−0.092	−0.011	**0.95**
Pct_Single_Parent	−0.087	0.029	0.97
Pct_Mobile_Homes	−0.027	0.038	1.01
Pct_No_Vehicle	−0.009	0.044	1.02
Retail_Jobs [log]	−0.157	0.114	0.98
Office_Jobs [log]	−0.171	0.127	0.98
Industrial_Jobs [log]	−0.046	0.263	1.11
Service_Jobs [log]	0.116	0.548	**1.39**
Roadway-related			
Bicycle_Lane_Density	−0.012	0.521	1.29
Unmarked_Crosswalk_Density	−1.469	2.589	1.74
Exposure/Proxy			
Road_Density_Speed25_Less_PedBike	−0.181	0.625	1.13
Road_Density_Speed30_40_PedBike	−0.218	0.792	1.33
Road_Density_Speed45_55_PedBike	−0.123	0.496	1.20
Mean_AADT_Overall_PedBike [log]	−0.409	0.231	0.92
Transit_Stop_Density	0.000	0.010	**1.00**
School_Density	−0.082	0.130	1.02

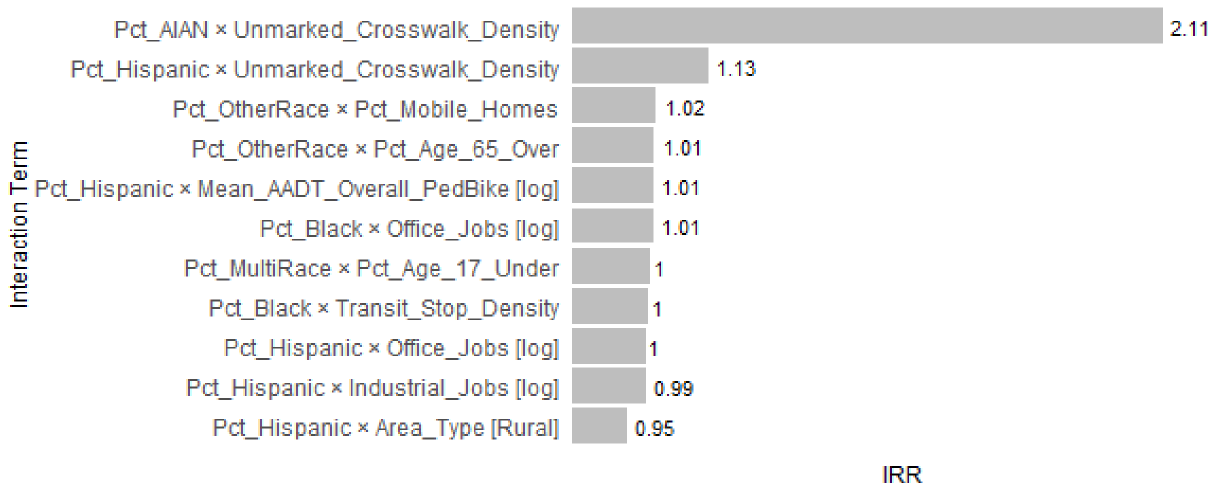


Figure B.18. Effects of Interacting Variables on KA Injury Rates of Bicyclists in Washington

Table B.12. Bayesian Model Results for MVOs in Washington

Variable	Pre-COVID			Post-COVID		
	2.5% HDI	97.5% HDI	IRR	2.5% HDI	97.5% HDI	IRR
Area type (reference: city/urban)						
Area_Type [Rural]	0.494	0.959	**2.07**	0.359	0.775	**1.76**
Area_Type [Suburban]	−0.329	0.025	0.86	−0.287	0.032	0.88
Area_Type [Town]	−0.897	−0.173	**0.59**	−0.902	−0.246	**0.56**
Race/Ethnicity						
Pct_Hispanic	−0.002	0.014	1.01	−0.006	0.008	1.00
Pct_Black	0.020	0.047	**1.03**	0.021	0.046	**1.03**
Pct_Asian	−0.017	−0.002	**0.99**	−0.019	−0.004	**0.99**
Pct_AIAN	−0.004	0.033	1.01	−0.020	0.013	1.00
Pct_NHPI	0.036	0.122	**1.08**	0.008	0.088	**1.05**
Pct_MultiRace	−0.040	0.002	0.98	−0.024	0.015	1.00
Pct_OtherRace	−0.042	0.088	1.02	0.028	0.148	**1.09**
Other sociodemographics and economics						
Pct_Age_17_Under	−0.035	−0.007	**0.98**	−0.026	−0.001	**0.99**
Pct_Age_65_Over	−0.027	−0.003	**0.99**	−0.014	0.007	1.00
Pct_Below_Poverty	−0.010	0.008	1.00	−0.003	0.014	1.01
Unemployment_Rate	−0.034	0.010	0.99	−0.024	0.015	1.00
Pct_Uninsured	−0.020	0.022	1.00	0.003	0.040	**1.02**
Pct_Disability	0.016	0.048	**1.03**	0.010	0.039	**1.02**
Pct_Single_Parent	−0.038	0.003	0.98	−0.029	0.008	0.99
Pct_Mobile_Homes	0.003	0.022	**1.01**	0.013	0.030	**1.02**
Pct_No_Vehicle	−0.026	−0.004	**0.98**	−0.021	−0.002	**0.99**
Retail_Jobs [log]	0.031	0.120	**1.08**	0.053	0.136	**1.10**
Office_Jobs [log]	−0.064	0.032	0.98	−0.016	0.074	1.03
Industrial_Jobs [log]	0.105	0.223	**1.18**	0.114	0.220	**1.18**
Service_Jobs [log]	−0.127	0.023	0.95	−0.099	0.037	0.97
Roadway-related						
Avg_Through_Lanes	0.068	0.242	**1.17**	0.054	0.213	**1.14**
Exposure/Proxy						
Road_Density_Speed30_40	0.008	0.183	**1.10**	−0.019	0.142	1.06
Road_Density_Speed45_55	0.152	0.387	**1.31**	0.056	0.254	**1.17**
Road_Density_Speed60_More	0.168	0.324	**1.28**	0.147	0.284	**1.24**

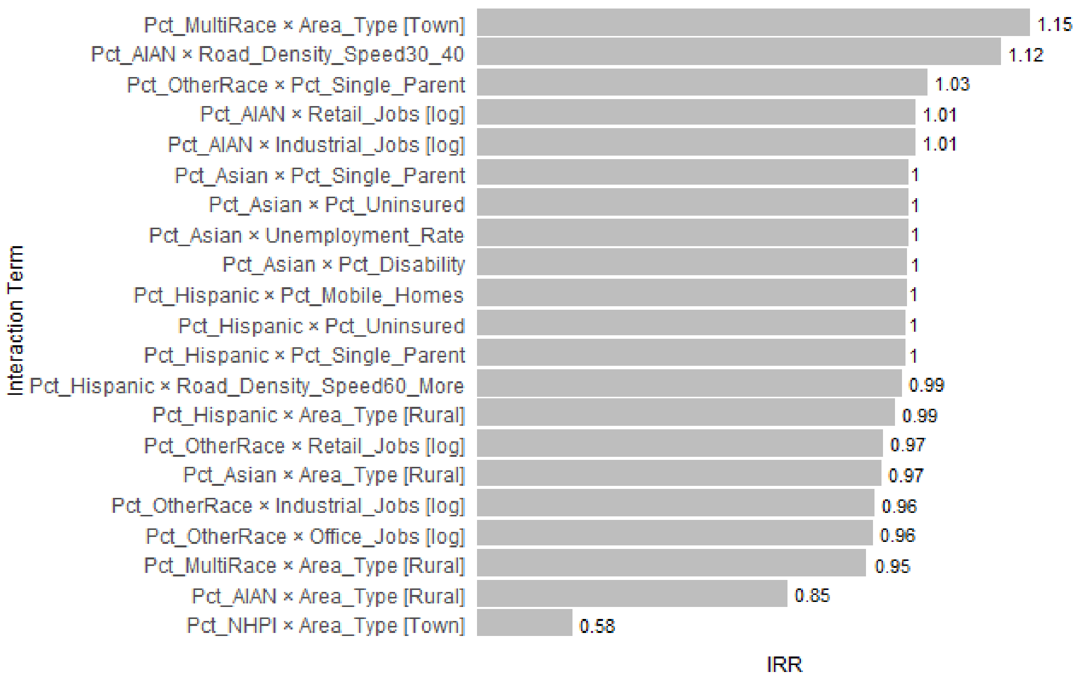


Figure B.19. Effects of Interacting Variables on KA Injury Rates of MVOs in Washington

Appendix B.5: Results for the individual race/ethnicity models for Texas

Individual race/ethnicity models were developed for White, Hispanic, and Black MVOs and pedestrians in Texas. Due to sample size limitations, models were created for these three race/ethnicity groups and two road user types. The population of each specific race/ethnicity served as the offset. Results are presented as IRRs for the pre-pandemic and post-COVID periods. The following presentation of results will focus on the post-COVID situation. Interested readers can look at the results deriving from the pre-COVID models.

B.5.1 Individual race models for pedestrians in Texas

Table B.13 summarizes the results of the individual race/ethnicity models for pedestrians in Texas. The results indicate that the rates of KA injuries sustained by White and Black pedestrians are lower in suburban tracts (49% and 36% decreases, respectively) compared to urban tracts. Rural and town tracts are also associated with 42% and 59% reductions in the rates of KA injuries of White pedestrians. Moreover, town tracts experienced a 95% decrease in the rates of KA injuries sustained by Black pedestrians compared to urban tracts.

Table B.13. Results (IRRs) of Individual Race/Ethnicity Models for Pedestrians in Texas

Variable	White		Hispanic		Black	
	Pre-COVID	Post-COVID	Pre-COVID	Post-COVID	Pre-COVID	Post-COVID
Area type (reference: city/urban)						
Area_Type [Rural]	**0.48**	**0.58**	0.91	1.22	0.88	0.73
Area_Type [Suburban]	**0.54**	**0.51**	0.99	0.98	**0.50**	**0.64**
Area_Type [Town]	**0.33**	**0.41**	0.93	0.72	0.53	**0.05**
Sociodemographics and economics						
Pct_Age_17_Under	0.99	1.00	0.99	**0.98**	1.00	1.00
Pct_Age_65_Over	**0.98**	1.00	**1.03**	0.99	0.97	0.99
Unemployment_Rate	1.00	**1.03**	1.01	0.99	1.00	1.01
Retail_Jobs [log]	1.03	**1.12**	1.10	1.08	0.96	1.06
Office_Jobs [log]	0.94	0.92	1.04	0.99	**0.91**	0.98
Industrial_Jobs [log]	**1.27**	1.08	0.97	1.05	**1.12**	**1.09**
Service_Jobs [log]	1.04	1.05	1.10	1.03	1.09	1.11
Pct_Disability	**1.04**	1.00	1.01	1.00	**1.03**	1.00
Pct_No_Vehicle	**1.05**	**1.04**	1.02	1.01	1.02	1.00
Pct_Mobile_Homes	**1.02**	**1.02**	1.01	**1.01**	1.01	1.01
Pct_Single_Parent	**1.03**	1.02	1.00	1.01	**0.96**	**0.97**
Exposure/Proxy						
Road_Density_Speed30_40_PedBike	1.07	1.14	**1.31**	**1.21**	1.06	1.15
Road_Density_Speed45_55_PedBike	0.99	**1.16**	1.03	1.07	1.02	0.99
School_Density	1.02	1.03	0.96	**1.04**	1.07	1.04
Mean_AADT_PedBike_Overall [log]	**1.41**	**1.35**	**1.27**	**1.23**	1.17	**1.35**

Note: *Bold values represent significant IRRs.*

Table B.13 also indicates that a 1% increase in the percentage of unemployment rate or retail jobs corresponds to a 3% and 12% increase in the rates of KA injuries sustained by White pedestrians. Tracts with a higher number of industry jobs are associated with a 9% increase in the rates of KA injuries of Black pedestrians. A 1% increase in the percentage of mobile homes of households with no vehicles corresponds to a 4% increase in the rates of KA injuries of White pedestrians. Tracts with a higher percentage of mobile homes are associated with a 1-2% increase in the rates of KA injuries sustained by White and Hispanic pedestrians. On the other hand, tracts with a higher percentage of single-parent households experience lower rates of KA injuries of Black pedestrians.

Census tracts with a higher density of roads with 30–40 mph or 45–55 mph speed limits experience higher rates of KA injuries sustained by Hispanic pedestrians (21% increase) and White pedestrians (16% increase). Moreover, tracts with a higher density of schools are associated with a 4% increase in KA injury rates of Hispanic pedestrians. A 1% increase in AADT is associated with a significant 23-35% rise in the rates of KA injuries of White, Hispanic, and Black pedestrians.

B.5.2 Individual race/ethnicity models for MVOs in Texas

Table B.14 presents the IRRs of variables from individual race/ethnicity models for MVOs in Texas. Most IRRs in these models for White, Hispanic, and Black MVOs show some consistency before and after the pandemic.

Table B.14. Results (IRRs) of Individual Race/Ethnicity Models for MVOs in Texas

Variable	White		Hispanic		Black	
	Pre-COVID	Post-COVID	Pre-COVID	Post-COVID	Pre-COVID	Post-COVID
Area type (reference: city/urban)						
Area_Type [Rural]	**1.65**	**1.70**	**1.72**	**1.68**	**1.88**	**2.02**
Area_Type [Suburban]	1.06	0.98	**0.86**	**0.86**	0.99	1.06
Area_Type [Town]	**0.63**	**0.75**	**0.34**	**0.45**	**0.53**	0.62
Sociodemographics and economics						
Pct_Age_17_Under	**1.01**	1.00	**0.99**	**0.99**	**1.03**	**1.03**
Pct_Age_65_Over	**1.01**	**1.01**	**1.03**	**1.04**	**1.09**	**1.08**
Unemployment_Rate	1.00	1.01	1.00	1.00	0.99	0.98
Retail_Jobs [log]	**1.06**	**1.04**	**1.03**	1.00	1.00	0.99
Office_Jobs [log]	**0.96**	**0.97**	**0.97**	1.00	**0.94**	0.97
Industrial_Jobs [log]	**1.17**	**1.18**	**1.13**	**1.16**	**1.17**	**1.17**
Service_Jobs [log]	**0.94**	**0.94**	0.97	0.98	**0.93**	**0.92**
Pct_Uninsured	**1.02**	**1.02**	**0.98**	**0.99**	**1.01**	**1.01**
Pct_Disability	**1.01**	**1.01**	1.00	1.00	**0.98**	0.99
Pct_No_Vehicle	**1.01**	1.00	1.00	1.00	**0.97**	**0.97**
Pct_Mobile_Homes	**1.01**	**1.01**	**1.01**	**1.01**	**1.04**	**1.03**
Pct_Single_Parent	**1.01**	**1.01**	1.00	1.00	**0.96**	**0.97**
Roadway-related						
Avg_Through_Lanes	**1.32**	**1.32**	1.08	1.06	1.10	1.04
Exposure/Proxy						
Road_Density_Speed30_40	1.04	**1.09**	0.98	0.99	1.10	1.05
Road_Density_Speed45_55	**1.05**	**1.07**	1.03	1.02	1.03	1.04
Road_Density_Speed60_More	**1.03**	1.02	1.00	1.02	1.04	1.04
Mean_AADT_Overall [log]	**1.42**	**1.42**	**1.55**	**1.53**	**1.33**	**1.41**

Note: *Bold values represent significant IRRs.*

Overall, these models indicate that the rates of KA injuries sustained by White, Hispanic, and Black MVOs are consistently higher in rural census tracts and lower in town tracts compared to urban tracts in Texas. Black MVOs are the ones at higher risk, with the rates of KA injuries being twice as high in rural tracts compared to urban tracts. Hispanic MVOs, on the other hand, experienced the lowest rates of KA injuries in suburban and town tracts, respectively, with 14% and 55% reductions compared to urban tracts.

Table B.14 also indicates that census tracts with a higher percentage of individuals aged 65+ years old experience higher rates of KA injuries sustained by White, Hispanic, and Black MVOs, reported as 1%, 4%, and 8% increases, respectively. Similar associations are observed between KA injury rates of Black MVOs and tracts, with a higher percentage of individuals aged 17 years old or younger. Tracts with a higher number of industrial jobs experience a 17% to 18% increase in the rates of KA injuries sustained by White, Hispanic, and Black MVOs. Tracts with a higher number of retail and office jobs experience a 4% increase and a 3% decrease in the KA rates of White MVOs. The number of service jobs is associated with a 6% and 8% decrease in the rates of KA injuries of

White and Black MVOs. A 1% increase in the percentage of individuals without insurance is associated with a slight increase of 1% to 2% in the rates of KA injuries of White and Black MVOs. The results also show that a 1% increase in the percentage of mobile homes is associated with a 1% to 3% increase in the rates of KA injuries of White, Hispanic, and Black MVOs.

An additional lane in the average number of lanes of census tracts corresponds to a 32% increase in the rates of KA injuries sustained by White MVOs. A 1% increase in AADT is associated with a significant 42% to 53% rise in the rates of KA injuries of White, Hispanic, and Black MVOs.

APPENDIX C: ROADWAY SEGMENT ANALYSIS APPENDICES

Appendix C.1: Road Segment Methodology

This section outlines the equity evaluation at a roadway segment level, where roadway safety is evaluated in terms of safety potential rather than crash outcomes. While the individual and neighborhood analyses focused on equity assessment regarding actual crash outcomes, the segment analysis focused on the roadway safety potential, covering areas with a high risk that may not have experienced crashes yet. In this context, the safety potential of a segment in a roadway network is quantified by its alignment with the overall SSA goals. By aligning the analysis with SSA objectives, this analysis evaluated how well the roadway network is structured to prevent potential KA crashes.

Turner and colleagues (2016) provided an SSA assessment framework designed to help roadway agencies methodically consider SSA objectives in road infrastructure projects. The framework considers key crash types that lead to fatal and serious injury outcomes and the risks associated with these crashes, i.e., exposure, likelihood, and severity. It provides prompts to ensure each pillar of the SSA is considered. To advance the implementation of the SSA, FHWA developed an SSA project-based alignment framework in 2024 (FHWA, n.d.). The criteria and use of this framework lend themselves to infrastructure projects and comparisons among alternatives for specific locations, including those found in the Safe System Roadway Design Hierarchy. It mainly intends to assess existing roadway conditions and supplement Road Safety Audits through a Safe System lens using quantitative (crash exposure, likelihood, and severity scores) and qualitative (safety prompts) site evaluations.

The current framework offers a method for scoring safety at the network or segment level, contingent upon the availability of comprehensive network-level data, including exposure metrics. While the framework is theoretically applicable across all networks worldwide, the availability of necessary data and data surrogates is often limited. Consequently, case studies were employed to develop the framework and establish relevant scoring ranges. Caution is advised when applying these ranges at the state level across all networks unless the ranges are predefined based on the available data or validated surrogates.

Estimating Roadway Safety Potential with the FHWA Framework

Based on the FHWA guidelines, the project-based alignment framework evaluates road safety by examining three critical aspects: *Exposure*, *Likelihood*, and *Severity*. Exposure includes factors that increase the potential for conflict, with scoring based on roadway geometry and user volumes (FHWA, 2024). Likelihood accounts for factors that elevate the chance of a fatal or incapacitating injury, scored based on roadway environment elements that increase crash risk and severity by influencing traffic conflicts or increasing user error rates (FHWA, 2024). Severity focuses on behavioral speeding factors that amplify the potential severity of crashes, which were assessed by analyzing travel speeds. These three aspects, described in detail in the next subsections, provide a comprehensive safety evaluation for both motor vehicle drivers and occupants, in addition to vulnerable road users.

Exposure Scoring. Exposure-related performance measures provide an overview of exposure (in terms of both motor vehicles and Vulnerable Roadway Users–VRUs). The key factors provided in the FHWA SSA Scoring framework for assessing exposure, as presented in Table C.1, include AADT, roadway width, number of lanes, and VRU counts. Each measure is associated with specific ranges scored on a scale from 1 to 10, where a higher score indicates greater exposure.

Table C.1. Scoring Criteria for Exposure-Related Performance Measures

Road User	Variable	Category	Score
Motor Vehicle	Motor Vehicle Volumes (AADT)	Less than 1,000	1
		1,000–5,000	4
		5,000–10,0000	6
		10,000–15,000	8
		Greater 15,000	10
	Roadway Width (ft)	Less than 30	1
		30–35	4
		36–41	6
		42–47	8
		48 or more	10
VRU	Crossing Distance (Max Number of Lanes)	One Lane	1
		Two Lanes	4
		Three Lanes	6
		Four Lanes	8
		More than Four Lanes	10
	Vulnerable Users Present (users per day)	Less than 10	1
		10–25	4
		25–50	6
		50–100	8
		Greater than 100	10

For motor vehicles, AADT captures the volume of vehicle traffic, with higher volumes reflecting increased exposure and thus receiving higher scores. Similarly, the width of the roadway is scored so that wider roads receive a higher score to reflect a greater exposure to potential conflicts due to the presence of more traffic across additional lanes. For the VRUs, such as pedestrians and bicyclists, scoring is based on the number of lanes a user has to cross and the count of VRUs per day. A greater number of lanes and higher counts of VRUs increase the potential for interactions with motor vehicles, resulting in higher scores to reflect the elevated risk of conflicts. This scoring system aids in identifying high-exposure areas, allowing for the prioritization of interventions to enhance road safety.

For Cleveland, AADT, lane width, and number of lanes were extracted from the ODOT's Transportation Information Mapping System (TIMS) (TIMS, n.d.). For missing AADT values, data imputation was performed using the Random Forest technique (Kumar, 2024; Pantanowitz & Marwala, 2009). The VRU counts were obtained from the Northeast Ohio Areawide Coordinating Agency's (NOACA) Geographic Information System (GIS) portal (NOACA, n.d.). For Seattle, AADT and lane width were extracted from the city of Seattle's Geodatabase (City of Seattle, 2024). The number of lanes was extracted from OSM (OpenStreetMap Foundation, n.d.). VRU counts were estimated using a calibrated model by Nordback and colleagues (2017).

For Austin, AADT, roadway width, and the number of lanes were obtained from the Texas roadway inventory data. Texas also operates a Bicycle and Pedestrian Count Exchange (BP|CX) program (Texas A&M Transportation Institute, n.d.), which provides counts of VRUs. In this study, VRU count data were collected from selected locations in Austin. Decision rules were then established to estimate VRU counts based on land use information and the number of lanes. Education Demographic and Geographic Estimates locale data (Geverdt, 2019) was used to calculate the mean value of VRU counts based on available count data from BP|CX. The mean value was next applied across the network within the same locale type. A key component of this data is the locale classification, which categorizes U.S. territories into four area types: City, Suburban, Town, and Rural, with each area further divided into three subtypes.

Likelihood Scoring. The SSA emphasizes the importance of creating road environments that minimize the risk of fatal crashes. The likelihood scoring framework provides a systematic method for evaluating how different factors contribute to crash likelihood and guiding safety interventions. Table C.2 provides a detailed scoring framework designed to assess the likelihood of fatal and serious injury crashes based on various roadway and environmental features, which are critical in the context of the SSA. A discussion on each variable is presented next.

Table C.2. Scoring Criteria for Likelihood-Related Performance Measures

Road User	Variable	Category	Score
For Both	Lighting condition	Yes	0
		No	3
		N/A	1.5
	Vertical curvature	< 3	0
		3-8	1.5
		> 8	3
		N/A	N/A
	Driveways	< 10	0
		11–20	0.75
		21-30	1.5
		31-40	2.25
		> 40	3
		N/A	N/A
	Horizontal curvature	< 3	0
		3-10	1.5
		> 10	3
		N/A	N/A
Motor Vehicle	Presence of Fixed Object	No	0
		Yes	3
		N/A	1.5
	Presence of Rumble Strip	Yes	0
		No	3
		N/A	
	Median Type	Roadway with median barrier	0
		Roadway with raised median	0.75
		Roadway with TWLTL or painted buffer 10 feet or greater	1.5
		Roadway with centerline buffer with rumble strip	2.25
		Undivided roadway	3
		N/A	N/A
VRU	Presence of Sidewalk	Shared used path	0
		Existing sidewalk	0.75
		Potential sidewalk	1.5
		Planned sidewalk, planned shared street	2.25
		Driveway	3
		N/A	N/A
	Presence of Bike Facility	Shared lane	0
		Trail—paved, bikeway with parking, bike lane buffered, Bike Lane protected two-way	0.75
		Bikeway protected one way, shoulder	1.5
		Wide curb lane, bike lane- climbing, neighborhood bikeway	2.25
		Trail—unpaved	3
		N/A	N/A

Lighting Condition. The lighting condition on each roadway segment evaluates the presence of street lighting, a crucial factor for road safety, especially for VRUs, as it directly affects visibility. In the scoring framework, segments with adequate lighting receive a score of 0, indicating lower risk, while those without lighting receive a score of 3, representing higher crash risk due to poor visibility. A score of 1.5 is assigned when the lighting condition is unknown, reflecting a moderate risk level. Without direct data on lighting infrastructure, surrogate measures were used, such as segment-specific crash counts classified as "dark, no lighting" or "dark with lighting," to estimate roadway lighting conditions. For each city, lighting conditions were inferred from nighttime crash records, with crashes on specific segments used to assign lighting status based on recorded light conditions at the time of the crash. Segments without assigned lighting conditions were given a default score of 1.5.

Curvature Measures. For Cleveland and Seattle, the information was obtained and merged directly from crash records. However, in Texas, roadway inventory (Texas Department of Transportation, n.d.), information on curvature (vertical and horizontal) is often incomplete. To address this limitation, curvature data for roadways in Austin were computed using surrogate measures. Many studies have highlighted the significant influence of geometric characteristics such as curvature and slope on both operating speed control and crash occurrence (American Association of State Highway and Transportation Officials , 2018; National Academies of Sciences, Engineering, and Medicine, 2022). The following method was used to calculate both horizontal and vertical curvature to gain a comprehensive understanding of the geometric characteristics of the road segments.

First, horizontal curves refer to the changes in direction along a roadway. This involved calculating the bearing or direction between two consecutive points on a segment and then determining the angle difference between consecutive bearings to understand how sharply the road turns, as illustrated in Figure C.1. Adjustments were made to ensure the angle differences fell within a standard range, providing an accurate measure of the curvature. The overall curvature is quantified by summing the individual angle changes for each segment. This measurement allowed for a comprehensive analysis of horizontal road geometry, aiding in understanding the relationship between road curvature, speed, and crash risk.

The bearing or direction between two consecutive points on a segment was calculated using the arctangent of the difference in their coordinates.

$$Bearing = arctan\left(\frac{y_2 - y_1}{x_2 - x_1}\right) \tag{C-1}$$

The angle difference between consecutive bearings determines how sharply the road turns. Adjustments were made to ensure the angle differences fall within the range of −180 to 180 degrees.

$$\text{Angle Difference} = \text{Angle}_2 - \text{Angle}_1 \tag{C-2}$$

If the difference is less than -180 degrees, 360 degrees were added to the difference. If the difference is greater than 180 degrees, 360 degrees were subtracted from the difference.

$$\text{Angle Difference} = \begin{cases} \text{Angle Difference}+360 \text{ if Angle Difference}<-180 \\ \text{Angle Difference}-360 \text{ if Angle Difference}>80 \end{cases} \tag{C-3}$$

The total angle change for each segment was calculated by summing the individual angle changes, providing a measure of the segment's overall curvature.

$$\text{Cumulative Angle Change} = \sum|\text{Angle Difference}| \tag{C-4}$$

In addition, vertical curves pertain to changes in elevation along the roadway. For these measurements, the study utilized the 1/3 Arc-second National Elevation Dataset data (U.S. Geological Survey, 2018). A Digital Elevation Model (DEM) is a 3D representation of a terrain's surface created from terrain elevation data, providing detailed elevation information at approximately a 10-meter resolution. Using the 10-meter resolution DEM, the slope measures of the segments were calculated to understand the vertical curvature and steepness of the roadways. Surface information was added to get vertical curvature measures. Segments shorter than 10 meters (33 ft) were removed due to the resolution limitations of the elevation data. This approach ensures a precise and comprehensive analysis of vertical curvature and its impact on roadway safety.

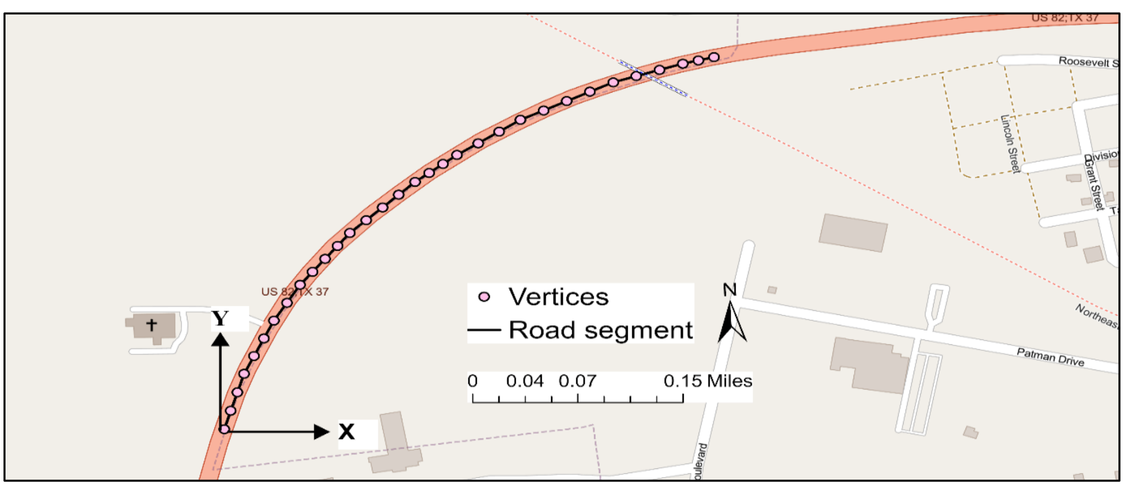


Figure C.1. Horizontal Curvature Calculation

Roads with low curvature scored at 0 are considered safer, while those with moderate curvature receive a score of 1.5. High curvature poses a significant safety risk and is scored at 3.

Driveways. The *Driveways* measure considers the number of driveways along a road segment, as a higher number of driveways increases conflict points for vehicles and VRUs (Das & Mills, 2024). Roads with fewer than ten driveways were scored at 0, indicating minimal risk. As the number of driveways increases, the score rises, with roads having more than 40 driveways receiving the highest score of 3. For Austin (TX), the research team had already collected the data as part of a project, TxDOT 0-7144. For Cleveland and Seattle, the number of driveways per mile was obtained by extracting driveway shapefiles from Open Streets Map (OpenStreetsMap Foundation, 2024).

Presence of Fixed Object. For motor vehicles, additional variables are considered, including the presence of Fixed Objects (FO) near the roadway. Fixed objects like poles or barriers can pose significant collision risks (Holdridge et al., 2005). If no fixed objects are present, the score is 0, indicating a safer environment. However, if fixed objects are present, the score increases to 3. In the absence of fixed object location points, the research team used surrogate measures (crash counts associated with fixed objects on the segment) to evaluate the presence of fixed objects on the roadways. This information was obtained from crash records from each of the three cities.

Presence of Rumble Strips. Rumble strips are generally not installed on roadways with a posted speed limit of 45 mph or less (Ramthun, n.d.). For rural high-speed roadways, rumble strips are recommended for new construction, reconstruction, and overlay projects unless engineering or safety assessments indicate they would be detrimental. On high-speed urban roadways, rumble strips are advised in areas with a significant number of crashes due to driver inattention, i.e., opposing direction or run-off-road crashes. The safety scoring system for road conditions highlights significant differences based on speed limits and the presence of safety features. A road with a speed limit exceeding 45 mph that includes a rumble stripe was assigned a score of 0 (Texas Department of Transportation, n.d.), indicating it is a safer option due to the enhanced warning provided to drivers, reducing the likelihood of run-off-road incidents. Conversely, a roadside with no rumble strips or recovery area and a significant drop-off was assigned a score of 3, representing a higher risk, as the absence of these critical safety features increases the potential for severe crashes.

Median Type. The different types of medians were assumed to contribute to safety impacts at varying levels. Roadways with median barriers were assumed to offer motor vehicles the highest level of traffic separation and protection and were scored as 0. Other median types, such as raised medians and painted buffers, received progressively higher scores, with undivided roadways receiving the highest score of 3, indicating the greatest risk for motor vehicles to crash onto opposing traffic (e.g., head-on collisions) or crossing traffic (e.g., angle collisions) often associated with more severe injury outcomes (Texas Department of Transportation, n.d.). Median type information was obtained from crash records for Seattle, the Open Data Portal for Austin, and ODOT TIMS for Cleveland.

Bikeway Facilities. For Austin, the bicycle-user infrastructure data was sourced from the City of Austin's open data portal (City of Austin, n.d.-a). Shared lanes or "sharrows" were assigned a score of 0, based on the assumption that they are typically implemented in low-speed, low-traffic areas where shared use can be safer. It was further assumed that shared lanes increase awareness between cyclists and drivers, helping to minimize speed differentials and reduce the likelihood of severe or fatal crashes. Various types of protected bikeways, such as one-way protected bikeways, buffered bike lanes, and two-way protected bike lanes, commonly present in busier roadways, were given a score of 0.75, reflecting a safer interaction with vehicles and a higher level of protection for bikes. Paved trails and shoulders scored 1.5, indicating a lower level of safety with less separation from traffic. Wide Curb Lanes (WCLs) and neighborhood bikeways that allowed vehicles and bikes to travel side by side with no physical barriers received a score of 2.25, suggesting these options offer even less protection for cyclists. Unpaved trails were assigned a score of 3, representing the least safe option with the highest level of separation or difficulty. Due to differences in the level of detail of available data, the criteria for scoring bike facilities were different for the three cities. The criteria presented in Table C.2 were only applied in Austin. For Cleveland and Seattle, the criteria for scoring bike facilities are presented in Table C.3. Bike facility data was sourced from ODOT TIMS (TIMS, n.d.) for Cleveland and from the Seattle geodatabase for Seattle (City of Seattle, 2024).

Table C.3. Scoring Criteria for Bikeway Facilities in Cleveland and Seattle

City	Bikeway Facility	
	Type	Score
Cleveland	Shared use path or trail	0
	Protected buffered bicycle lane	0.75
	Unprotected buffered bicycle lane	1.5
	On-Street bicycle lane	2.25
	No designated bicycle lane	3
Seattle	Shared use path or trail	0
	Existing bicycle lane (Unknown type)	1.5
	No designated bicycle lane	3

Sidewalk Facilities. For Austin, the sidewalk infrastructure data was sourced from the City of Austin's open data portal (City of Austin, n.d.-c). This section outlines a safety scoring system for different pedestrian pathways. A shared-use path, or a multi-use path designated for non-motorized users and often located within a street right-of-way, received a score of 0, reflecting the safest option with the highest degree of separation from traffic. An existing sidewalk received a score of 0.75, indicating basic pedestrian infrastructure that offers a moderate level of safety. A potential sidewalk, which is planned but not yet constructed, is scored at 1.5, representing a slightly lower level of safety due to its incomplete status. Planned sidewalks and planned shared streets both scored 2.25, indicating a significant reduction in safety. A driveway scored the highest at 3, representing the least safe option due to its vehicle-oriented design. Similar to bike facilities, the criteria for scoring sidewalk facilities differed for the three cities because of differences in the level of detail in the available data. The criteria presented in Table C.2 were only applied to Austin. For Cleveland and Seattle, the pedestrian scoring criteria are outlined in Table C.4. Data for Cleveland was sourced from the Northeast Ohio Areawide Coordinating Agency (2024), and for Seattle, it was obtained from the city's geodatabase (City of Seattle, 2024).

Table C.4. Scoring Criteria for Sidewalk Facilities in Cleveland and Seattle

City	Sidewalk Facility	
	Type	Score
Cleveland	Separated shared use path	0
	Buffered sidewalk (continuous on both sides)	0.75
	Buffered sidewalk (discontinuous on either side)	1.5
	Back-of-curb sidewalk on either side	2.25
	No existing sidewalk	3
Seattle	Separated shared use path	0
	Buffered sidewalk (Unknown width)	1.5
	No existing sidewalk	3

Severity Scoring. Severity-related performance measures indicate how likely the severity of crashes is based on average speeds for both motor vehicles and VRUs, as shown in Table C.5. Speed is a critical factor in crash severity, with higher speeds correlating with more severe outcomes. Accordingly, scoring increases with speed to reflect the elevated risk of serious injuries or fatalities. For Austin, operating speed data was obtained from INRIX XD for 2017–2022. Where operating speed data was unavailable (approximately 8% of segments), the FHWA guidelines (FHWA, 2024) were followed, estimating speed as the posted limit plus 7 mph. For Cleveland and Seattle, the posted speed limit data was extracted from existing roadway segment shapefiles (City of Seattle, 2024; TIMS, n.d.).

Motor vehicle speeds are categorized into ranges, with higher speeds receiving higher scores, indicating a greater severity risk. For example, speeds of 25 mph or less were given a low score of 1, while speeds above 55 mph received a maximum score of 20, underscoring the elevated risk associated with higher speeds. VRUs, such as pedestrians and cyclists, are particularly vulnerable to severe injuries even at lower speeds. The VRU scoring reflects this, with speeds of 20 mph or less receiving a score of 1, but with scores escalating more rapidly beyond this range. For instance, speeds over 35 mph were assigned the highest score of 20, emphasizing the increased danger to VRUs, as survival rates drastically decline in high-speed impacts. This differential scoring highlights that on roads with higher vehicle speeds, VRUs face a much greater likelihood of severe injury or fatality compared to motor vehicle occupants, due to the greater force of impact and reduced reaction times. The scoring system is thus calibrated to prioritize speed reduction interventions in areas frequented by VRUs, supporting a targeted approach to enhancing safety for all road users.

Table C.5. Scoring Criteria for Severity-Related Performance Measures

Road User	Measure	Category	Score
Motor Vehicle	Average Speed (mph)	25 or lower	1
		26–30	3
		31–35	6
		36–40	9
		41–45	12
		46–50	15
		51–55	18
		Greater than 55	20
VRU	Average Speed (mph)	20 or lower	1
		21–25	5
		26–30	10
		31–35	15
		Over 35	20

Table C.6 summarizes the maximum SSA Scores for different safety performance measures, focusing on motor vehicles, VRUs, and both road users. The scoring framework, which follows the guidelines of the FHWA SSA framework, is divided into three main categories: Exposure, Likelihood, and Severity. Each category contributes to the overall safety score of a road segment. Exposure and Severity scores were equally weighted for motor vehicles and VRUs, with a maximum of 20 points each. In contrast, the Likelihood score was distributed differently, with motor vehicles having a higher possible score (9) compared to VRUs (6) based on available road and exposure information. The total possible score for these three categories was 107 points.

Table C.6. Total Maximum SSA Scoring for a Segment

Criteria	Maximum SSA Scores for Motor Vehicles	Maximum SSA Scores for VRUs	Maximum SSA Scores for Both	Total Maximum Score
Exposure	20	20	-	40
Likelihood	9	6	12	27
Severity	20	20	-	40
Total Maximum Score for a Segment				**107**

Structural Equation Modeling

Structural Equations Modeling (SEM) was applied to examine the relationships among demographic and socioeconomic factors and SSA Scores. SEM is particularly suited to this analysis as it allows for modeling both direct and indirect effects, accommodating complex relationships among multiple factors. This technique has been widely used in various fields to analyze disparities (Mudrazija & Butrica, 2024; Zhu et al., 2024). Figure C.2 illustrates the two main pathways hypothesized in this study. The first pathway explored the direct relationship between demographic factors and SSA Scores. On the other hand, the second pathway investigated the indirect influence of socioeconomic factors on SSA Scores, considering their potential mediating effects. By examining these pathways, the analysis aimed to reveal both direct and indirect mechanisms through which socioeconomic and demographic factors contribute to roadway safety disparities.

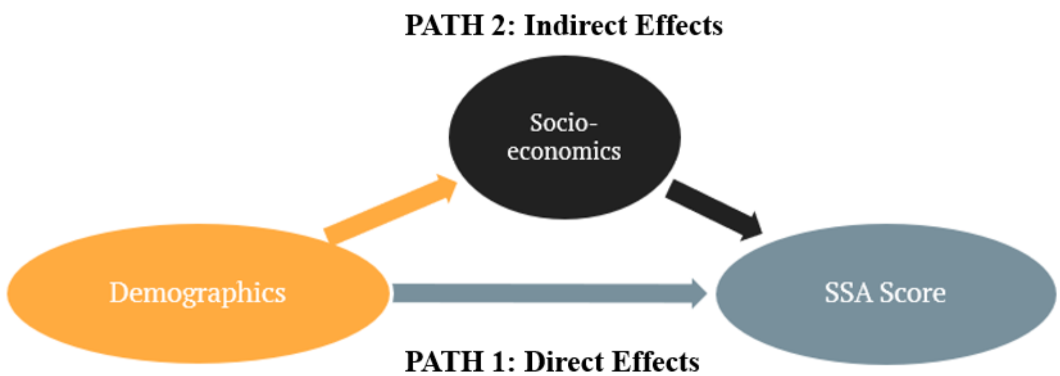


Figure C.2. Pathways for Equity Evaluation

The SEM combines Confirmatory Factor Analysis (CFA) and regression or path analysis, and is widely used in transportation equity and safety studies (Zhu et al., 2024). It enables the modeling of complex causal paths, including mediating variables (Dash & Paul, 2021; Zhu et al., 2024). This study used SEM to test the mediating effect of socioeconomic factors. Unlike multiple regression, which is limited to identifying bivariate associations while controlling for other variables, SEM allows for a more comprehensive analysis of complex relationships between variables. A mediating variable explains how an independent variable influences a dependent variable. In SEM, mediating variables are typically represented as latent or observed variables mediating the relationship between other variables.

One of SEM's key advantages over traditional modeling techniques is its ability to capture multi-dimensional constructs, such as socioeconomic disadvantage, which cannot be adequately represented by a single observed variable. Using CFA, multiple indicators can be combined to create a composite factor (latent variable) that reduces measurement errors (Bentler, 2010; Mueller & Hancock, 2018). The SEM analysis was conducted using a Python package called "*SEMOPY*" and the maximum likelihood estimation approach (Igolkina & Meshcheryakov, 2019). Mathematically, the SEM constitutes the *measurement model* (Equation C-5), which measures latent variables based on their indicators using CFA, and the *structural model* (Equation C-6), which tests the hypothetical dependencies among the variables (latent or observed) by path analysis (Bentler, 2010; Dash & Paul, 2021; Zhu et al., 2024).

For this analysis, a latent variable, SED, was created to represent the socioeconomic status of a roadway segment in a given census tract. Equation C-5 presents the measurement model for the latent variable SED.

$$SED = \Lambda_{\mathrm{X}}\xi + \delta \tag{C-5}$$

where SED denotes the explicit latent exogenous variable, i.e., the socioeconomic disadvantage; ξ represents a vector of observed independent variables used to measure SED; Λ_{X} represents the vector of factor loadings (regression coefficients) for latent variable SED; and δ represents the vector of measurement errors for variable SED. The structural model is presented in Equation C-6.

$$SSA\ Score = \gamma(\mathrm{X}) + \beta(SED) + \zeta \tag{C-6}$$

where γ denotes the vector of direct effects of observed exogenous variables X to observed endogenous variable SSA Score; β denotes the vector of direct effects of observed exogenous variables X to latent variable SED; ζ is the vector of error terms for endogenous variables.

The calibration of the measurement model included five potential variables, as outlined in Figure C.3: the percentage of people above 150% poverty, the unemployment rate, the percentage of persons with a housing cost burden, lack of health insurance, and lack of a high school diploma.

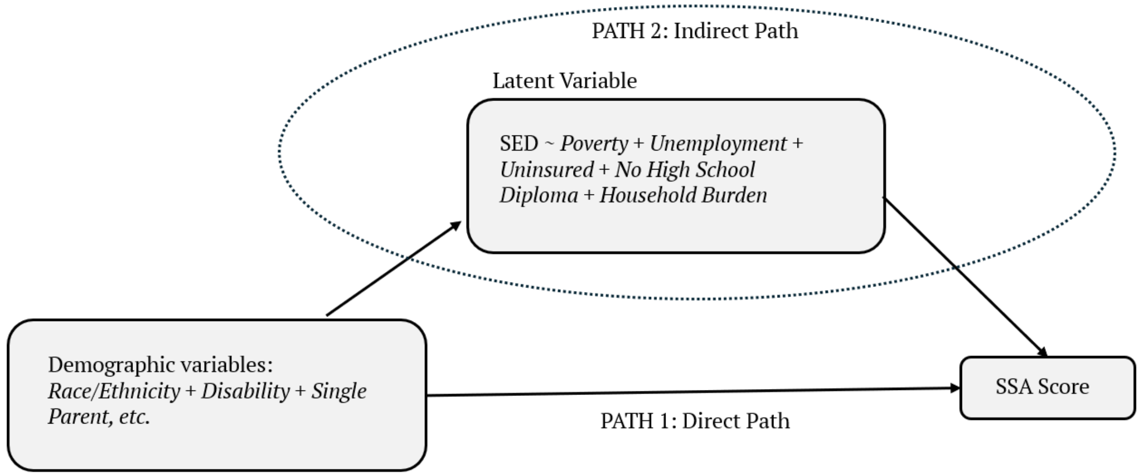


Figure C.3. General SEM Model Specification

The final model specification was determined by evaluating all possible combinations of these indicators to optimize model fit. For the structural model, demographic and selected household factors were included as observed variables, also presented in Table C.8. A summary of the SEM specification is provided in Figure C.3. During the model-fitting process, outliers were identified and removed to prevent distortion of parameters and statistical estimates. Outliers, defined as data points significantly deviating from the norm for a given variable or population (Osborne, 2014), were addressed using established methods informed by best practices in the literature (Aguinis et al., 2013; Dixon, 1953; Kwak & Kim, 2017; Osborne, 2014; Zygmont & Smith, 2014).

The reliability of the analysis was evaluated by examining the fit of the SEM model. Several fit indices, which measure how well the model aligns with the data, are summarized in Table C.7 (Ahmad et al., 2016; Cheung et al., 2024). Definitions of these indices, as outlined by Dash and colleagues (2021), are also included in Table C.7.

To establish a robust measurement model, its reliability and validity must be thoroughly evaluated before further analysis. Reliability is assessed using *composite reliability (CR)*, which aggregates the contributions of the indicators for each latent variable. A composite reliability value of 0.6 or higher is considered acceptable (Ahmad et al., 2016). Another critical metric is the *Average Variance Extracted (AVE)*, which should exceed 0.5 for each construct to confirm adequate reliability (Ahmad et al., 2016; Dash & Paul, 2021). Additionally, factor loadings for all indicators linked to a latent variable should surpass 0.4, demonstrating strong convergent validity (Cheung et al., 2024).

Interpretation of the structural part (path analysis) is based on the direct and indirect effects of demographic factors on the SSA Score presented below.

- The *Direct Effect* is represented by statistically significant direct path coefficients.
- The *Indirect Effect* is represented by the product of the statistically significant indirect path coefficients.
- The *Total Effect* is the sum of the direct and indirect effects if both are statistically significant. If only one of the two is significant, it becomes the total effect. If neither is statistically significant, then the total effect is 0.
- The *Mediating Effect* of the mediating variable (SED) is the percentage of the indirect effect on the total effect.

Table C.7. SEM Fitness Indexes

Index Name	Description	Level of Acceptance
Goodness of Fit Index (GFI)	Estimates the proportion of variance explained by the model's projected covariance.	> 0.90
Adjusted Goodness of Fit Index (AGFI)	Adjusts the GFI to account for degrees of freedom.	> 0.90
Normed Fit Index (NFI)	Compares the chi-square value of the model to a null model (model where all the measured variables are uncorrelated).	> 0.90
Tucker-Lewis Index (TLI)	Addresses NFI limitations by promoting simpler models and discouraging overcomplexity.	> 0.90
Comparative Fit Index (CFI)	Adjusts NFI to accommodate small sample sizes and focuses on latent factors instead of indicators.	> 0.90
Root Mean Square Error of Approximation (RMSEA)	Emphasizes parsimony by favoring models with fewer parameters while achieving optimal fit to the population covariance matrix.	< 0.08

After scoring the segments for all three case study cities, the descriptive statistics are presented below in Table C.8.

Table C.8. Descriptive Statistics of the SSA Scores

Descriptive Statistics	Cleveland, Ohio	Seattle, Washington	Austin, Texas
Mean Score	57.37	51.53	61.00
Standard Deviation	9.76	10.51	13.12
Median Score	55.50	48.00	62.50
Maximum Score	102.00	101.50	92.00
Minimum Score	34.75	33.25	20.00

Table C.9 presents the descriptive statistics of the SVI variables merged into the roadway segments, representing the socioeconomic and demographic characteristics of the respective roadway segments. From Table C.9, based on 2022 data, Cleveland had the highest poverty and unemployment rate, proportion of Blacks, proportion of persons with disability, and no access to the internet. Meanwhile, Seattle had the highest proportion of Asians and Whites and the lowest poverty rate. Lastly, Austin had the highest proportion of Hispanics.

Table C.9. Descriptive Statistics of SVI Variables

Variable	Statistic	Cleveland, Ohio	Seattle, Washington	Austin, Texas
Census tract and roadway segments				
Number of populated census tract		146	180	240
Number of roadway segments		6005	17075	2912
Number of roadway segments per census tract	Mean	41.13	94.86	12.13
	Max	194.00	375.00	61.00
	Min	1.00	1.00	1.00
	SD	26.82	63.79	10.21
Socioeconomic variables				
Percentage of persons below 150% poverty	Mean	45.54	12.33	17.74
	Max	93.40	80.10	85.70
	Min	4.60	1.90	0.50
	SD	16.69	8.88	13.65
Unemployment rate	Mean	12.58	3.59	3.98
	Max	44.20	11.30	15.60
	Min	0.00	0.30	0.40
	SD	8.69	2.03	2.60
Percentage of housing cost-burdened occupied housing units with annual income less than $75,000	Mean	37.44	22.44	27.46
	Max	66.30	81.70	78.00
	Min	11.10	6.20	0.00
	SD	10.49	8.86	12.17
Percentage of persons with no high school diploma	Mean	17.96	4.44	8.05
	Max	38.00	23.70	48.60
	Min	0.00	0.00	0.00
	SD	8.08	5.07	9.33
Percentage uninsured in the total civilian noninstitutionalized population	Mean	7.51	4.37	10.72
	Max	20.60	15.40	32.90
	Min	0.00	0.00	0.00
	SD	4.34	3.19	7.37
Demographic and household variables				
Percentage of Black/African American	Mean	42.14	6.05	6.91
	Max	100.00	34.80	38.70
	Min	0.90	0.00	0.00
	SD	32.93	6.70	7.00
Percentage of Hispanic	Mean	12.85	7.56	29.53
	Max	56.50	26.80	83.90
	Min	0.00	0.70	0.00
	SD	12.98	3.88	18.64
Percentage of Asian	Mean	2.86	14.88	7.59
	Max	37.70	53.90	59.30
	Min	0.00	1.40	0.00
	SD	5.50	10.02	7.29
Percentage of AIAN	Mean	0.10	0.36	0.12
	Max	2.30	4.70	2.40
	Min	0.00	0.00	0.00
	SD	0.25	0.72	0.29

Variable	Statistic	Cleveland, Ohio	Seattle, Washington	Austin, Texas
Percentage of NHPI	Mean	0.03	0.23	0.06
	Max	0.80	3.00	1.60
	Min	0.00	0.00	0.00
	SD	0.13	0.58	0.21
Percentage of White	Mean	37.26	63.51	52.07
	Max	92.40	85.60	93.70
	Min	0.00	10.50	5.10
	SD	25.05	16.41	19.74
Percentage of single-parent households	Mean	12.12	3.48	4.85
	Max	82.10	13.80	43.40
	Min	0.00	0.00	0.00
	SD	11.69	2.74	4.40
Percentage of disability	Mean	20.41	9.22	9.35
	Max	38.90	30.90	34.70
	Min	4.40	2.10	1.50
	SD	6.93	4.20	5.05
Percentage of crowded housing	Mean	1.48	2.96	3.84
	Max	15.50	30.20	24.20
	Min	0.00	0.00	0.00
	SD	2.07	3.13	4.04
Percentage of no internet	Mean	22.10	5.82	7.63
	Max	53.10	39.50	49.70
	Min	1.90	0.00	0.00
	SD	10.56	4.65	7.05

Appendix C.2: Structural Equation Modeling Results

This section presents the SEM analysis, which examines the relationship between socioeconomic disadvantage and roadway safety, as measured by the SSA Score. In this context, the SSA Score reflects the safety potential of road infrastructure, where lower scores indicate safer road conditions. This section includes discussions on model fitness, the adequacy of the measurement models, findings from the path analysis, and the mediating effects of socioeconomic disadvantage.

The SEM results for the three case study cities—Cleveland, Seattle, and Austin—illustrate the influence of socioeconomic and demographic factors on roadway segment safety. The SSA Score, which is used as an indicator of roadway alignment with Safe System principles, identifies segments that are less safe with higher scores. The analysis demonstrates that for each city, the SEM model achieves a good fit with the data, as indicated by model fit metrics within acceptable ranges, ensuring the reliability of the findings (Table C.10). Specific findings on the measurement and structural models for each case study city are presented next.

Table C.10. Overall SEM Fit Metrics

Metric	Criteria	Cleveland	Seattle	Austin
RMSEA	< 0.08	0.0438	0.0192	0.0436
GFI	> 0.95	0.9860	0.9967	0.9835
CFI	> 0.95	0.9871	0.9971	0.9860
NFI	> 0.95	0.9860	0.9967	0.9835
TLI	> 0.95	0.9815	0.9959	0.9800

Socioeconomic Disadvantage and Roadway Safety in Cleveland, Ohio

The measurement model for Socioeconomic Disadvantage (SED) was based on SVI's poverty (EP_POV150) and unemployment (EP_UNEMP) variables derived from ACS. Poverty demonstrated a high standardized factor loading of 0.9014, signaling its strong contribution to socioeconomic disadvantage, while unemployment also played a significant role with a loading of 0.6884. Together, these indicators explained approximately 64% of the variance in SED, with an AVE of 0.6431, suggesting that these indicators reliably represented SED. Additionally, the CR for SED was 0.7798, indicating satisfactory internal consistency.

Table C.11 presents the direct and indirect associations between demographic and socioeconomic factors and the SSA Score. Figure C.4 presents a schematic diagram of the SEM model associations and coefficients for the city of Cleveland. The influence of SED on the SSA Score itself is evident in Cleveland, with a positive significant effect of 0.1213. The table also highlights the substantial role of indirect effects mediated by SED in shaping the overall SSA Score. For example, the Hispanic population (EP_HISP) exhibited a positive indirect effect of 0.0373, fully accounting for its total effect. This suggests that the increased SSA Scores associated with Hispanic demographics are entirely mediated by socioeconomic disadvantage. Similarly, the African American demographic (EP_AFAM) showed an indirect effect of 0.0284, also constituting its total effect, indicating that SED adversely influences segments with a higher proportion of African American residents in terms of safety alignment.

For the White population (EP_WHITE), the indirect effect is a smaller negative value (−0.0695), which counteracts a positive direct effect, resulting in a total effect of 0.2101. This indicates that while segments with higher White demographics experience some alignment challenges, SED reduces the total effect by 33.08%, mitigating the overall impact on safety alignment.

Table C.11. Effect of Demographic Factors on the SSA Scores in Cleveland, Ohio

		Direct Effect (Path 1)		Indirect Effect (Path 2)		Total Indirect Effect (Path 2)	Total Effect
		Variable→SSA Score		Variable→SED		Variable→SED→SSA Score	DE + IE
Variable	Identifier	Coef.	*P*-value	Coef.	*P*-value	Coef.	Coef.
Disability	EP_DISABL	−0.0231	0.1642	0.1608	**0.0000**	0.0195	0.0195
Crowded Housing	EP_CROWD	−0.0326	**0.0168**	0.1269	**0.0000**	0.0154	−0.0172
African American/Black	EP_AFAM	0.0628	0.5626	0.2339	**0.0031**	0.0284	0.0284
Hispanic	EP_HISP	−0.0312	0.5023	0.3075	**0.0000**	0.0373	0.0373
Asian	EP_ASIAN	0.0987	0.**0000**	0.1050	**0.0000**	0.0127	0.1114
AIAN	EP_AIAN	0.0056	0.6772	0.0328	**0.0008**	0.0040	0.0040
NHPI	EP_NHPI	0.0318	**0.0147**	0.0329	**0.0005**	0.0040	0.0358
White	EP_WHITE	0.2796	**0.0010**	−0.5730	**0.0000**	−0.0695	0.2101
				SED→SSA Score			
Socioeconomic Disadvantage	SED	-	-	0.1213	**0.0000**		

***Note**: Coef. = Coefficient; Variables in bold are significant at the 95% confidence level.*

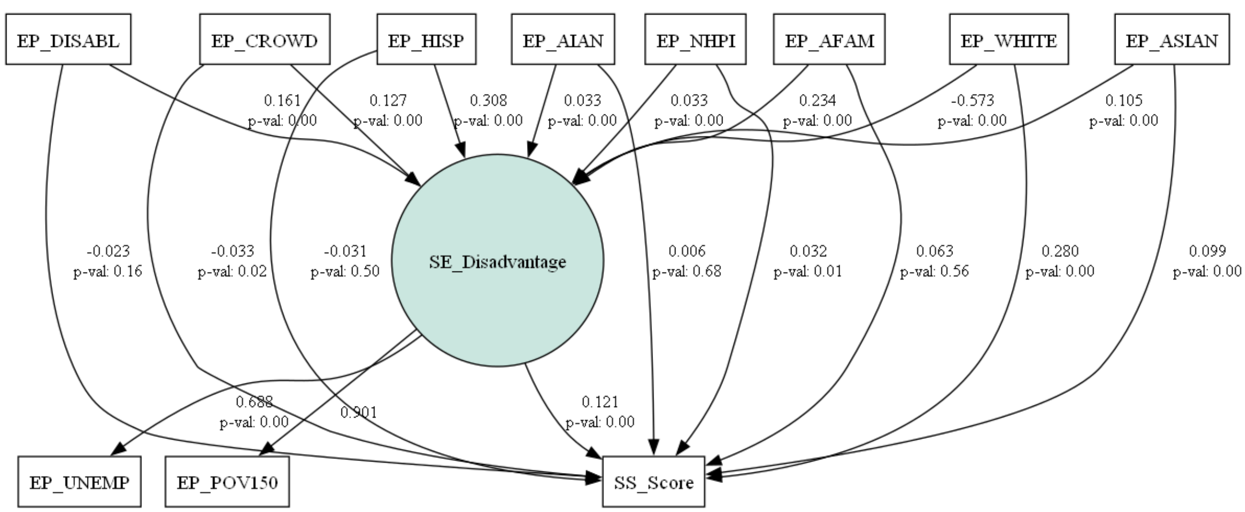


Figure C.4. SEM for Cleveland, Ohio

Examining the effects of other factors on SSA Score, the model shows that segments in areas with higher percentages of individuals with disabilities (EP_DISABL) experience a positive indirect effect on SSA Score via SED (0.0195), contributed 100% by SED, indicating that segments in these areas tend to have lower safety alignment due to socioeconomic factors. The direct effect was not statistically significant. Similarly, in segments associated with high percentages of crowded housing (EP_CROWD), there is a modest positive indirect effect on the SSA Score (0.0154), meaning that SED slightly elevates the SSA Score. However, the direct impact has a negative statistically significant effect.

Socioeconomic Disadvantage and Roadway Safety in Austin, Texas

The measurement of SED in Austin was represented by poverty (EP_POV150) and unemployment (EP_UNEMP), with poverty exhibiting a maximum standardized factor loading of 1.000, indicating it fully represents socioeconomic disadvantage. This construct showed moderate internal consistency, with an AVE of 0.6089 and CR of 0.7333.

The structural model for the city of Austin is presented in Table C.12 and schematically in Figure C.5. The analysis of Austin's SED and its relationship with safety alignment under Vision Zero has significant policy implications for equitable infrastructure improvements (Figure C.5). Austin's SED factor shows a strong inverse association with safety scores (SSA Score: −0.2702, $p < 0.001$), indicating that counterintuitively, economically disadvantaged segments are often better aligned with safety goals compared to similar areas in Cleveland and Seattle. For example, the Hispanic demographic has a positive indirect effect of 0.8670, offset by a total negative effect of −0.2342 when accounting for SED. Similarly, the African American demographic showed a positive indirect effect of 0.3118, yet the overall impact remained slightly negative at −0.0842.

Other demographics show varied influences on the SSA Score. Asian-majority segments (EP_ASIAN) exhibited a positive direct effect on the SSA Score (0.1260) mitigated by a negative indirect effect (−0.1001), leading to a slight overall misalignment. Finally, areas with a higher percentage of White residents (EP_WHITE) showed a substantial negative indirect effect (−0.1422).

Table C.12. Effect of Demographic Factors on the SSA Scores in Austin, Texas

Variable	Identifier	Direct Effect (Path 1)		Indirect Effect (Path 2)		Indirect Effect (Path 2)	Total Effect
		Variable→SSA Score		Variable→SED		Variable→SED→SSA Score	DE+IE
		Coef.	*P*-value	Coef.	*P*-value	Coef.	Coef.
Disability	EP_DISABL	−0.0535	**0.0188**	0.2470	**0.0000**	−0.0667	−0.1202
Single Parent Households	EP_SNGPNT	0.1502	**0.0000**	0.0071	0.6918	0.0000	0.1502
African American/Black	EP_AFAM	0.1010	0.0815	0.3118	**0.0000**	−0.0842	−0.0842
Hispanic	EP_HISP	0.2590	0.0695	0.8670	**0.0000**	−0.2342	−0.2342
Asian	EP_ASIAN	0.1260	**0.0373**	0.3705	**0.0000**	−0.1001	0.0259
AIAN	EP_AIAN	−0.0114	0.5322	0.1149	**0.0000**	−0.0310	−0.0310
NHPI	EP_NHPI	−0.0421	**0.0352**	0.0263	0.1423	0.0000	−0.0421
White	EP_WHITE	0.2303	0.1296	0.5263	**0.0001**	−0.1422	−0.1422
				SED→SSA Score			
Socioeconomic Disadvantage	SED	-	-	−0.2702	**0.0000**		

***Note**: Coef. = Coefficient; Variables in bold are significant at the 95% confidence level.*

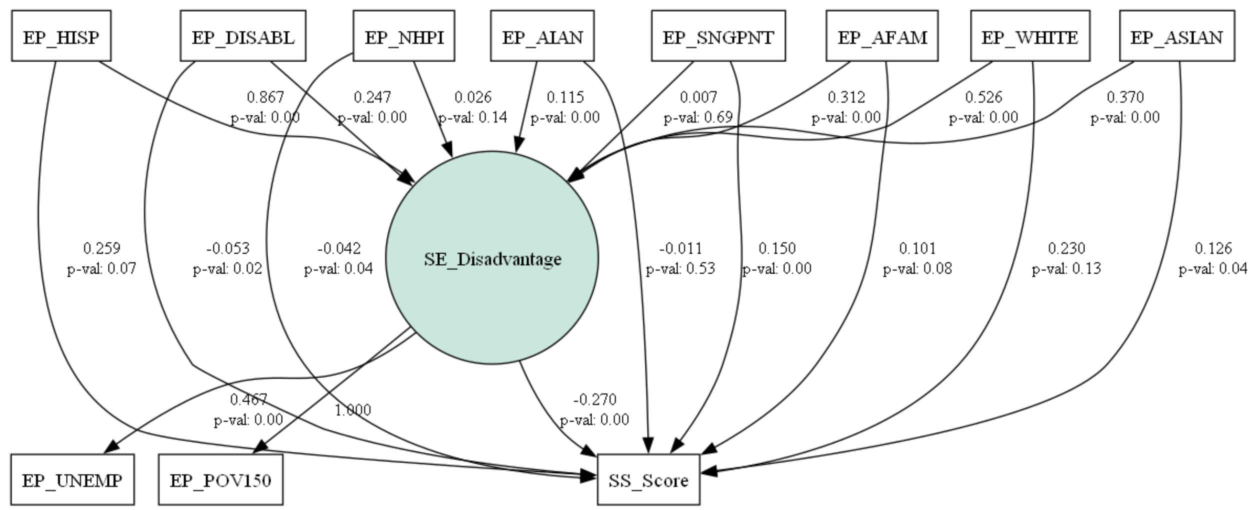


Figure C.5. SEM for Austin, Texas.

Socioeconomic Disadvantage and Roadway Safety in Seattle, Washington

For Seattle, the measurement of SED was also represented by indicators of poverty (EP_POV150) and unemployment (EP_UNEMP). Poverty had a high standardized factor loading of 0.9749, indicating it played a dominant role in the measure of SED, while unemployment, with a load of 0.4636, contributed slightly. Together, these indicators reflect moderate internal consistency for socioeconomic disadvantage in Seattle, as indicated by the Composite Reliability (CR) of 0.7126 and Average Variance Extracted (AVE) of 0.5826. The SEM results are in Table C.13, and the model's schematic is in Figure C.6 for Seattle. SED had a strong and significant positive effect on the SSA Score (0.2223), underscoring that segments in disadvantaged areas tend to have reduced alignment with safety objectives.

As shown in Figure C.6, SED exerts a notable influence on the total effects for several demographic groups. The African American demographic (EP_AFAM) exhibited a positive indirect effect of 0.0702, partially offsetting a negative direct effect, resulting in an overall total effect of −0.0493. This pattern suggests that SED intensifies the alignment challenge for segments with higher African American representation, though it also offsets some of the direct alignment issues. The Asian demographic (EP_ASIAN) had a total effect of 0.0350, 100% of which was contributed by the indirect effect through SED, suggesting that socioeconomic disadvantage positively impacts the alignment of segments with higher Asian presence with SSA objectives.

Analyzing the effects of other variables on the SSA Score for Seattle, segments in areas with high single-parent households (EP_SNGP) showed a strong negative direct effect on the SSA Score (−0.1204), indicating these segments are better aligned with safety objectives. However, a minor indirect positive effect (0.0304) through socioeconomic disadvantage raises the overall alignment score slightly, but still results in an improved total effect for alignment. Areas with a higher prevalence of households lacking internet access (EP_NOIN) showed a significant positive indirect effect on the SSA Score (0.4697), meaning segments in these areas are less aligned with safety objectives due to underlying socioeconomic challenges.

These results highlight how the combination of socioeconomic and demographic factors around segments correlates with safety alignment in Seattle. Roadway segments in disadvantaged areas or those with specific demographic characteristics, i.e., minority-majority populations or lacking internet access, may benefit from targeted safety interventions to achieve better alignment with safe system principles.

Table C.13. Effect of Demographic Factors on the SSA Scores in Seattle, Washington

Variable	Identifier	Direct Effect (Path 1)		Indirect Effect (Path 2)		Indirect Effect (Path 2)	Total Effect
		Variable→SSA Score		Variable→SED		Variable→SED→SSA Score	DE+IE
		Coef.	*P*-value	Coef.	*P*-value	Coef.	Coef.
Single-Parent Households	EP_SNGP	−0.1204	**0.0000**	0.0304	**0.0000**	0.0067	−0.1137
No Internet	EP_NOIN	0.0168	0.1157	0.4697	**0.0000**	0.1044	0.1044
African American/Black	EP_AFAM	−0.1195	**0.0000**	0.3158	**0.0000**	0.0702	−0.0493
Hispanic	EP_HISP	−0.0379	**0.0089**	0.0507	**0.0000**	0.0113	−0.0266
Asian	EP_ASIA	0.0400	0.1390	0.1576	**0.0000**	0.0350	0.0350
AIAN	EP_AIAN	0.0096	0.2617	0.1902	**0.0000**	0.0423	0.0423
NHPI	EP_NHPI	−0.0129	0.1448	−0.1443	**0.0000**	−0.0321	−0.0321
White	EP_WHITE	−0.0708	0.1068	0.0009	0.9754	0.0000	0.0000
				SED→SSA Score			
Socioeconomic Disadvantage	SED	-	-	0.2223	**0.0000**		

***Note**: Coef. = Coefficient; Variables in bold are significant at the 95% confidence level.*

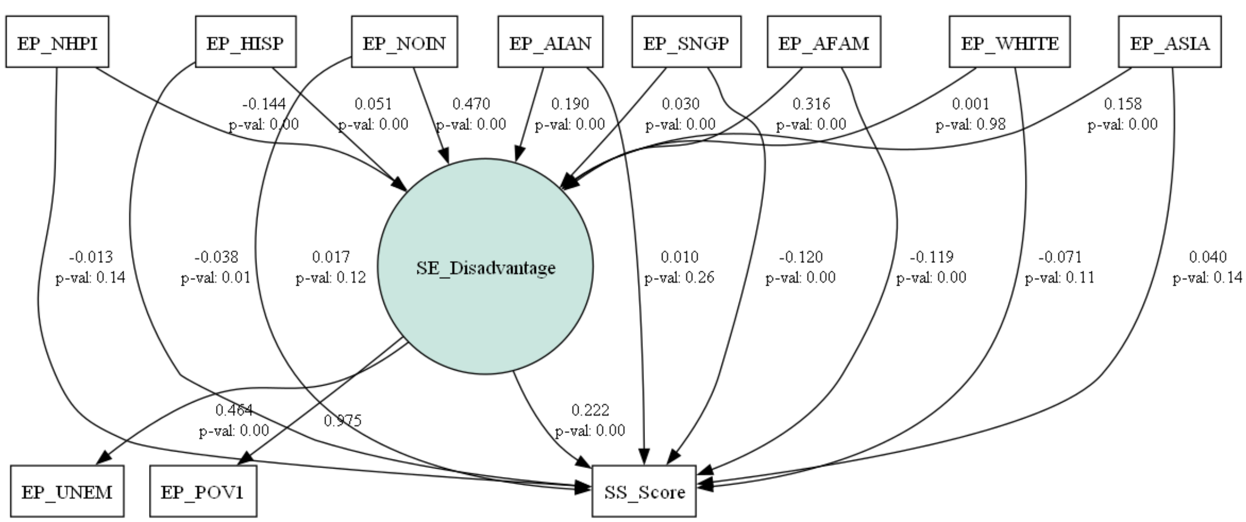


Figure C.6. SEM for Seattle, Washington