VULNERABLE ROAD USERS
TECHNICAL REPORT

FOUNDATION FOR TRAFFIC SAFETY

Examining Traffic Safety Across Communities: A National Perspective and Case Studies in Arizona, Maryland, North Carolina, and Oregon

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Title

Examining Traffic Safety across Communities: A National Perspective and Case Studies in Arizona, Maryland, North Carolina, and Oregon

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Foreword

Traffic crashes cause substantial physical, psychological and economic burdens whenever they occur. While it is well known that there is an unequal distribution of this burden across communities, less is known about factors that contribute to disparities or practical ways for transportation professionals to address them. The AAA Foundation for Traffic Safety commissioned this work to inform approaches aimed at achieving safer mobility for all road users.

This report reviews the current state of knowledge on disparities in traffic safety across multiple U.S. communities, explores the relative influence of different contributing factors nationally and in four states, and collects perspectives from key stakeholders regarding potential countermeasures. Recommendations consider the Safe System approach to provide practical and evidence-based solutions to improve traffic safety. This report should be of interest to transportation policy makers, researchers, advocates, and practitioners interested in promoting safe mobility across all communities.

C. Y. David Yang, Ph.D.

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About the Sponsor

AAA Foundation for Traffic Safety
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List of Abbreviations and Acronyms

ACIS	Arizona Crash Information System
ADI	Activity Diversity Index
ADOT	Arizona Department of Transportation
BIPOC	Black, Indigenous, and People of Color
DEA	Data envelopment analysis
DMU	Decision Making Unit
EMS	Emergency Medical Services
FARS	Fatality Analysis Reporting System
FHWA	Federal Highway Administration
NCDOT	North Carolina Department of Transportation
NEMSIS	National Emergency Medical Services Information System
NHTSA	National Highway Traffic Safety Administration
NOS	Not Otherwise Specified
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
SHAP	Shapley Additive exPlanations
SLD	Smart Location Database
SVI	Social Vulnerability Index
TIGER	Topologically Integrated Geographic Encoding and Referencing
TRB	Transportation Research Board
TRID	Transport Research International Documentation

Executive Summary

Background

Road safety continues to pose a public health challenge in the United States, with persistent disparities in crash outcomes across diverse demographic and geographic groups. These disparities are influenced by a combination of historical developments in transportation infrastructure, uneven resource allocation, and long-standing policy decisions. In addition, sociodemographic factors such as gender, sex, age, race, and socioeconomic status often interact in complex ways that may affect individuals' exposure to risk and severity of injury in traffic crashes. Understanding these relationships is critical for identifying at-risk populations and informing equitable strategies that improve safety outcomes for all communities. Together, these components provide a foundation for understanding where disparities exist, why they persist, and how they can be addressed through targeted, equity-centered solutions.

This study examines and addresses disparities in traffic safety through three primary objectives. It begins by identifying and analyzing differences in traffic safety outcomes across various sociodemographic and socioeconomic groups. Next a comprehensive quantitative analysis explores the interconnected sociodemographic, infrastructural, and systemic factors that may contribute to these disparities. Finally, the study develops targeted policy recommendations and solutions based on both interview data and quantitative analysis, with the goal of promoting more comprehensive safety outcomes. These proposed interventions may help reduce the most significant disparities while also offering broader benefits to all road users.

Methods

The study framework consists of three main components: a review of existing literature to establish context, a quantitative analysis to identify and measure disparities, and a qualitative assessment that uses interviews to gain deeper insights and inform policy recommendations. The quantitative and qualitative analyses are conducted at the national level and in four states: Arizona, Maryland, North Carolina, and Oregon.

The literature review focused on studies examining crash disparities across various sociodemographic and socioeconomic groups in the United States, primarily covering the years 2019 to 2024, and was further divided into crashes involving motor vehicles, pedestrians, and bicyclists. The quantitative analysis began by analyzing crash rates nationally and within the four selected states, disaggregated by sex, age group, and race for drivers, pedestrians, and bicyclists. Crashes were mapped to geographic boundaries using an area-based method. To identify crash risks, double-bootstrap data envelopment analysis and machine learning models were applied at the county level nationwide and the census tract level in four selected states. Finally, interviews were conducted with individuals from federal and state agencies, industry, and the academy to explore underlying factors contributing to these disparities and possible policy interventions.

Results

The study revealed significant variations in traffic safety outcomes across demographic groups and geographic regions. Nationally, male fatality rates were approximately 3.5 times higher than female rates per 100,000 population, with notable state-by-state differences observed across the United States. American Indian and Alaska Native (Native American) populations experienced the highest fatality rates among racial groups, while Arizona consistently showed higher pedestrian and bicyclist fatality rates across nearly all demographic categories compared to both national averages and other benchmark states (Oregon, Maryland, and North Carolina).

Data envelopment analysis results indicated that crash risks and injury severity patterns differ substantially by both demographic composition and geographic location. While higher poverty rates were consistently associated with higher crash risks, other variables such as racial characteristics differed across state- and national-level findings. In Arizona, higher proportions of White, Black, and Hispanic residents were linked to greater risks. In Maryland, risks rose with Black, Asian, Hispanic, and multiracial populations, while White populations experienced safer outcomes. In Oregon, risks were higher in areas with more White, Asian, Hispanic, and multiracial residents, but lower in areas with higher Black and Pacific Islander residents. Machine learning analysis confirmed that no single demographic group or community maintained consistently higher or lower risk levels across all regions, with injury severity and crash-related costs showing strong regional dependence.

Qualitative findings highlighted data limitations related to tribal communities and emphasized the importance of community-centered engagement approaches. The interview findings also revealed institutional biases toward motorist safety in transportation planning practices, along with the compounded challenges faced by lower-income communities. These populations frequently experience both deficient transportation infrastructure and greater reliance on higher-risk transportation modes, creating a dual disadvantage in traffic safety outcomes.

Conclusions

Data and interviews from this study reveal persistent, place-based disparities in traffic safety, highlighting the complex interplay of demographic, geographic, and socioeconomic factors that shape outcomes across population groups and regions. The findings emphasize the need for community-tailored interventions that account for localized risk patterns while addressing systemic challenges. By combining diverse analytics and data-driven information with meaningful community engagement, transportation agencies can develop more effective safety strategies that prioritize high-risk populations and generate solutions that create safer outcomes for all road users.

This study highlights the potential to move from traditional standardized approaches toward more nuanced and targeted solutions, underscoring the importance of sustained stakeholder collaboration, culturally responsive planning, and strategic infrastructure investments in underserved communities with the greatest need. These insights offer guidance for policymakers aiming to align equity objectives with practical measures to improve safety for all road users, including through targeted infrastructure investments, revised decision-making standards, and community-driven planning approaches. The findings also underscore the need to identify and address gaps in data that may obscure disparities or limit the effectiveness of safety interventions.

Introduction

The landscape of surface transportation in the United States bears the enduring imprint of historical inequities, which have shaped transportation infrastructure, funding, education, and policies (Fry et al., 2020). These deeply-rooted disparities, stemming from practices like redlining and policy biases, have fostered systemic and intersectional inequalities across communities and demographic groups (Schell et al., 2020). In 2023, 40,901 people were killed in traffic crashes across the U.S. (National Highway Traffic Safety Administration [NHTSA], 2024) and evidences indicate that underserved communities are more prone to such crashes (Chimba et al., 2018). Due to systematic and intersectional inequities and other contributing factors, traffic safety is not experienced at similar levels across different communities and demographic groups (Glassbrenner, 2022). Research looking into sociodemographic differences in crash injury severity outcome is well documented with research showing crash risks differing by sex (Ryan, Tainter, et al., 2022), age groups (Edwards & Leonard, 2022), race and ethnic groups (Johnson et al., 2019), and socioeconomic status (Yocum & Gayah, 2022). In recent years, more safety studies have also begun to include more extensive demographic variables across different road user types in their analyses to ensure more equitable designs and policies (Hurwitz et al., 2023). Research has also linked the built environment to traffic safety (Merlin et al., 2020), highlighting the need for a comprehensive understanding of how exposure intersects with sociodemographic factors. Different population groups often reside in areas with distinct built environments that shape their exposure to crash risks (Ulak et al., 2025).

The observed disparities in crash outcomes stem from the complex interplay of multiple interconnected factors. Key determinants include sociodemographic characteristics, racial and ethnic disparities, behavioral differences across population groups, and socioeconomic inequalities. These inequities are further compounded by intersecting variables such as age, educational attainment, geographic location, gender identity, disability status, and cultural background (Anderson & Galaskiewicz, 2021; Holler et al., 2021; Morris et al., 2020; Smith et al., 2021). A comprehensive analytical approach that examines how key demographic factors including gender, sex, age, race, and socioeconomic status impacts crash occurrence and injury severity is essential for understanding how sociodemographic characteristics influence traffic safety risks (Babaei et al., 2022). This multidimensional perspective is particularly important because single-factor analyses often fail to capture the complex ways these characteristics intersect to affect traffic safety. By considering how these elements interact, transportation professionals can better identify vulnerable populations and develop more targeted safety interventions that can in turn benefit all individuals and communities.

This study develops and demonstrates an integrated framework to examine the influence of sociodemographic factors on traffic safety outcomes through multiple analytical approaches. Statistical significance testing analyzes crash rate disparities across sex, race, and age groups. Data envelopment analysis (Simar & Wilson, 2007) is applied to evaluate how sociodemographic and socioeconomic factors affect crash risk while accounting for exposure through road mileage and population size. Machine learning models are used to identify correlations between sociodemographic characteristics and both injury severity outcomes and associated costs at census tract and county levels. Following, interviews with transportation agency officials and organizational representatives investigate the policy implications of these disparities and how equity considerations are incorporated into transportation planning and safety interventions.

Research Objectives

This study systematically examines and addresses equity disparities in traffic safety through three key objectives:

1. **Characterize Traffic Safety Disparities**: Identify and analyze inequities in traffic safety outcomes across racial, ethnic, educational, socioeconomic, and demographic dimensions including race, age groups, gender, sex, and geographic region. This objective seeks to answer the core question: *What traffic safety disparities are experienced by different groups of people?*
2. **Determine Contributing Factors**: Investigate the intersecting sociodemographic, infrastructural, and systemic factors that drive observed disparities, recognizing that identity groups are multidimensional and overlapping. This objective seeks to answer the core question: *What factors explain these disparities and how do they interact across subgroups?*
3. **Identify Targeted Solutions**: Propose solutions and policy changes obtained from interviews and quantitative findings to advance equitable safety outcomes. This objective seeks to answer the core question: *What policies or interventions can reduce the largest disparities?*

These three objectives integrate quantitative analysis of disparities, qualitative investigation of contributing factors, and the development of targeted, actionable solutions to address traffic safety inequities in a comprehensive and evidence-driven manner. The policies and interventions are designed to benefit not only the identified target populations but also the broader community. By focusing on solutions that improve safety for the most vulnerable groups, these efforts ensure that positive impacts extend across the entire population.

Research Scope

This study focuses exclusively on physical safety outcomes in surface transportation, analyzing crash frequency and severity. The investigation is limited to these measurable safety metrics and does not address other safety-related factors such as personal security or harassment. Additionally, while the research examines sociodemographic disparities in crash outcomes, it does not evaluate broader transportation equity dimensions such as accessibility, affordability, or mobility justice.

Terminologies

Transportation equity and social justice generally refer to the fair distribution of the benefits and burdens of transportation systems across different populations and geographies, with a central concern for how access, mobility, and negative externalities are experienced by different marginalized communities (Karner & Niemeier, 2013; Pereira et al., 2017). It involves questions of "equity of what," "for whom," and "how much," with access to opportunities often identified as the core benefit (Karner et al., 2020). In this research, equity is defined as a condition in which crash-related risks, including injury severity and crash occurrence, do not differ across sociodemographic groups or communities. Throughout this document, terminology used to describe racial and ethnic groups reflects common usage in research and official reporting. Because different agencies and organizations use varying terms in their data, some labels are used interchangeably in this report to refer to the same population groups. For example, "Black" and "African American," "Hispanic" and "Latino/a," and "American Indian or Alaska Native" and "Native American" are used interchangeably; however, for the sake of clarity, the labels used in this report have been standardized to Black, Hispanic, and Native American.

Literature Review

A systematic literature review was conducted to examine the influence of social equity factors, which included gender, sex, age, race, ethnicity, socioeconomic status, and other impacting factors, including infrastructure and geography, on road safety. Searches were carried out in Scopus, ScienceDirect, Taylor & Francis, and Transport Research International Documentation (TRID), following Transportation Research Board (TRB) recommendations (Avni et al., 2015) and Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) reporting guidelines (Page et al., 2021). The search of literature was confined to U.S.-based studies published between 2019 and 2024 focused on aspects of transportation safety related to crashes and excluded other transportation safety concerns such as harassment or comfort. Additional literature sources were identified through the snowballing method, where articles cited within the initially selected studies were systematically reviewed to uncover relevant references. After screening and removing duplicates, a total of 353 studies were selected for review, out of an initial pool of 454, based on their alignment with the core concept of equity in transportation safety.

The literature review identified articles across three modes: motor vehicles, pedestrians, and bicycles/motorcycles, and across six factors: gender and sex, race and ethnicity, age, socioeconomic status, infrastructure, and geography. The following subsections summarize the key findings from the literature review, highlighting the relevant studies and insights.

Motor Vehicles

Existing literature has extensively explored disparities in injury rates and severity across genders and sexes. While sex (biological attributes) and gender (sociocultural roles) are distinct concepts, many studies conflate the two, primarily analyzing differences between male and female populations without accounting for gender-related influences, nor specifying in the data which factor the authors are referring to. As a result, it remains challenging to disentangle the effects of biological sex from gender-related influences in these analyses, limiting one's ability to accurately assess disparities. Therefore, this distinction is not addressed separately in this review.

Empirical evidence suggests a higher incidence of severe and fatal injuries among males relative to females. Additionally, males tend to be overrepresented in crash-related incidents compared to their female counterparts. Nickkar et al. (2024) found that the likelihood of severe injuries was higher among male drivers, and this risk increased further with age. Jashami et al. (2023) examined contributing factors to right-turn crashes at signalized intersections using five years of Oregon crash data and findings revealed that male drivers exhibited a significantly higher risk of severe crashes when executing right turns at signalized intersections.

Other studies have identified that females have a higher risk for crash occurrence and injury severity outcome in similar crash conditions (Ryan, Tainter, et al., 2022). However, this is crash-type dependent in some cases; for example, while female drivers show higher involvement in single-vehicle run-off-road crashes compared to males, they experience lower rates of fatal/severe injuries in such events (Duddu et al., 2020). Longitudinal analysis of 1975–2010 crash data revealed that females sustain greater injury severity in crashes of equivalent magnitude (Kahane, 2013). Ryan, Tainter, et al. (2022) identified distinct injury patterns between sexes in comparable crashes, with female drivers more frequently sustaining abdominal, chest, neck, and lower extremity injuries, while male drivers more often had no injury or general/back injuries. Ryan and Knodler (2022) further found these patterns held for angle and rear-end crashes, with females consistently less likely to avoid injury regardless of airbag deployment. Although airbags reduced injuries for both sexes, females remained at greater risk of injury than males in equivalent crash scenarios.

Concerning racial disparities, Haggerty et al. (2021) found that Black residents in Multnomah County, Oregon, experienced nearly double the traffic fatality rate of White residents from 2013 to 2017. Johnson et al. (2019) determined that in comparison to all other races, people who are White were less likely to be involved in motor vehicle crashes. Haddad et al. (2024) reported that Black individuals had a lower risk of potential, non-incapacitating, and serious injury crashes than White people. Discrepancies in crash race reporting were evident in Lombardi and colleague's (2022) analysis, which revealed greater representation of Black and Hispanic individuals in hospital records compared to crash reports (36.7% vs. 46.0% White representation). Dumbaugh et al. (2020) observed racial differences in crash risk primarily in lower-income areas, with disparities diminishing in wealthier neighborhoods. Patwary et al. (2024) likewise explored the connection between traffic safety and disadvantaged communities and found that a higher proportion of Black and Native American individuals were linked to a greater frequency of fatal crashes compared to other groups.

In analyzing injury severity across age groups, minors (generally under 18 years of age), and seniors (generally 65 years of age or older) exhibited a higher propensity for experiencing severe crash outcomes compared to those between these age groups. Individuals at the lower end of the minor age range, aged 15 to 17, reported the highest rate of crash involvement (Edwards & Leonard, 2022). While younger drivers exhibited elevated crash rates, those aged 20 and below demonstrated a reduced likelihood of severe injury or fatality crashes, whereas individuals aged 75 and older showed an increased likelihood of such severe outcomes (Yocum & Gayah, 2022). In studies relating age groups and crash hotspots, the minor age group exhibited fewer identified hotspots compared to other age groups, with most occurrences observed during midday off-peak hours. Yet, they still demonstrated a higher probability of crash involvement compared to the mid-aged group (Kocatepe et al., 2019; Mafi et al., 2019). Concerning the mid-aged group, the largest number of hotspots also occurred during mid-day off-peak hours (Mafi et al., 2019). Conversely, the senior age group showed fewer hotspots than the mid-aged group, yet it experienced a higher frequency of severe injury crashes during daytime hours (Kocatepe et al., 2019; Mafi et al., 2019).

Research demonstrates a clear association between socioeconomic factors and motor vehicle crash outcomes. Gu et al. (2022) discovered that the median household income of drivers' domiciles significantly impacts the likelihood of at-fault crashes in interchange crashes. Liu et al. (2024) identified spatial correlations between contributing elements such as demographics, traffic exposure, road attributes, and crash rates and observed that areas characterized by a higher number of low-income workers, increased employment, greater household diversity, and a higher percentage of households without cars generally exhibit higher frequencies of crashes. Yocum et al. (2022) found that Pennsylvania counties with lower socioeconomic status (higher poverty/unemployment) experienced more fatal and injury crashes than wealthier counties. Additionally, Okaidjah et al. (2023) observed that median income serves as a socioeconomic factor associated with an increase in the frequency of intersection crashes. Concerning poverty rates, Roberts et al. (2021) found that higher poverty rates were significantly linked to an increased frequency of crashes among participants during the first 12 months after obtaining their license.

Pedestrians

Studies have also investigated variations in pedestrian crash involvement and injury severity across sociodemographic and socioeconomic groups. Study results have identified elevated risks for male pedestrians, particularly in unlit non-intersection areas during weekend nights (Hossain, Sun, Thapa, et al., 2023) and among distracted middle-aged male pedestrians on poorly-lit road segments (Hossain et al., 2024). Their work also established higher overall pedestrian crash involvement rates for males at both crossings and mid-block locations. Li and Fan (2022) further quantified these differences, finding males had a 60.4% greater likelihood of sustaining incapacitating injuries despite lower fatality rates compared to females. In another study, the results indicated that young female pedestrians (15–24 years) walking against traffic flow were associated with more severe pedestrian crashes (Hossain, Sun, Zafri, and Codjoe, 2023).

Raifman and Choma (2022) analyzed racial and ethnic disparities in traffic fatality rates using exposure adjusted metrics based on person-miles traveled. They found that fatality rates while walking were more than twice as high for Black individuals compared to White individuals, with Hispanic individuals also experiencing elevated rates. These disparities persisted across modes but were especially severe in vulnerable modes such as walking and cycling. Yu et al. (2022) demonstrated that areas with higher proportions of Black, Indigenous, and People of Color (BIPOC) and low-income residents experience significantly greater numbers of pedestrian–vehicle crashes, particularly fatal and injurious ones, with no statistically significant variations in no-injury crashes.

Dumbaugh et al. (2024) observed that pedestrian crashes in Black neighborhoods exhibit the highest rates of fatality and injury outcomes, irrespective of affluence. Furthermore, Glassbrenner (2022) found Asian pedestrians accounted for 29% of fatalities while walking 50% more than White pedestrians, with Hispanic individuals showing similar fatality rates to White individuals despite 30% more walking. Edwards and Leonard (2022) highlighted disparities in pedestrian crash victims, noting that White seniors were significantly overrepresented as victims in pedestrian and bicycle crashes; although White individuals comprised approximately 47% of overall cases, they accounted for more than 57% of crashes involving seniors. Similarly, Black individuals were identified as overrepresented among pedestrian and bicycling crash victims.

Empirical evidence suggests that age plays a factor in injury severity with younger (less than 26 years of age) and middle-aged (26 to 65 years of age) pedestrians having a significantly lower risk of crashes than those in the older age group (Kakhani et al., 2024). Older adults were shown to experience more severe injuries in pedestrian crashes, with studies indicating that crash severity increases with age. The elevated risk of serious injuries or fatal outcomes was especially noted among 55+ groups (Kakhani et al., 2024). Children's pedestrian safety was also identified as a significant concern, underscored by the tragic statistic of 922 children aged 7–12 killed in pedestrian crashes between 2012 and 2021 (Schwebel et al., 2024).

Regarding crash severity and outcome differences across socioeconomic groups, Zhu et al. (2023) conducted a comprehensive analysis coupling the driver and pedestrian/bicyclist involved in the same incident to gain deeper insights into the socioeconomic and demographic characteristics of both parties, alongside the geographical distribution of these crashes and contributing factors. Their findings revealed that crashes involving low-income drivers and BIPOC victims were more likely to occur in areas with increased pedestrian/bicyclist exposure, higher speed limits, and wider roads. Younes et al. (2023) explored the association between minority and low-income communities and non-motorist crashes, uncovering a disproportionate occurrence of non-motorist crashes in these populations. Additionally, Tokey et al. (2023) identified urban areas, regions with low median incomes, fewer seniors, and a higher mix of Black, White, and Hispanic residents as significantly linked to increased occurrences of non-motorist crashes. Soto et al. (2022) revealed a strong correlation between the proportion of individuals earning less than $30,000 annually and the prevalence of households without a vehicle with pedestrian crashes. Moreover, they noted that an increase in the fraction of households without a vehicle corresponded to a rise in the likelihood of pedestrian crashes. Another study by Haule et al. (2019) observed that individuals in low-income areas were more likely to experience crashes at greater distances from their residences. Additionally, they found that higher residential property values were linked to a lower probability of elderly pedestrian crashes occurring close to home. Lastly, Guerra et al. (2020) examined the association between pedestrian crashes and neighborhood socioeconomic status, finding increased pedestrian crashes in neighborhoods with lower socioeconomic status and a higher proportion of Black residents during both weekdays and weekends.

Bicycles and Motorcycles

Studies highlight significant differences in bicycle and motorcycle crash outcomes across sociodemographic groups. Lu et al. (2022) found that male and alcohol-impaired drivers cause more severe cyclist injuries, while Dong et al. (2019) found that male non-motorists, compared to female non-motorists, were significantly more likely to experience higher injury severity in pedestrian-involved crashes. However, this gender difference was not statistically significant in bicyclist-involved crashes, suggesting that the effect of gender on injury severity is more evident among pedestrians than cyclists. Shah et al. (2021) reported higher male involvement in cyclist–vehicle crashes, while finding that females were more involved in e-scooter crashes. Males generally face greater risks of fatal or minor cycling injuries (Lin & Fan, 2021b, 2021a), though the same studies also found that male cyclists were 21.21% less likely than female cyclists to experience possible injuries at non-intersection locations, potentially due to differences in physical condition, reaction time, and riding behavior between genders. Motorcycle literature revealed male dominance in fatalities and spine injuries (Allen et al., 2022). Conversely, some studies have indicated that female cyclists exhibit higher serious injury rates in traffic crashes (Alnawmasi & Mannering, 2023; Liu et al., 2020, 2021), with female e-bike riders more prone to braking failures due to hand positioning (Chai et al., 2022). Das et al. (2023) observed that male cyclists more frequently are left uninjured.

Analyzing racial disparities, Dadashova et al. (2022) analyzed crash data from 2010 to 2017 to examine how equity-related factors relate to bicycle crash outcomes. They found that block groups with a higher percentage of Black residents experienced increases in both fatal/injury and property damage only bicycle crashes, with fatal/injury crashes increasing by 1.2% and property damage only crashes by 1.1% per unit increase in the Black population. This suggests a slightly stronger link between Black population concentration and more severe crash outcomes. Glassbrenner et al. (2022) observed that while Asian cyclists had higher cycling rates than Black, Hispanic, and Native American individuals, they exhibited the lowest traffic fatality rate per 100 million miles cycled among all race and ethnicity groups. Additionally, Das et al. (2023) found that White bicyclists had an increased risk of minor injuries but decreased likelihood of severe and no injury outcomes. Furthermore, Hosseini et al. (2022) analyzed cyclist injury outcomes in California using yearly models from 2012 to 2017, identifying consistent racial and ethnic disparities. Black cyclists were associated with a reduced likelihood of experiencing no injuries in most annual models (2013, 2014, 2015, 2016, and the pooled 2012–2017 model). Hispanic cyclists were linked to an increased likelihood of sustaining severe injuries in the 2015 and 2016 models. White cyclists were also associated with a lower probability of experiencing no injuries in multiple models (2012, 2014, 2015, 2017, and the pooled model). Meanwhile, Braun et al. (2021) found that White and Asian bicyclists were associated with lower fatality risk, while Hispanic individuals were associated with higher fatality risk.

Research consistently demonstrates that socioeconomic factors significantly influence bicycle and pedestrian crash risks. Dadashova et al. (2022) revealed that the frequency and severity of bicyclist crashes were higher in low-income and racially diverse communities. Younes et al. (2023) identified that cyclists involved in crashes in impoverished areas face an elevated risk of fatality, indicating a stark disparity in safety outcomes based on economic circumstances. Adding depth to the discussion, Mahmoud et al. (2021) highlighted how the increase in the proportion of the population below the poverty line contributes to more vulnerable users on the road, leading to increased bicycle crashes. Expanding on these insights, Gehrke et al. (2023) found a correlation between a rise in the percentage of households earning less than $75,000 annually and a higher probability of bicycle-related crashes within certain geographical areas. Mahmoudi et al. (2023) observed a correlation between increased pedestrian and bicycle crashes at intersections and a higher proportion of low-wage workers and households lacking access to private vehicles within the census block group. Their findings suggest that reliance on alternative transportation modes may amplify crash risks, leading to a heightened incidence of pedestrian and bicycle crashes at intersections. Lee et al. (2020) discovered that a higher percentage of households below the poverty line correlates with an increased probability of bicycle fatal crashes, particularly in models incorporating bicycle miles and bike hours. Contrarily, in models integrating bicycle miles and hours, the fraction of households below the poverty line exhibited a favorable effect on other crash rates, indicating a complex relationship between poverty and crash outcomes. Rebentisch et al. (2019) noted the highest pedestrian/bike collision rates in the poorest New York City boroughs (excluding Manhattan) and disparities in protected bike lane installations, which were least likely in wealthier areas.

Summary of Literature Review

The comprehensive literature review presented here sheds light on the intricate relationship between social equity factors and road safety outcomes in the United States. Through rigorous analysis of research spanning multiple dimensions of equity, the literature review identifies significant disparities and underlying determinants influencing transportation safety. Research shows clear disparities in motor vehicle, pedestrian, bicycle, and motorcycle crash involvement and severity across sex, race, age, and socioeconomic status. Males generally face higher risk across all modes, though females sometimes experience more severe outcomes. Racial and ethnic minorities particularly Black, Hispanic, and Native American populations are consistently overrepresented in crash data. Low-income and disadvantaged communities also exhibit significantly higher crash rates and injury severity. Age plays a key role, with older adults more susceptible to severe outcomes and younger age group identified as a particularly vulnerable group.

The existing literature on road safety equity presents several limitations that hinder a comprehensive understanding of disparities. A primary concern is the frequent conflation of biological sex and sociocultural gender in crash analyses. Most studies do not distinguish between these concepts, making it difficult to identify whether observed differences are due to physiological factors or socially influenced behaviors. This lack of clarity limits the development of targeted interventions.

Research also often overlooks the complex interactions between exposure, infrastructure, and sociodemographic characteristics. While disparities in crash outcomes are well-documented, few studies explore how these factors mediate safety outcomes relative to actual exposure and infrastructure. As a result, it remains unclear whether certain communities face higher crash burdens due to elevated risk or systemic inequities in the built environment. Spatial analysis within the field remains inconsistent. Studies tend to focus either on large-scale regions or highly localized areas, with limited integration across scales. This fragmented approach limits the ability to generalize findings or conduct meaningful cross-jurisdictional comparisons. Additionally, there is a notable absence of longitudinal research that tracks how safety risks change over time, especially in response to policy or infrastructure changes affecting vulnerable populations.

Methodologically, the field is reliant on quantitative approaches, which often overlook the contextual and lived experiences influencing safety outcomes. Few studies incorporate qualitative insights to enrich or validate statistical findings. Moreover, evaluations of whether safety interventions benefit all demographic groups equitably are rare, leaving decision-makers with limited guidance for equitable policy design.

Selected Literature Review Findings

Motor Vehicles

- **Males:** Higher severe/fatal crash rates.
- **Females:** More severe injuries in similar crashes (e.g., neck/abdominal vs. male back injuries).
- **Race:** Black individuals face higher fatality rates; disparities worsen in low-income areas.
- **Age:** Minors (15–17) and seniors (65+) at highest risk.
- **SES:** Lower income = more crashes.

Pedestrians

- **Males:** More nighttime crashes.
- **Seniors/kids:** Higher fatal injury risk.
- **Race:** Black/Hispanic pedestrians face two times higher fatality rates than White pedestrians.
- **SES:** Low-income areas have more deadly crashes, often on high-speed roads.

Bicycles & Motorcycles

- **Males:** More fatalities.
- **Females:** Higher severe injury risk in e-bike crashes.
- **Race:** Black/Hispanic cyclists more likely to sustain severe injuries.
- **SES:** Poorer areas = more frequent/severe cyclist crashes.

Methodology

The next component of this study conducted a quantitative analysis integrating equity and safety metrics to characterize traffic safety disparities and to examine contributing factors. This was complemented by expert interviews to contextualize the findings and to identify targeted recommendations.

Quantitative Analysis

The quantitative analysis comprised four distinct components. First, crash rates were analyzed across sex, age, and race for drivers, pedestrians, and bicyclists. Second, chi-square tests were employed to examine whether injury severity varied substantially across sex and age groups. Not all case study states collected race information in state crash databases, therefore analyses did not examine injury severity by race. Third, a double bootstrapping data envelopment analysis model was implemented using road miles and population as inputs. Lastly, two types of machine learning models were developed: one to identify sociodemographic and socioeconomic factors associated with higher injury severity, and another to examine the factors linked to higher crash costs at the county and census tract levels.

Study Area and Datasets

This study employed a multi-level geographic approach, conducting analyses at both national and state levels. Nationally, the research examined patterns across U.S. counties, while state-level investigations focused on census tract analyses within four representative states: Arizona, Maryland, North Carolina, and Oregon. Numerous datasets were explored and analyzed for which results are presented in the main text of this report and appendices. Table 1 represents the different datasets used in this study.

Table 1: Datasets used in the study.

Dataset Type	Dataset Name	US	AZ	MD	NC	OR
	Fatality Analysis Reporting System (FARS)	✓				
	Arizona Crash Information System (ACIS)		✓			
Crash	Maryland Crash Data			✓		
	Oregon Crash Data				✓	
	North Carolina Crash Data					✓
Infrastructure	CENSUS TIGER/Line Shapefile	✓	✓	✓	✓	✓
	American Community Survey (ACS)	✓	✓	✓	✓	✓
Demographics	LEHD Origin-Destination Employment Statistics	✓	✓	✓	✓	✓
	Social Vulnerability Indes	✓	✓	✓	✓	✓
Stop	Stanford Open Policing		✓	✓	✓	
Health	National Emergency Medical Services Information System (NEMSIS)	✓				

✓ *Used in primary analysis*

✓ *Used in supplementary analyses (in Appendices)*

Crash Assignment

To accurately account for crashes occurring near the edges of census tracts, a spatial weighting approach was developed. Census tract boundaries were obtained from the TIGER (Topologically Integrated Geographic Encoding and Referencing) Line Shapefiles, a digital database of geographic features developed and maintained by the U.S. Census Bureau. These were converted into polylines using the “Polygon to Line” tool in ArcGIS. Crash data containing geographic coordinates was imported and spatially evaluated to determine each crash’s proximity to tract and county boundaries. Crashes were classified as either boundary or interior based on their distance from the boundary lines (Siddiqui & Abdel-Aty, 2012). To determine a suitable buffer threshold for this classification, the “Generate Near Table” tool in ArcGIS was used to calculate distances from crashes to the nearest tract boundaries. These distances were analyzed by plotting cumulative distributions at 50-foot intervals. The buffer threshold was selected at the point where the curve leveled off, indicating diminishing returns in additional crash coverage.

Using the selected buffer distance, crash buffers were created and intersected with surrounding census tracts or counties to calculate area-based weights. Crashes that overlapped multiple boundaries were assigned proportional weights based on the percentage of the buffer area within each geographic unit. This allowed for a more accurate representation of crash influence across community boundaries and is referred to in this study as the “Area Method.” Interior crashes that did not fall near boundaries were assigned fully to the tract or county in which they occurred as seen in Figure 1.

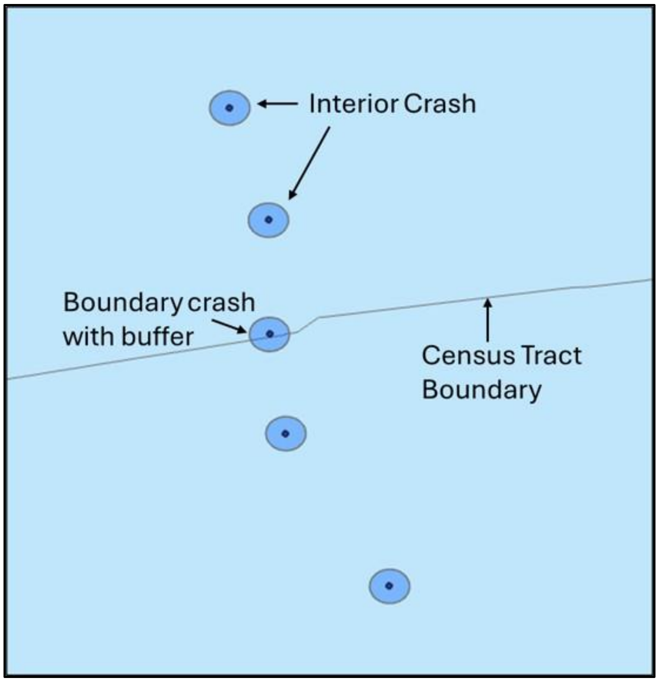


Figure 1: Boundary and interior crashes as determined using the area method

Data Envelopment Analysis

This study employs Data Envelopment Analysis (DEA) to assess the relative efficiency of different geographic areas in managing crash severity and occurrence relative to their exposure levels, as measured by roadway length or population size. DEA benchmarks each area against the most efficient peers to identify those achieving better safety outcomes, meaning fewer or less severe crashes than expected based on their infrastructure or population. For illustration, this concept can be compared to evaluating the performance of grocery stores. Consider one large store with many employees and significant space that generates only modest profit, and a smaller store with fewer employees and limited space that achieves higher profit. DEA would identify the smaller store as more efficient because it produces better outcomes relative to its resources. Similarly, in this study, a geographic area with extensive roadway networks or a large population that nonetheless maintains relatively low crash rates is considered more efficient in promoting road safety. To deepen the analysis, a two-stage DEA approach is used, which incorporates intermediate variables such as sociodemographic and socioeconomic factors. These intermediate variables help explain how community characteristics influence safety efficiency, allowing for a more comprehensive assessment that accounts for underlying social and economic differences. This methodology provides a clearer understanding of transportation safety performance and helps target areas where improvements are most needed.

DEA is a non-parametric, linear programming-based method used to evaluate the relative efficiency of decision-making units (DMUs) that utilize multiple inputs to produce multiple outputs. For example, in the context of grocery stores, each store can be viewed as a DMU, with inputs such as employees and floor space compared against outputs like profit to determine efficiency. In this study, census tracts (in state level analyses) and counties (in national analyses) serve as the DMUs, where inputs include roadway length or population and outputs are represented by safety outcomes such as crash frequency and severity. Developed by Charnes et al. (1978), DEA differs from conventional statistical methods by eliminating the need for predefined assumptions about production relationships. Rather than imposing a specific functional form, DEA empirically constructs an efficiency frontier based on the most productive DMUs. All other units are then evaluated relative to this benchmark, with their efficiency measured by the distance from this optimal frontier.

This study utilizes a two-stage bootstrap DEA approach (Simar & Wilson, 2007) that builds upon but differs from both the original DEA model framework (Charnes et al., 1978) and standard two-stage DEA methods. Traditional DEA models focus exclusively on direct inputs and outputs, while the two-step DEA models incorporate intermediate factors. These intermediate factors represent important system influences that are neither direct inputs nor outputs but can pointedly affect results if omitted. In our analysis, these intermediate factors consist of demographic characteristics at the census tract and county levels. The two-stage DEA methodology involves an initial optimization process where inputs and outputs are evaluated to generate efficiency scores, representing the relative performance of DMUs in terms of either maximizing outputs given inputs or minimizing inputs for given outputs. In the subsequent stage, these efficiency scores are analyzed in relation to intermediate variables through regression techniques.

The double bootstrap DEA approach developed by Simar and Wilson (2007) addresses critical limitations in conventional two-stage DEA analysis by providing statistically valid estimates of how intermediate factors influence efficiency scores. This method offers three principal advantages for empirical research: first, it explicitly incorporates contextual variables like demographic factors as intermediate inputs in the efficiency analysis; second, it employs bootstrapping techniques to correct for inherent biases in DEA efficiency estimates; and third, it produces more reliable statistical inferences than traditional DEA models. **Error! Reference source not found.** presents the DEA framework used in this study.

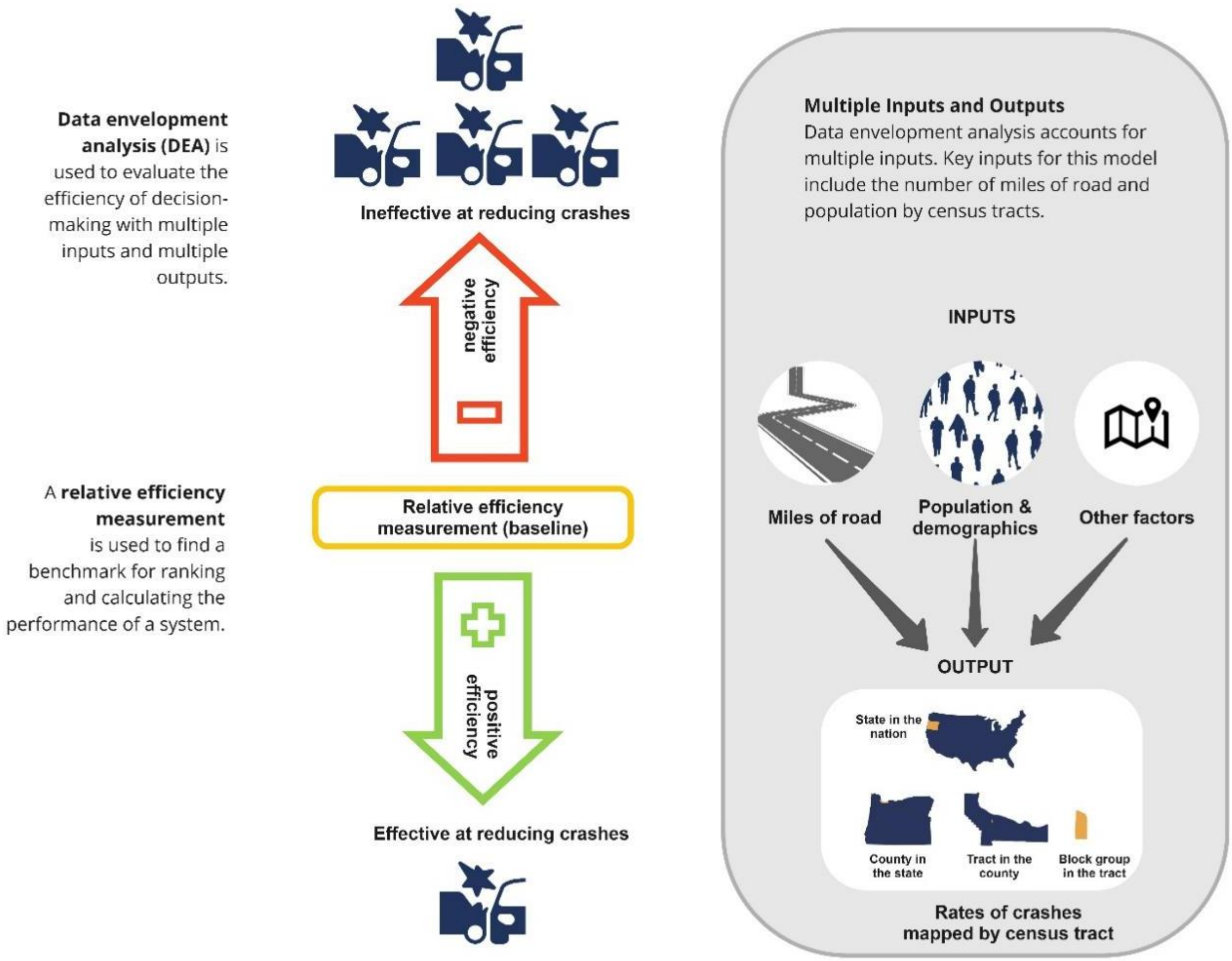


Figure 2: Presentation of the data envelopment analysis framework used in this study

Input. This study implemented two distinct DEA model types to evaluate road safety efficiencies. The first model utilizes total roadway miles within each geographic unit as its primary input variable. This approach specifically examines infrastructure-based exposure to crash risks, recognizing that longer road networks typically support greater traffic volumes and consequently present increased opportunities for crashes to occur.

The second DEA model employed population counts within each geographic unit as its key input variable. This population-based approach captures demographic exposure to crash risks, acknowledging that areas with higher population experience greater vehicle and pedestrian activity, leading to higher crash probabilities.

Intermediate Factors. The analysis incorporated a set of sociodemographic and economic variables as intermediate factors to examine how community characteristics influence the relationship between crash exposure and safety outcomes. These variables capture two critical dimensions: sociodemographic representation and socioeconomic status. Racial and ethnic composition measures include percentages of White, Black, Native American, Asian, Pacific Islander, other races, and multiracial populations, along with the proportion of Hispanic residents. Educational attainment, poverty rate, and unemployment rate were added as socioeconomic factors. These intermediate factors help control unobserved heterogeneity across geographic units, ensuring that efficiency estimates more accurately reflect actual safety performance rather than being confounded by underlying demographic or economic differences.

Output. The number of crashes weighted according to the area method for each geographical area was the output. This weighted crash frequency for each geographical unit was further weighted according to the Equivalent Property Damage Only method (Ryan et al., 2021). This approach standardizes different crash severity types into a single comparable metric. Each fatal, injury, or possible injury crash was assigned a weight of 21, while property damage only crashes received a weight of 1. This method was adapted from the original cost method developed by Federal Highway Administration (FHWA) (Harmon et al., 2018). Compared to the cost method, the 21/1 weighting method allows for a more realistic and balanced consideration of injury crashes compared with fatal outcomes. The cost method, on the other hand, very heavily weights fatal outcomes compared to injury crashes, which leads to a phenomenon of "chasing fatal crashes," even when these are rare events. Furthermore, injury crashes can often almost result in a fatal outcome; one minor variable (such ambulance arrival time) could make all the difference. Thus, this weighting scheme has been shown to produce more robust safety models compared to the cost method, or considering all crash types evenly (Ryan, Ai, et al., 2022; Massachusetts Department of Transportation, n.d.).

Since crashes represent undesirable outcomes, higher crash frequencies indicate poorer safety performance. However, DEA conventionally interprets larger output values as indicators of better performance. To align with this methodological assumption, the Equivalent Property Damage Only values were transformed by calculating their reciprocals. This transformation effectively inverts the scale, such that higher transformed values correspond to better safety outcomes, consistent with DEA's evaluation framework. To accommodate geographic areas with zero crashes, where the reciprocal is undefined, a small positive constant (0.01) was added to these cases. This adjustment preserves all observations for analysis while ensuring computational feasibility.

Machine Learning and SHAP Interpretation

The two-stage DEA provided insight into how community characteristics influence roadway safety efficiency; however, the DEA approach does not provide a complete picture because it relies on aggregate exposure measures such as roadway length and population. To complement DEA analyses and more directly examine the factors contributing to crash outcomes, a machine learning modeling framework was further considered. This study applied a machine learning framework combined with SHAP (SHapley Additive exPlanations) analysis to investigate equity-related disparities in traffic safety outcomes. The aim was to identify and interpret the factors that contribute to differences in crash severity and fatality frequency across sociodemographic groups. Machine learning refers to a subset of artificial intelligence methods that utilize algorithms to iteratively learn complex, nonlinear relationships within high-dimensional datasets, enabling modeling without relying on pre-specified parametric assumptions. By leveraging this data-driven approach, the models can capture intricate interactions among a diverse set of explanatory variables, including detailed sociodemographic indicators such as age distribution, racial composition, educational attainment, unemployment rates, and poverty levels. Two types of models were developed: injury severity models and crash cost models.

The injury severity analysis employed machine learning techniques to analyze high severity crash injury outcomes, with model interpretation conducted through SHAP analysis. Crash records were spatially assigned to their corresponding census tracts for state-level models and to counties for the national-level model. Each geocoded crash record was then enriched with sociodemographic characteristics from the U.S. Census Bureau’s American Community Survey data, based on its assigned geographic unit. After evaluating multiple machine learning approaches, the XGBoost algorithm demonstrated superior predictive performance, particularly in recall metrics, and was consequently selected for the final SHAP interpretation. The modeling framework treated each individual crash as a distinct observation in the dataset, with the injury severity outcome serving as the target variable and the sociodemographic factors as predictors.

The crash cost analysis employed a standardized costing methodology to quantify the economic impact of traffic crashes across different geographic areas. Following FHWA guidelines (Harmon et al., 2018), injury and property damage costs were calculated for each census tract (state-level analysis) and county (national-level analysis). The original 2016-dollar values from FHWA were adjusted to 2018–2022 equivalents using inflation rates derived from the Bureau of Labor Statistics Consumer Price Index. For each geographic unit, total crash costs were computed by aggregating all applicable injury and property damage expenses associated with reported crashes. These cost estimates served as the target variable for subsequent predictive modeling. Machine learning algorithms analyzed relationships between these economic outcomes and various sociodemographic indicators, with SHAP values subsequently applied to interpret the models and identify the most influential factors contributing to higher crash-related expenses. The modeling framework treated each geographic unit (census tract or county) as an individual observation, with total crash costs as the dependent variable and community characteristics as predictors. The XGBoost Regressor model was used as this model had the lowest root mean squared error amongst all models, and hence ensured high precision compared to all other models.

Qualitative Analysis

This study further employed a qualitative research approach using primary and probe-based question interviews to examine the systemic factors that contribute to traffic safety disparities and explore how transportation agencies integrate equity considerations into their policies and practices. The methodology was designed to complement the quantitative DEA analysis by capturing expert perspectives on the underlying causes of inequities and current approaches to addressing them.

A series of questions were created to form a semi-structured interview. The questions focused on four core discussion topics, which included the following:

1. **Data Collection and Analysis**: How agencies gather and utilize demographic and crash data to identify disparities
2. **Investment and Prioritization**: The role of equity metrics in funding decisions and infrastructure improvements
3. **Policy Implications**: Challenges and opportunities in addressing inequities through legislation, enforcement, and community engagement
4. **Validation of Findings**: Professional interpretations of the study's results, including unexpected trends or gaps in existing data

Based on the findings of the quantitative analysis, interview questions were tailored for each case study state and to capture a national perspective. For an indicative list of interview questions, see Appendix A. The interview was approved by the University of Arizona Institutional Review Board and outreach to potential participants occurred in March and April of 2025.

Participant selection followed a purposive sampling strategy to capture specialized knowledge from key stakeholders in the field. The recruitment pool was strategically categorized to capture both state-specific and national perspectives on transportation safety equity. Representatives from the four focus states (Arizona, Maryland, North Carolina, and Oregon) provided targeted insights into their respective states' unique safety trends, data collection practices, and policy responses to identified inequities. Complementing these state-level perspectives, federal agency representatives and experts from other regions (including Washington, DC) contributed broader understandings of nationwide patterns, funding allocation mechanisms, and systemic barriers impacting equitable safety outcomes across the United States. Interviews were conducted until data saturation, when interviews no longer provided new insights.

The prospective participants were contacted via email in which a meeting was requested, additional information regarding the nature of the project was provided, and a statement as to why the individual was being contacted was included. Interviews were arranged at mutually convenient times. Figure 3 displays an overview of the distribution of participants across the four states and at the national level.

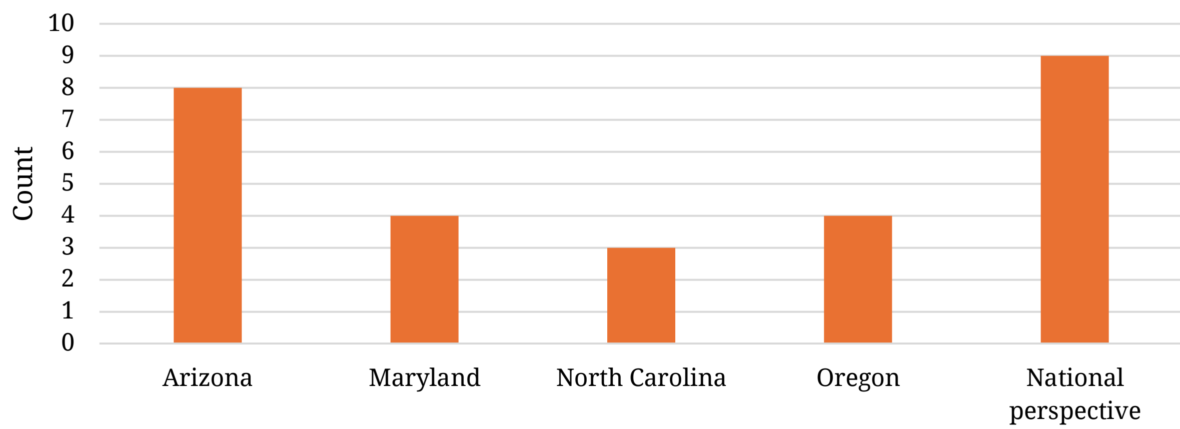


Figure 3. Distribution of interview participants

Between March 2025 and April 2025, a total of 27 individuals were interviewed with their positions varying by agency at the state, local, and federal level, along with those at universities and in industry. Figure 4 displays this distribution. All interviews except for one were conducted via ZOOM® online meetings. One was conducted via Microsoft® Teams at the request of the participant. After obtaining consent from the participants, the interview was recorded and transcribed verbatim. Interviews lasted 30 to 50 minutes and all transcripts underwent rigorous individual review by the research team to ensure accuracy before analysis.

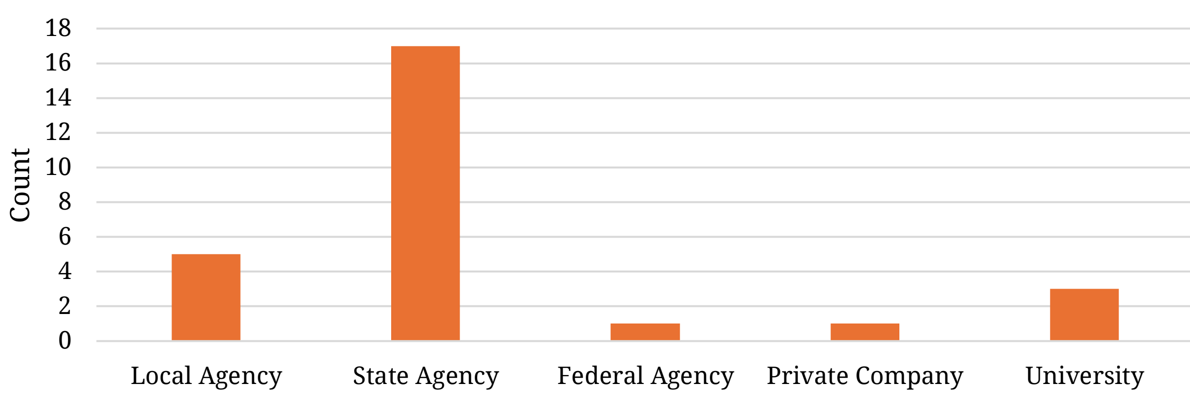


Figure 4. Distribution of interviews across agencies.

The transcripts then underwent systematic coding to categorize and analyze responses thematically. This coding process facilitated the identification of recurring patterns and critical insights. Finally, the coded data was synthesized into concise summaries to distill key findings as presented in the results.

Results

The research findings are presented in two integrated segments, beginning with the quantitative results and followed by qualitative insights. The first segment reports the comprehensive quantitative analysis, including comparative crash rate statistics, crash risk differences from data envelopment analysis models, and patterns identified through machine learning algorithms, all derived from the datasets and methodologies outlined in the methods section. The second segment presents the key thematic findings from expert interviews, which provide contextual understanding, practical implementation perspectives, and policy-relevant interpretations of the quantitative results.

Quantitative Analysis Findings: Statistical, DEA, and Machine Learning Results

The quantitative findings are organized into three subsections. The first subsection presents crash rate results across drivers, pedestrians, and bicyclists using data from the national level as well as from Arizona, Maryland, North Carolina, and Oregon. The second subsection presents the results of the Data Envelopment Analyses, nationally and in the four case study states. Finally, the third subsection presents results from the machine learning models, nationally and the four case study states. Additional analyses supporting the main findings, including injury severity patterns, EMS responses, traffic stop rates, and DEA model results across states, are presented in Appendices.

Crash Rates

The crash rates are presented below, summarizing crash rates for three distinct user types: drivers, pedestrians, and bicyclists. This study primarily focused on assessing fatal outcomes, with an emphasis on understanding how these incidents vary across different sexes, races, and age groups. Suspected serious injury rates by sex and age group for the four states are also provided in Appendices B and C. Traffic stop rates for Arizona, Maryland, and North Carolina are included in Appendices D through F.

Drivers—Overall Crash Rates. The crash rates for various injury severity levels across the four states analyzed are shown in Figure 5. North Carolina consistently stands out with the highest fatality rates, ranging from 11.7 to 14.6 per 100,000 people, while Maryland maintains the lowest fatal outcome rates, ranging between 4.8 and 6.0 per 100,000 people. Oregon showed increases in both suspected serious injury rates and suspected minor injury rates from 2018 to 2022, highlighting a rise in non-fatal outcomes. Both Arizona and Oregon experienced the highest percentage increases in fatal outcome rates over the years analyzed, with Arizona witnessing a 27.5% rise from 2018 to 2022 and Oregon seeing a 28.6% increase between 2019 and 2021.

North Carolina consistently records the most crashes per 100,000 people across all severity levels, with its crash rates for fatal outcomes as well as for lower-severity injuries being significantly higher than the other three states. Oregon, while maintaining lower overall crash rates, shows a sharp rise in both suspected major injuries and minor injuries in recent years, suggesting a growing severity in crash outcomes. In contrast, Maryland exhibits the most consistent crash rates across all injury categories, with minimal changes throughout the five-year period, indicating more consistent traffic safety outcomes compared to the other states.

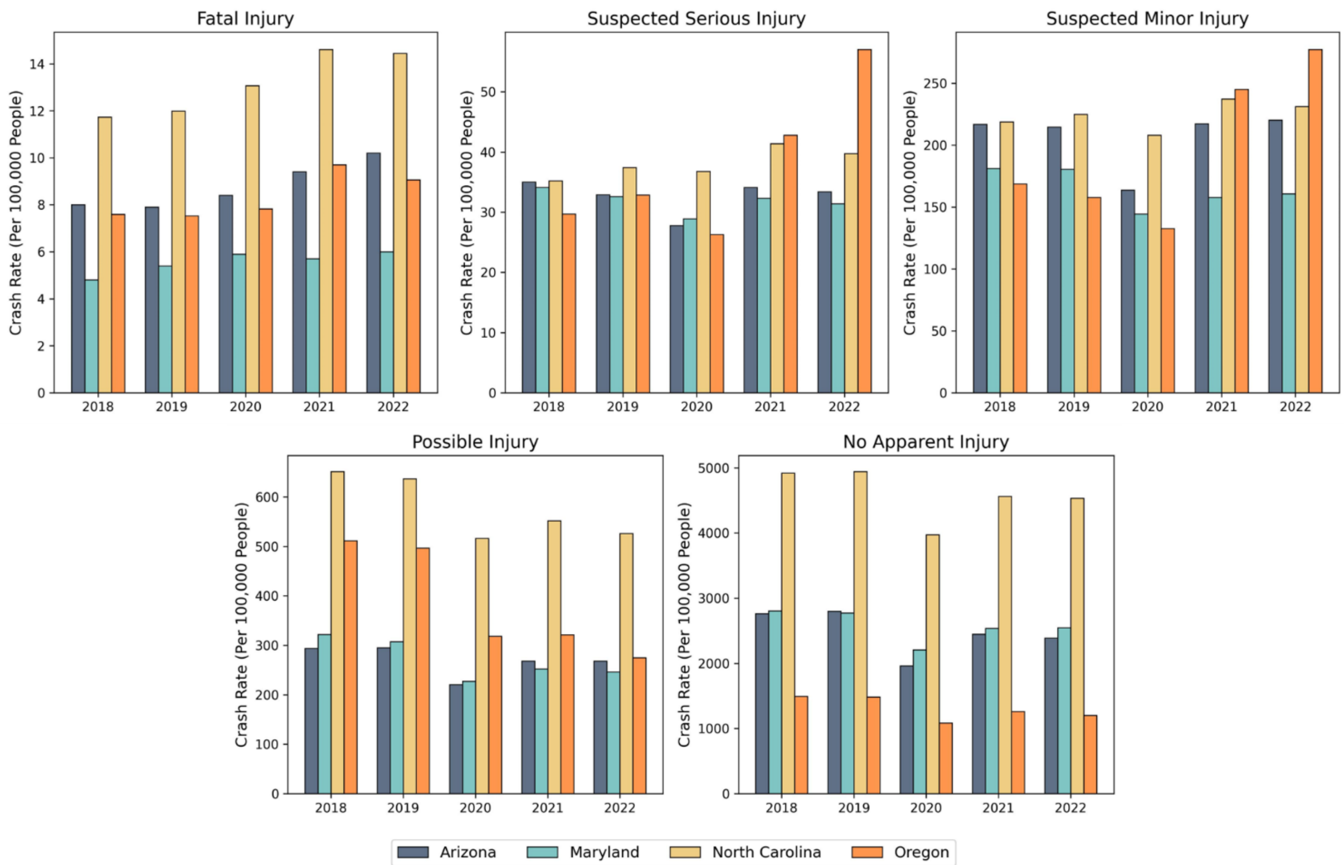


Figure 5: Comparison of crash severity rates across four states per 100,000 people (2018–2022)

Drivers—Sex-Related Differences. Male and female fatality rates were calculated by dividing the fatal crash counts for male drivers by the male population to obtain the male fatality rate. Similarly, the female fatality rate was determined by dividing the fatal crash counts involving female drivers by the female population. Figure 6 illustrates the fatality rates for male and female drivers as well as the male driver to female driver ratio for fatal outcome rates across Arizona, Maryland, North Carolina, and Oregon, along with the national ratio from 2018 to 2022. The ratios consistently exceed 2.5, demonstrating that male drivers were significantly more likely to experience fatal outcomes than female drivers throughout the five-year period. These ratios remain consistent at the census tract level with male drivers exhibiting higher crash rates in both urban and rural census tracts across all four states. Appendix G presents maps displaying crash rates at the census tract level.

Maryland exhibited the highest disparity between male and female fatal outcome rates, as particularly noted in 2020 and 2021, where male drivers were approximately four times more likely to sustain fatal outcomes than females. Arizona and Oregon displayed fluctuations in their ratios, with Oregon peaking at about 4.26 in 2020 before declining to approximately 3.79 in 2022. Meanwhile, the national average remained stable, ranging from 3.4 to 3.7, with a slight increase observed toward the end of the reporting period.

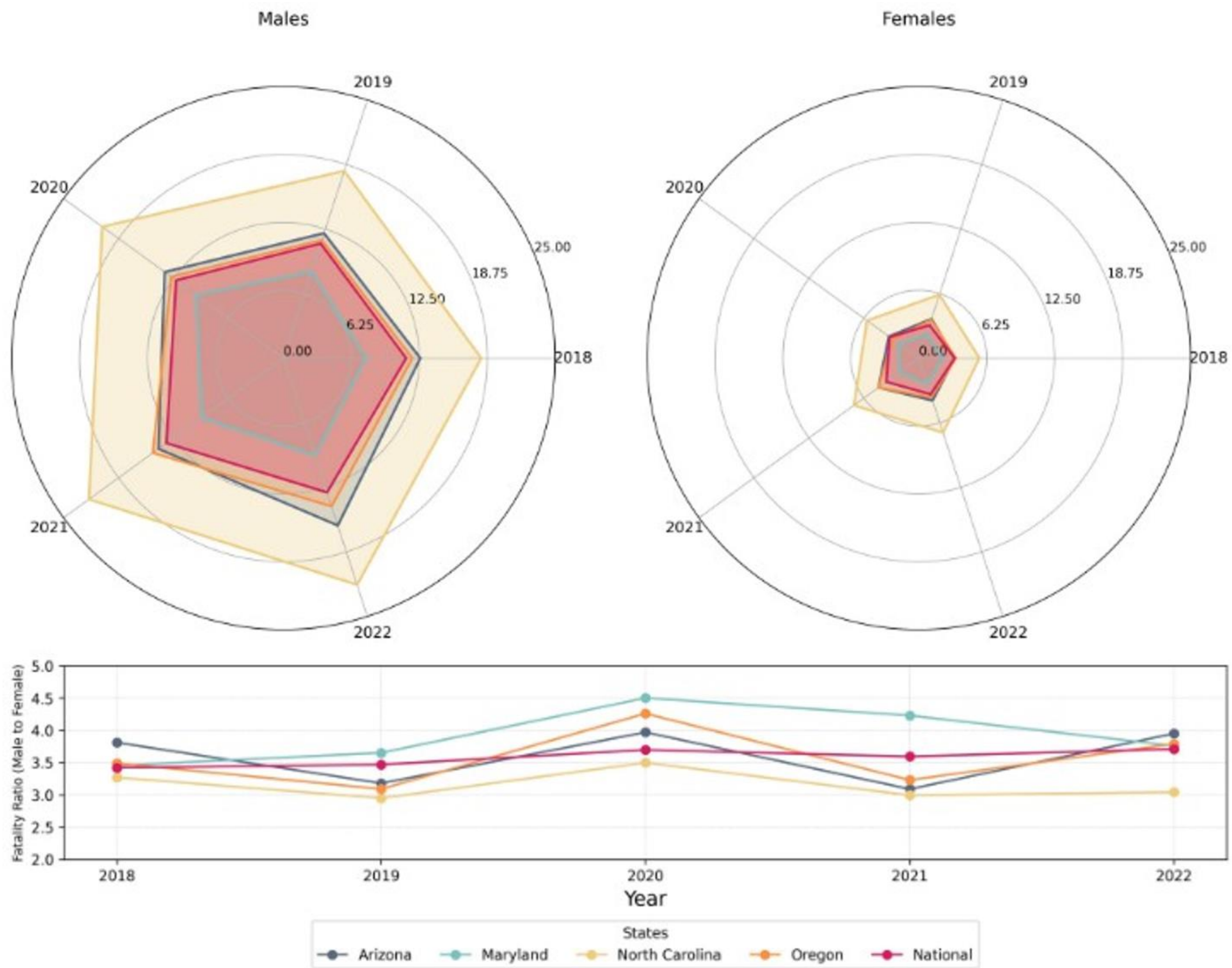


Figure 6: Fatality rate and ratio across sexes for drivers per 100,000 people (2018–2022)

As an extension, differences in primary symptoms by sex, as well as chief complaint anatomic locations in traffic crashes as reported in the National Emergency Medical Services Information System (NEMSIS) and Maryland EMS data, are presented in Appendices H and I, respectively.

Drivers—Age-Related Differences. Figure 7 highlights fatality rates for drivers across four age groups over five years in Arizona, Maryland, North Carolina, Oregon, and at the national level. Overall, the 25–44 age group consistently showed higher fatality rates across most states, particularly in North Carolina, where the rates remained higher than others. In contrast, the 15–24 and 45–64 age groups experienced some fluctuations but generally stayed within a moderate range. The 65+ age group exhibited more varied trends, with some states seeing increases in recent years while others, like Maryland, maintained relatively lower rates for this older population. Appendix J presents the maps displaying crash rates at the census tract level.

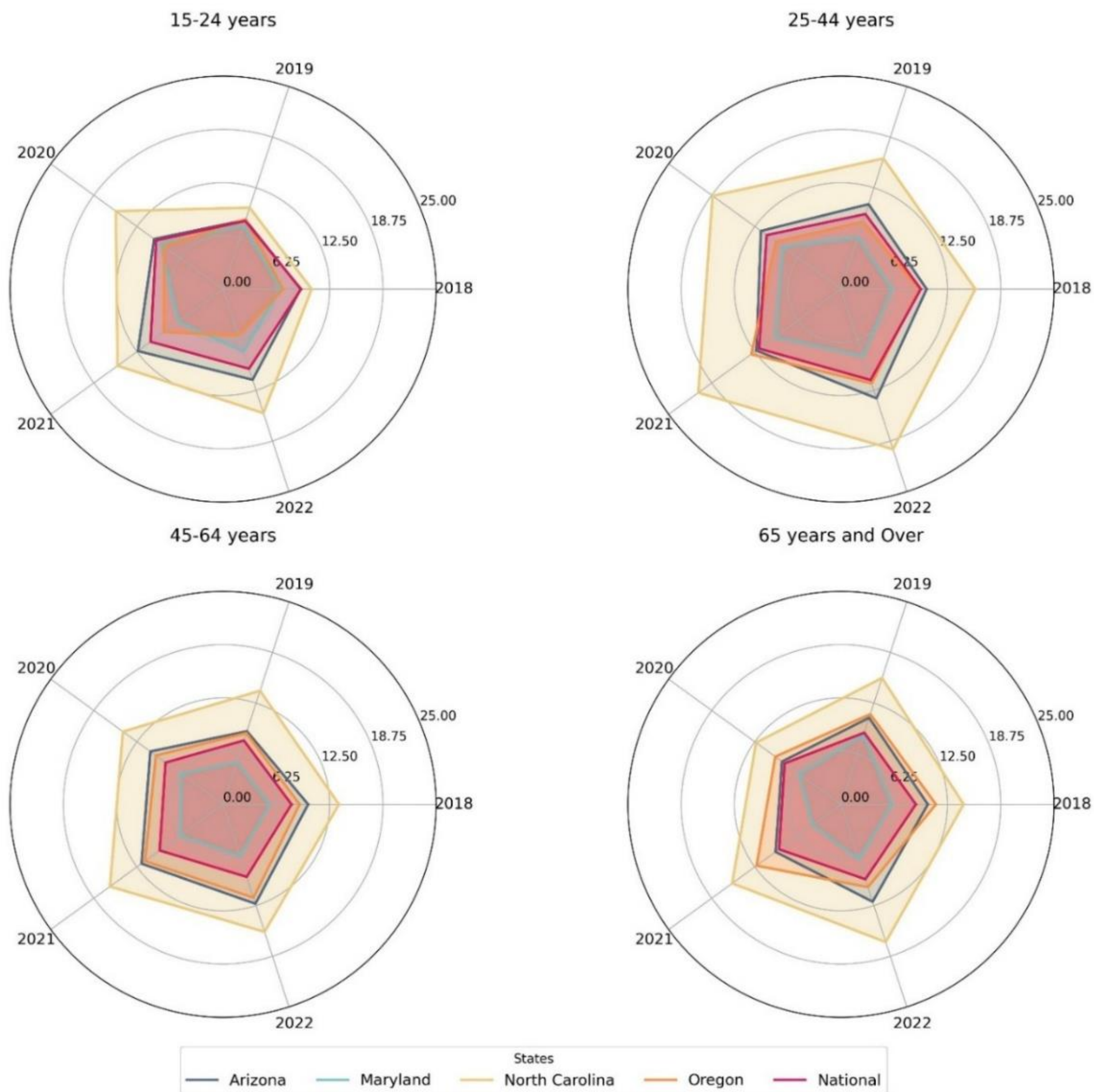


Figure 7: Fatality rate across age groups for drivers per 100,000 people (2018–2022)

Arizona showed a steady upward trend across all age groups, peaking in the most recent years, suggesting rising fatality risks statewide. Maryland maintained the lowest rates among the states, particularly for younger and older drivers, although it also showed some variability year by year. Oregon presented a mixed pattern, with increases for middle-aged and older drivers in certain years. North Carolina consistently reported the highest fatality rates across nearly all groups, indicating a persistent safety concern. Nationally, the trend mirrored some of these state-level patterns, with middle-aged drivers facing the greatest risk and slight improvements or stability among older drivers. Additionally, differences in primary symptoms and chief complaint anatomic locations by age group, based on NEMSIS and Maryland EMS data, are shown in Appendices H and I.

Drivers—Race-Related Differences. Fatality rates were calculated by dividing the fatal crash counts for each race by the total population of that race to obtain the rates. The races analyzed were White, Black, Native American, and Asian. The fatality rates for drivers from 2018 to 2022 reveal significant differences across different racial groups as shown in Figure 8, with Native Americans consistently experiencing the highest fatality rates across most states. In North Carolina, the fatality rate for Native Americans peaked at 43.67 per 100,000 in 2022, nearly 20 times higher than the rate for Asian populations. Oregon also exhibited concerning rates for Native Americans, reaching 32.56 per 100,000 in 2021.

Black populations generally faced higher fatality rates compared to their White and Asian counterparts. In North Carolina, the fatality rate for Black drivers increased from 14.63 fatalities per 100,000 people in 2018 to 20.77 fatalities per 100,000 people in 2022. Maryland presented an exception, with Black and White rates showing a closer alignment. Meanwhile, Asian populations consistently recorded the lowest fatality rates nationally, ranging from 1.72 to 2.52 fatal injuries per 100,000 people between 2018 and 2022. However, Arizona witnessed a notable increase in Asian fatality rates, rising from 3.34 fatal injuries per 100,000 people in 2020 to 7.06 fatal injuries per 100,000 people in 2022.

State-specific trends further underscore the disparities, as North Carolina consistently reported higher fatality rates across all racial groups compared to other states and the national average. Arizona exhibited an upward trend in fatality rates for all races from 2018 to 2022, while the national fatality rate saw a general increase from 2018 to 2021, followed by a slight decrease in 2022. Overall, the national fatality rates for 2022 were 13.75 per 100,000 people for Native American individuals, 9.42 fatalities per 100,000 people for Black individuals, 8.54 fatalities per 100,000 people for White individuals, and 1.81 fatalities per 100,000 people for Asian individuals.

In addition, differences in primary symptoms and chief complaint anatomic locations by race, based on NEMSIS and Maryland EMS data, are provided in Appendices H and I.

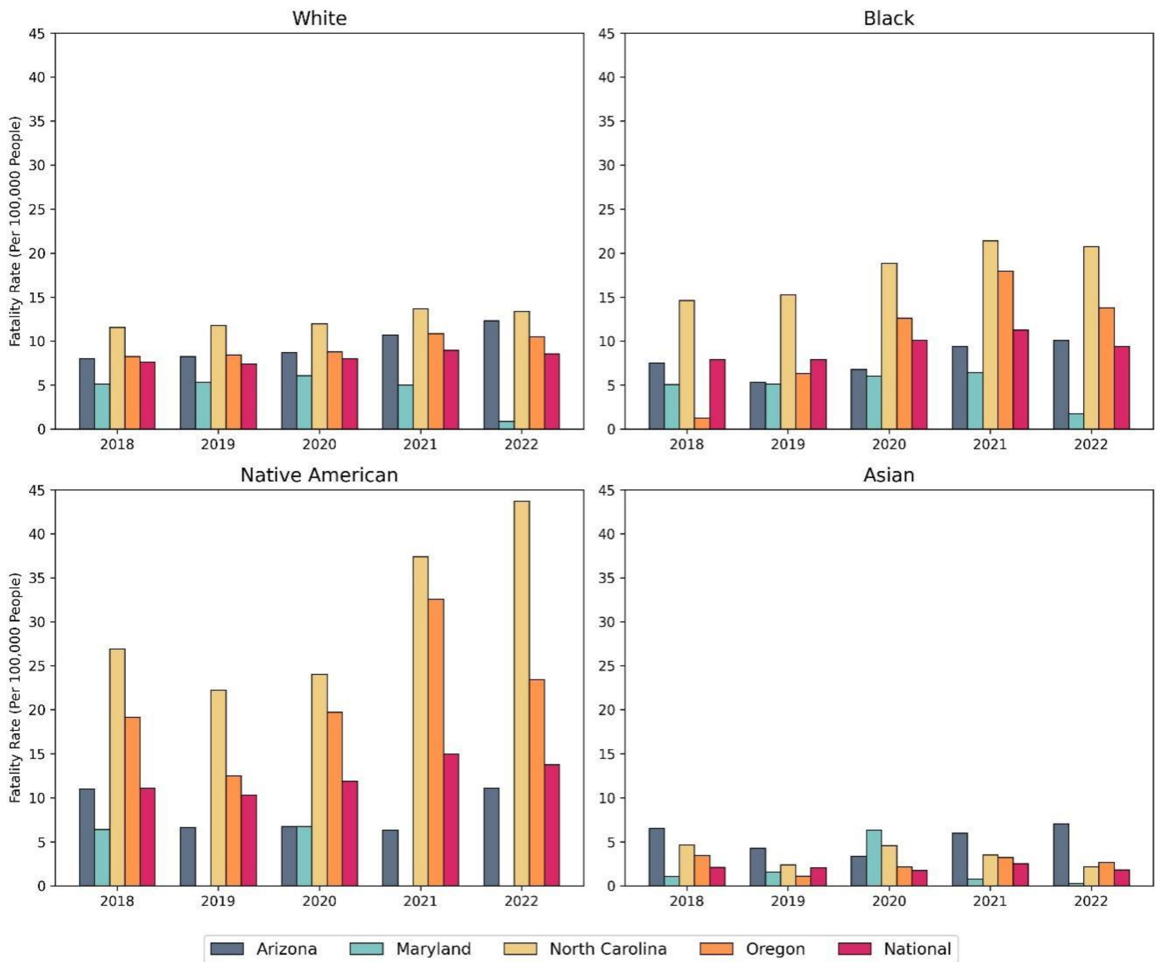


Figure 8: Fatality rate across races for drivers per 100,000 people (2018–2022).

Pedestrian—Sex-Related Differences. The sex-related differences in pedestrian fatality rates are shown in Figure 9. The data consistently shows that male pedestrian fatality rates were higher than female rates across all states and time periods, often by a factor of two to three.

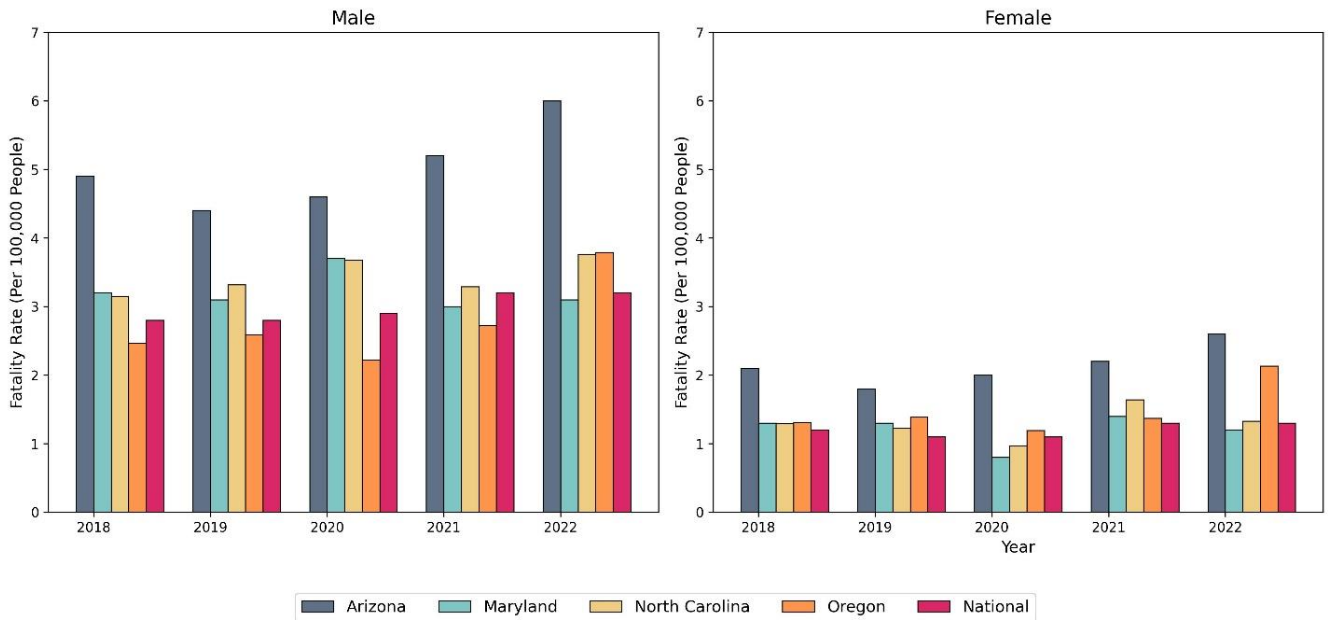


Figure 9: Fatality rate across sexes for pedestrians per 100,000 people (2018–2022).

Arizona emerged as a state with high fatality rates, surpassing both national averages and those of the other states. Over the five-year period, the male pedestrian fatality rate in Arizona increased from 4.9 to 6.0 per 100,000, while the female rate rose from 2.1 to 2.6, significantly exceeding national figures, which rose from 2.8 to 3.2 for males and remained stable at around 1.2 to 1.3 for females.

North Carolina ranked second in fatal pedestrian rates amongst the states analyzed, with male rates rising from 3.15 to 3.76 per 100,000 and female rates fluctuating between 0.97 and 1.64. Maryland showed similar male pedestrian fatality rates, remaining stable between 3.1 and 3.7 per 100,000. Oregon's male pedestrian fatality rates were lower but increased notably from 2.47 to 3.79 over the same period. The national averages indicate a general stability over time, with male rates showing a slight increase from 2.8 to 3.2 per 100,000, while female rates remained largely unchanged. Overall, the data reveals an upward trend in fatal pedestrian rates, particularly among males, who were more likely than females to be fatal by a factor of over two.

Pedestrians—Age-Related Differences. The pedestrian fatality rate data by age group across five years, as seen in Figure 10, indicates higher fatality rates among middle-aged and older adults. The 25–44 and 45–64 age groups recorded higher fatality rates in most states, with Arizona and North Carolina consistently reporting higher rates compared to national averages. Maryland's rates were more stable and lower across all groups, while Oregon displayed fluctuations, including a spike among older pedestrians in recent years. The 65+ age group often had higher fatality rates, especially in Oregon and Arizona, underscoring ongoing challenges for older pedestrians.

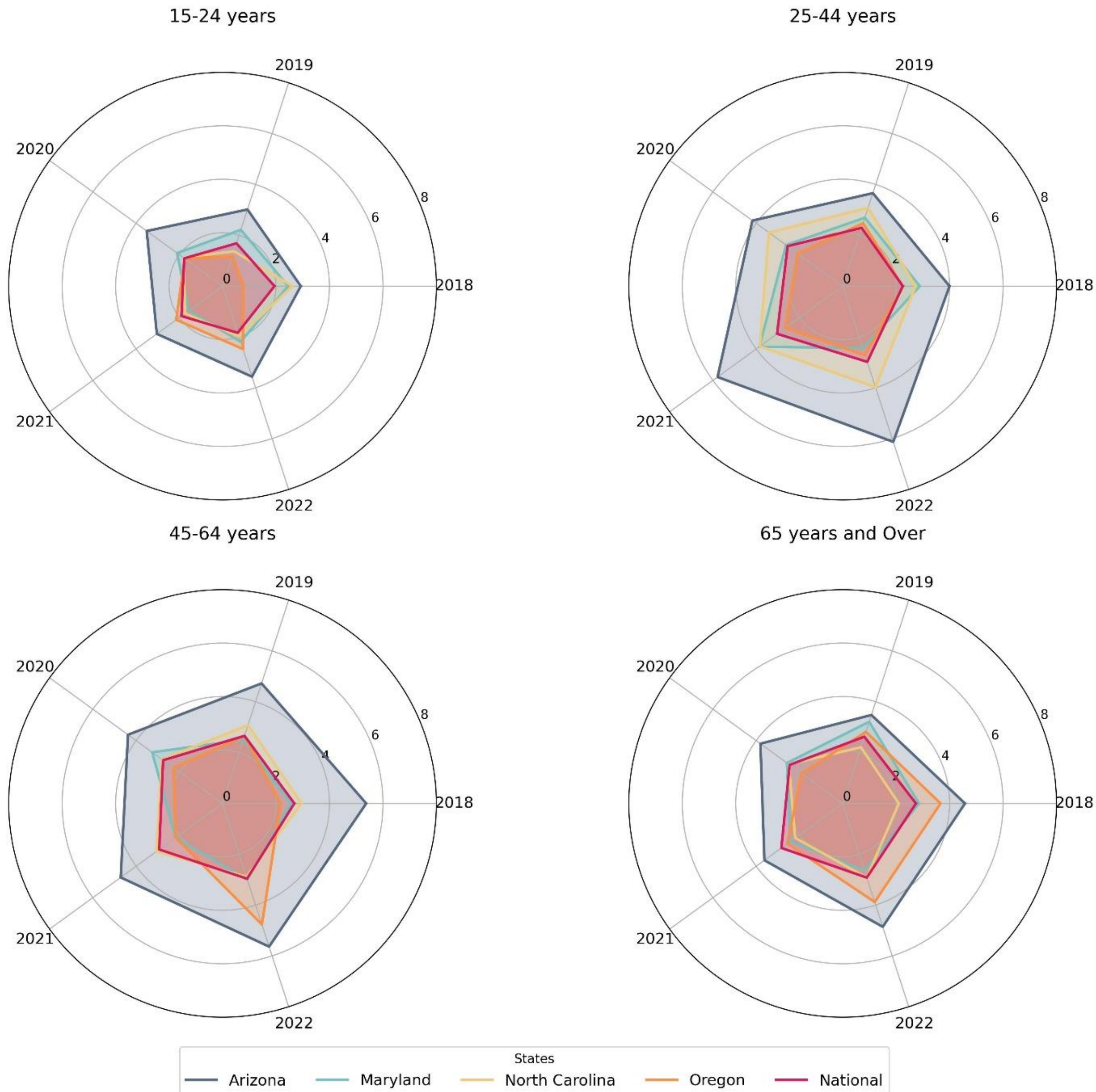


Figure 10: Fatality rate across age groups for pedestrians per 100,000 people (2018–2022)

Across the board, pedestrian safety appears to be a persistent concern, with no state showing consistent improvement across all age groups. Arizona and Oregon showed increases in later years, especially among middle-aged and elderly populations. North Carolina exhibited moderate but steady growth in pedestrian fatality rates for younger adults. National data reflected a gradual increase across all age groups, with middle-aged pedestrians seeing the highest rates.

Pedestrians—Race-Related Differences. The pedestrian fatality rates indicate that Native American and Black populations consistently face higher fatality rates across states and years as shown in Figure 11. Native Americans exhibit the highest rates, particularly in states like Arizona, Oregon, and North Carolina. In Arizona, the Native American pedestrian fatality rate peaked at 11.96 fatalities per 100,000 people in 2018 and remained high at 11.09 fatalities per 100,000 people in 2022. Similarly, Oregon saw a sharp increase for Native Americans, rising from 2.13 fatalities per 100,000 people in 2018 to a staggering 19.53 fatalities per 100,000 people in 2021. North Carolina experienced a notable rise, with the Native American fatality rate reaching 13.1 fatal injuries per 100,000 people in 2022.

Black populations also show elevated pedestrian fatality rates compared to White and Asian groups. Nationally, Black fatality rates ranged between 3.12 and 4.11 per 100,000 people from 2018 to 2022, with Arizona seeing an increase from 4.91 in 2018 to 6.42 per 100,000 people in 2022. In contrast, Asian populations consistently report the lowest fatality rates, with national rates between 0.77 and 1.32 fatal injuries amongst pedestrians per 100,000 people, although Oregon showed slightly higher rates for Asians compared to other states.

State-specific trends highlight the persistence of these disparities. Arizona demonstrates consistently higher rates for all racial groups compared to national averages, while North Carolina shows growing disparities, particularly for Native American and Black populations. Oregon exhibits high variability, especially for Native Americans, with their rates fluctuating dramatically over the years.

On a national scale, pedestrian fatality rates for most racial groups increased from 2018 to 2021, with a slight decline in 2022. Native Americans consistently had the highest national rates (5.46 per 100,000 in 2022), followed by Black populations (3.63), White populations (1.92), and Asian populations (0.77). The data underscores race-based differences in pedestrian fatality risks, with Native American and Black populations disproportionately affected across most states and years examined.

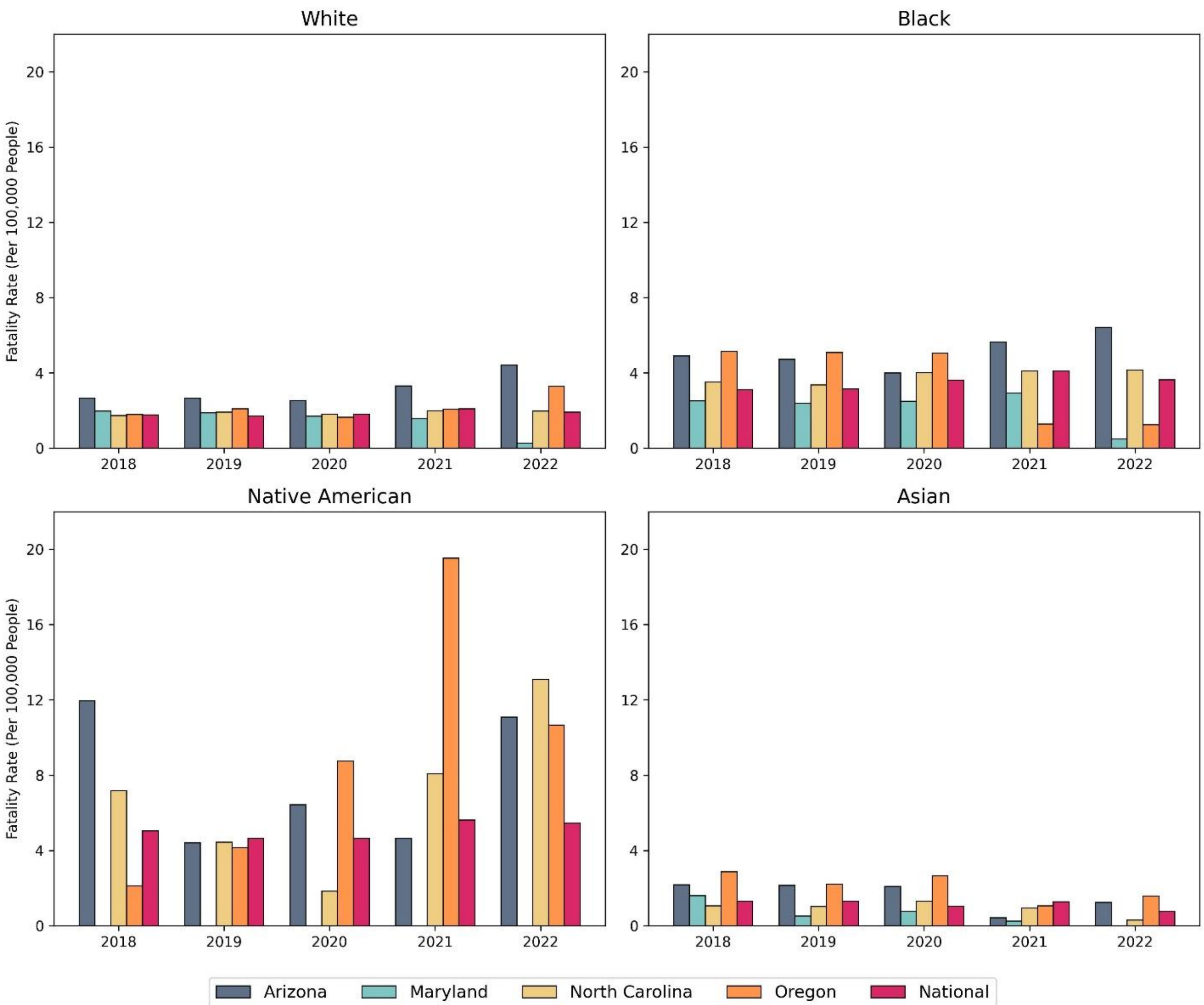


Figure 11: Fatality rate across races for pedestrians per 100,000 people (2018–2022)

Bicycle—Sex-Related Differences. The analysis of bicyclist fatality rates highlights significant sex-related differences across various states and years as shown in Figure 12, underscoring the persistent trend of higher male fatality rates compared to their female counterparts. This disparity is particularly visible at the national level, where male cyclist fatality rates are 7 to 8 times higher than those of female cyclists.

In Arizona, the trend of high fatality rates is significant. By 2022, the male cyclist fatality rate in Arizona reached 1.1 male bicyclist fatalities per 100,000 males, while the female rate stood at 0.279 female bicyclist fatalities per 100,000 females. This fourfold difference highlights the heightened risk faced by male cyclists in the state. The state has witnessed a steady upward trajectory in fatality rates for both sexes from 2018 to 2022, with the male fatality rate nearly doubling during this period, from 0.6 fatalities to 1.1 fatalities per 100,000 males.

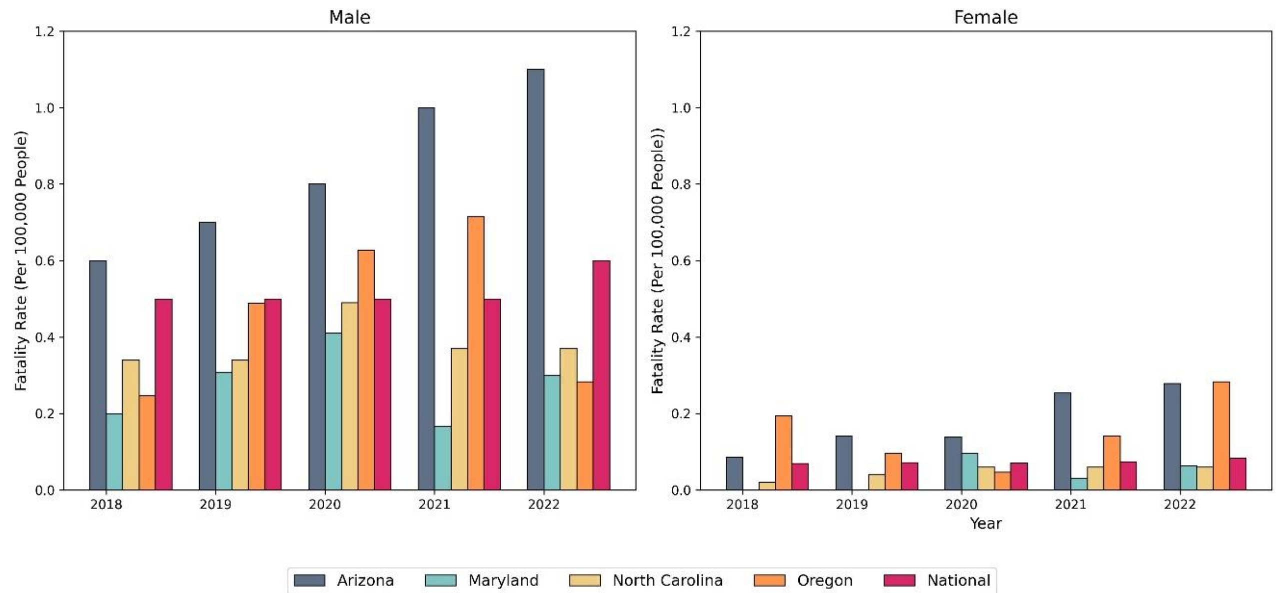


Figure 12: Fatality rate across sexes for bicyclists per 100,000 people (2018–2022)

Oregon presents an interesting case, highlighting the most volatile patterns in cyclist fatality rates among the states examined. The male fatality rates peaked in 2021 at 0.72 fatalities per 100,000 people before experiencing a sharp decline to 0.28 fatalities per 100,000 in 2022. Female fatality rates in Oregon were higher than those in other states, indicating an upward trend. Maryland and North Carolina exhibit more moderate rates, aligning with national trends but with some unique characteristics. Maryland experienced periods of zero female fatalities between 2018 and 2019. Male fatality rates in Maryland showed considerable year-to-year variation but remained lower than those in Arizona and North Carolina. North Carolina also reported stable fatality rates for both sexes.

At the national level, cyclist fatality rates have shown relative stability overall, with the male fatality rate increasing slightly from 0.5 fatalities to 0.6 fatalities per 100,000 males between 2018 and 2022. Female fatality rates, on the other hand, have remained consistently low, fluctuating between 0.07 fatalities and 0.08 fatalities per 100,000 females during the same period.

Bicycle—Age-Related Differences. The analysis of bicyclist fatality data as seen in Figure 13 shows geographic and demographic variations in fatality rates patterns across states. Arizona exhibits changing crash rates with significant annual fluctuations, particularly among middle-aged cyclists, while maintaining consistently higher fatality rates than other states and national averages. Maryland shows relatively stable fatality trends overall, with occasional increases in specific age groups. North Carolina reports higher fatality rates for cyclists aged 45–64, though other age groups demonstrate lower fatality rates compared to most states. Oregon displays atypical patterns that contrast with national trends, especially for younger cyclists, with fatality rates second only to

Arizona across most age groups. The national data indicates two persistent concerns: steadily rising risks for older cyclists and consistently stable vulnerability among younger riders.

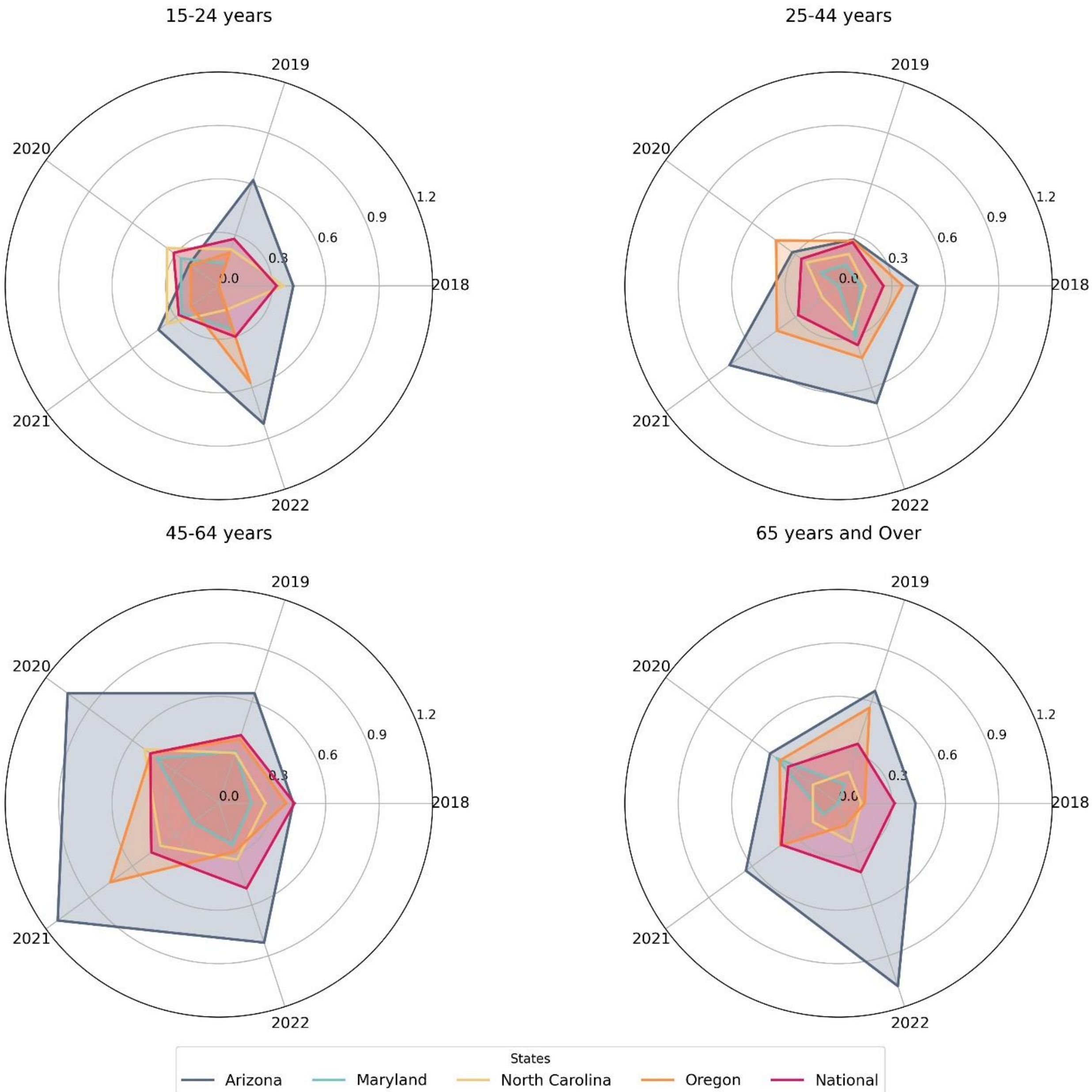


Figure 13: Fatality rate across age groups for bicyclists per 100,000 people (2018–2022)

Bicycle—Race-Related Differences. Figure 14 shows the bicyclist fatality rate across different races. Nationally, Native American bicyclists consistently experienced the highest fatality rates across all years, ranging from 0.36 to 0.55 fatalities per 100,000 people. In contrast, Asian bicyclists had the lowest rates, between 0.13 and 0.15 fatalities per 100,000. White and Black cyclists showed relatively similar fatality rates, averaging around 0.3 fatalities per 100,000. Across the five-year period, national rates remained relatively stable with slight variations, though Native Americans faced disproportionately higher fatality rates.

State-specific data highlighted stark differences. Oregon saw a dramatic spike for Native American bicyclists in 2020, with a fatality rate of 6.57 per 100,000 people, while North Carolina consistently recorded higher rates for this group compared to others. Arizona showed an upward trend, with fatality rates for White bicyclists nearly doubling between 2018 and 2022, and Black bicyclists reaching 1.22 fatalities per 100,000 in 2022. Maryland generally had lower fatality rates across all racial groups, with no consistent trend.

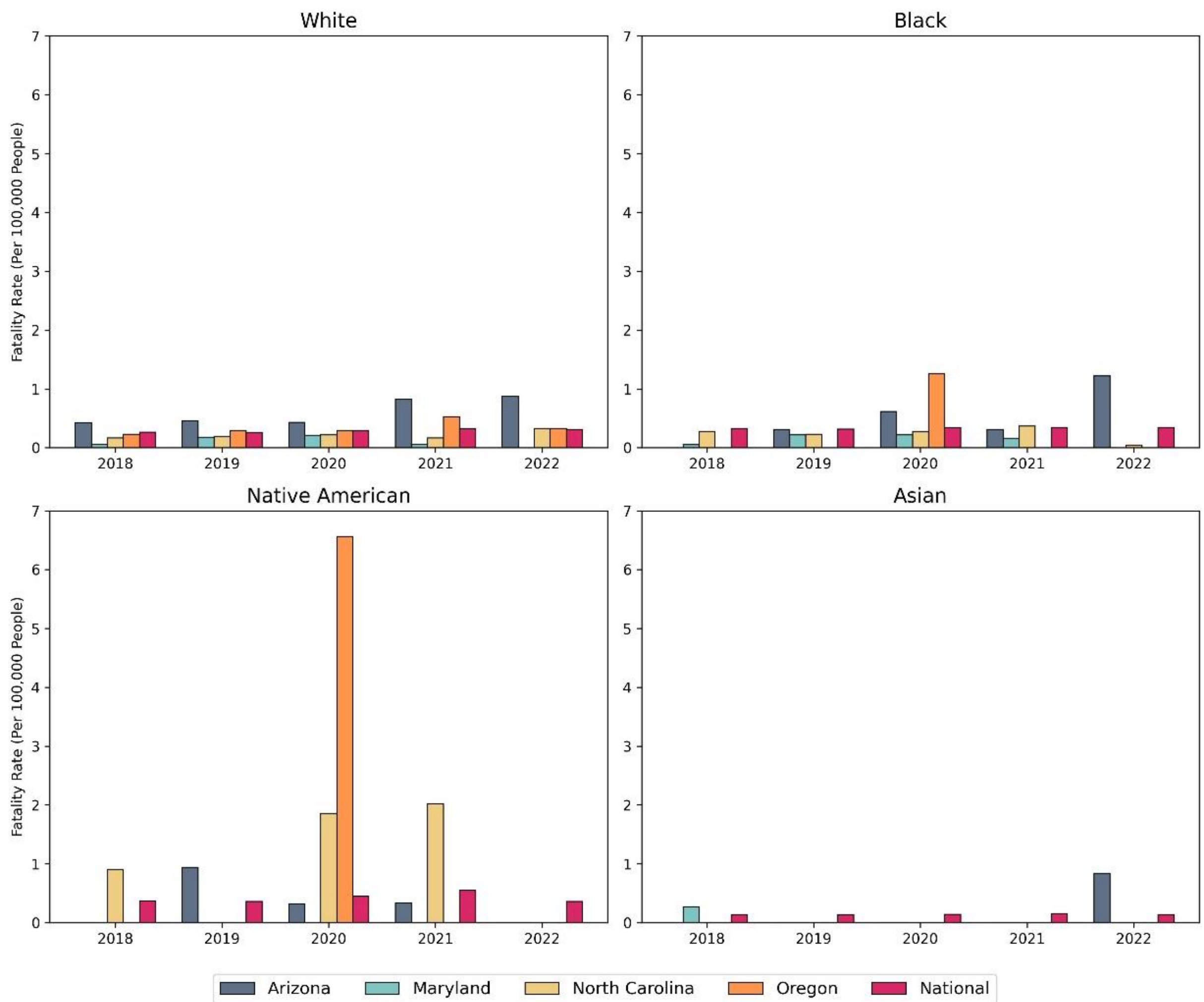


Figure 14: Fatality rate across races for bicyclists per 100,000 people (2018–2022)

Overall, Native Americans faced disproportionately higher fatality rates in several states, with spikes in Oregon and North Carolina. Meanwhile, Asian bicyclists often showed zero fatalities in almost all states. The pandemic year of 2020 saw notable spikes across different racial groups, particularly in Oregon and Arizona, with an overall upward trend in fatal injuries observed from 2018 to 2022.

*[**Note:** Although a spike in Native American bicyclist fatality rates was observed in Oregon in 2020, there were only three bicyclist fatalities in 2020 and none in other years. Given the small population size of minority race groups and the low incidence of bicycling fatalities, fatality rates for bicyclists across race should be interpreted with caution.]*

Statistical Analyses: National Perspective. This study applies chi-square tests of independence with standardized residual analysis to assess whether severe injury rates among different demographic groups are disproportionately high or low relative to their share of the total population. The analysis is done across drivers, pedestrians, and cyclists.

Table 2: Chi-square test results for fatal crashes nationally

Road-User Type	**Group**	**Severity Rate (Per 100,000 Pop.)**	**p-value**
Drivers	Male	14.5	<0.001
	Female	4	
	15–24	4.8	<0.001
	25–44	5.2	
	45–64	4.2	
	65+	4	
Pedestrians	Male	3.5	<0.001
	Female	1.4	
	15–24	0.7	<0.001
	25–44	1.3	
	45–64	1.4	
	65+	1.2	
Bicyclists	Male	0.6	<0.001
	Female	0.1	
	15–24	0.1	<0.001
	25–44	0.1	
	45–64	0.2	
	65+	0.2	

Table 2 presents national chi-square test results examining fatal crash severity rates (per 100,000 population) across demographic groups. Among drivers, males had a substantially higher fatal crash rate (14.5) than females (4.0) ($p < 0.001$). Severity rates by age group also varied significantly ($p < 0.001$), peaking at 5.2 for the 25–44 age group, followed by 15–24 (4.8), 45–64 (4.2), and 65+ (4.0).

For pedestrians, males again had a higher fatality rate (3.5) than females (1.4) ($p < 0.001$). Age-based disparities were also notable ($p < 0.001$), with rates highest among the 45–64 group (1.4), followed by 25–44 (1.3), 65+ (1.2), and lowest among 15–24 (0.7).

Bicyclist fatality rates followed the same trend, with males at 0.6 compared to 0.1 for females ($p < 0.001$). By age group, rates were slightly higher for 45–64 and 65+ (both 0.2), while younger groups (15–24 and 25–44) had the lowest rate at 0.1. These differences were also statistically significant ($p < 0.001$). Overall, the results indicate consistent and significant demographic disparities in fatal crash severity across road user types.

Statistical Analysis: Case Study States. A chi-square test was conducted to evaluate whether serious injury severity rates among drivers differ significantly across sex and age groups within individual states. Table 3 presents the statistical results for Arizona, Maryland, North Carolina, and Oregon.

Table 3: Chi-square test results analyzing serious injury differences across sex and age groups amongst drivers

State	Group	Severity Rate (Per 100,000 Pop.)	p-value
Arizona	Male	124.9	<0.001
	Female	60.0	
	15–24	65.8	<0.001
	25–44	64.7	
	45–64	50.8	
	65+	31.1	
Maryland	Male	63.7	<0.001
	Female	25.6	
	15–24	27.0	<0.001
	25–44	29.3	
	45–64	18.6	
	65+	11.4	
North Carolina	Male	72.7	<0.001
	Female	29.4	
	15–24	71.2	<0.001
	25–44	77.6	
	45–64	54.2	
	65+	38.8	
Oregon	Male	59.1	<0.001
	Female	31.7	
	15–24	57.7	<0.001
	25–44	59.3	
	45–64	54.2	
	65+	44.6	

Across all four states, male drivers consistently exhibited higher serious injury rates than female drivers, with all comparisons yielding statistically significant differences ($p < 0.001$). In Arizona, the male injury rate was 125 per 100,000 persons, compared to 60 for females ($p < 0.001$). Large disparities were observed in Maryland

(63.7 vs. 25.6; p<0.001), North Carolina (72.7 vs. 29.4; p < 0.001), and Oregon (59.1 vs. 31.7; p < 0.001).

Age group comparisons indicate that the 15–24 and 25–44 age groups consistently experienced the higher serious injury rates compared to older cohorts across all states, while the 65+ age group experienced the lowest rates. All age-based differences were statistically significant (p < 0.001), confirming demographic disparities in serious injury severity. Full results from the statistical analysis on these three modes of transportation can be found in Appendix K.

Data Envelopment Analysis: National Perspective

To examine how safety outcomes vary across counties with similar levels of exposure and contextual characteristics, a two-step bootstrapped DEA was conducted using county-level data across the United States. Two separate DEA models were developed. The first model used total road miles as the input, while the second model used total county population. This approach allows for the identification of counties that achieve relatively better or worse safety performance despite having comparable population sizes and infrastructure given their sociodemographic compositions. In both models, the output was defined as the inverse of the number of reported crashes, such that higher output values reflect better safety outcomes (that is, fewer crashes). A consistent set of intermediate variables representing sociodemographic and socioeconomic conditions, such as racial composition, education level, poverty rate, and unemployment rate, were included in both models to capture contextual influences that are not directly controlled by the counties but are known to impact safety performance.

The factor weights, or coefficients, assigned to intermediate variables provide insight into the relative influence of each condition on safety efficiency. A positive weight indicates that higher values of the corresponding variable are associated with improved safety outcomes. In contrast, a negative weight suggests that the variable is associated with decreased safety outcome. For example, a positive coefficient for education level would imply that counties with higher educational attainment tend to be more efficient in preventing crashes. Conversely, a negative coefficient for poverty rate would indicate that higher poverty levels are linked to reduced safety performance. The magnitude of the coefficients reflects the relative strength of association with safety efficiency. Positive coefficients indicate a stronger association with higher safety efficiency (i.e., lower crash risk), while negative coefficients reflect stronger associations with lower safety

Interpreting DEA Results

Positive Value: An increase in that variable will lead to lower crash and injury risk

Negative Value: An increase in that variable will lead to higher crash and injury risk.

Statistical Significance:

If the 2.5% and 97.5% bounds are both positive or both negative, the result is statistically significant at the 95% confidence interval. If the bounds have mixed signs (i.e., one positive, one negative), it is not statistically significant.

efficiency (i.e., higher crash risk). Larger absolute values signify stronger relationships in either direction. These findings offer valuable insight into the structural and community-level factors that either support or hinder efficient safety outcomes and can inform targeted interventions aimed at enhancing transportation safety across diverse demographic and infrastructural contexts. Table 4 presents the results from the DEA model, which analyzes data at the national level for fatal injuries only from the NHTSA (2024) Fatality Analysis Reporting System (FARS). In conjunction with the two DEA models completed in this section, a separate sensitivity analysis was performed utilizing (a) the Activity Diversity Index (ADI) and (b) Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry's Social Vulnerability Index (SVI) to further explore additional variables that could influence crash rates and injury severity with full results found in Appendix L.

Table 4: Results from the DEA models from FARS data.

	Mile Model			**Population Model**		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	3963.64*	8914.97	10994.63	110.84*	5153.49	12142.71
Unemployment Rate	646.10*	1106.26	1273.50	119.73	−310.18	217.17
Male-to-Female Ratio	−1210.99*	−2401.88	−2111.16	−1481.56*	−2927.28	−2069.42
% White	−495.87*	−999.7	−890.81	−3333.93*	−6507.16	−5414.64
% Black	−77.06*	−175.91	−147.04	580.66*	936.88	1472.98
% Native American	−761.4*	−1522.76	−1334.96	−933.38*	−2024.34	−534.49
% Asian	160.96*	255.52	310.16	1305.86*	2075.35	2503.59
% Pacific Islander	−92.67*	−184.84	−126.94	−1206.85*	−2344.81	−114.12
% Other Race	184.34*	293.33	355.05	1546.67*	2512.56	2981.95
% Two or More Race	63.10*	69.70	118.37	1704.06*	2875.00	3300.66
% Hispanic	319.61*	564.38	633.47	2253.44*	3819.26	4378.99
% Education Less than High School	−127.64*	−264.95	−216.13	−528.16*	−1320.74	−614.05
% High School Graduate	−319.91*	−634.85	−557.78	−3829.23*	−7445.38	−6748.75
% Graduate Degree	125.30*	214.89	251.78	−459.46*	−1063.96	−587.38
% Below Poverty	−551.19*	−1090.67	−957.50	−1636.07*	−3216.46	−2721.48

**Indicates statistical significance at the 95% confidence level*

The county-boundary DEA analysis, incorporating road mile length, revealed significant sociodemographic influences on weighted crash counts. Poverty levels (% Below Poverty) and male-to-female ratios showed strong negative coefficients (−551.19 and −1210.99), indicating reduced efficiency (i.e., higher crash risks) in areas with greater economic disadvantage or higher male-to-female ratio. Educational attainment showed a significant association with crash occurrence and severity, with tracts having higher percentages of residents without high school diplomas exhibiting experiencing higher crash rates per mile as well as per resident population. Racial composition analysis yielded divergent patterns: predominantly Asian (coefficient: +160.96) and Hispanic (+319.61) areas correlated with higher safety efficiency (lower crash risks), while White-majority tracts showed markedly lower safety efficiency (coefficient: −495.87), suggesting high crash likelihoods. Counties with higher percentage of Native American and Black residents also had negative coefficients indicating higher fatal crash risks among these communities.

The population-adjusted DEA model demonstrated consistent racial disparities in crash outcomes. White population percentage maintained a strong negative association, contrasting with positive coefficients for Black, Asian, Hispanic, and multiracial communities indicating their protective effects against crash incidence. However, areas with higher proportions of Native American and Pacific Islander residents showed increased crash risks. Socioeconomic factors proved equally consequential: poverty rates (% Below Poverty) and lower educational attainment (% Education Less than High School and % High School Graduate) were strongly associated with higher crash rates per capita. Regarding the sensitivity analysis, neither model indicated an impact on crash risks due to either ADI or SVI (Appendix L).

The differences between DEA models that use road miles and those that use population highlight how the exposure metric affects the interpretation of crash risk patterns. When the results differ between these models, it shows that sociodemographic factors impact crash outcomes differently depending on whether risk is measured by road infrastructure or resident population. These variations demonstrate that crash risk is complex. Some areas may have higher crash rates per mile of road due to traffic volume or road conditions, while others may have higher crash rates per capita because of population density, travel behavior, or demographic characteristics. Examining both models provides a fuller understanding of transportation safety disparities and helps design interventions tailored to specific risk factors in different communities.

Data Envelopment Analysis: Case Study—States

Like the models at the national level, two types of DEA models were developed. The first one considers length of road in census tracts as input while other considers population as the input. The output is the inverse of the crash count as detailed in the methodology. The subsequent sections present the results for each of the four states with additional tables found in Appendix L of the supplementary analysis that considers ADI and SVI compared against total road miles and population at the state and national level.

Arizona. The results of the two DEA models developed for Arizona are presented in Table 3. The analysis identifies key sociodemographic characteristics at the census tract level that are significantly associated with both increased and reduced risks of crash occurrence and injury severity.

Table 3: Results from the DEA models for Arizona.

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	−602.79*	−4685.12	−3534.81	−442.16*	−3527.49	−2579.29
Road Miles				−3059.37*	−4883.58	−3246.59
Population	2980.52*	5143.131	6908.204			
Unemployment Rate	5420.89*	2939.608	7353.295	4508.90*	4896.01	7084.66
Male-to-Female Ratio	−65.75*	−124.37	−89.0878	−53.44*	−115.12	−84.45
% White	−23377.96*	−41296.90	−33071.00	−18909.60*	−34888.10	−32566.57
% Black	−3883.98*	−7046.66	−5956.31	−3191.12*	−5982.16	−5618.02
% Native American	1815.53*	2958.809	4734.36	1721.34*	3352.26	4446.33
% Asian	−1496.18*	−2702.91	−2268.41	−1216.32*	−2326.70	−2127.37
% Pacific Islander	224.53*	657.2736	1019.801	213.63*	499.97	657.13
% Other Race	−2163.50*	−3914.29	−3248.89	−1757.28*	−3340.09	−3142.63
% Two or More Race	−2966.77*	−4753.97	−3127.92	−2388.16*	−4115.64	−3611.91
% Hispanic	−6914.53*	−11761.90	−8577.38	−5555.08*	−10043.25	−9188.58
% Education Less than High School	−3332.92*	−6271.87	−4959.35	−2723.69*	−5248.79	−4359.73
% High School Graduate	−5208.28*	−8170.21	−5218.70	−3838.87*	−6699.40	−5810.44
% Graduate Degree	−8499.90*	−14736.4	−11699.2	−6891.88*	−12518.1	−11540.84
% Below Poverty	−1378.50*	−3166.54	−2285.13	−913.42*	−2276.56	−1764.59

** Indicates statistical significance at the 95% confidence level*

The DEA model results reveal significant associations between sociodemographic factors and crash risks in Arizona, with consistent patterns across both the mile-based and population-based models. Higher proportions of White, Black, and Hispanic populations show negative coefficients, indicating increased crash risks in areas with greater representation of these groups. Conversely, census tracts with higher percentages of Native American residents demonstrate positive coefficients, suggesting reduced crash likelihoods. Educational attainment and poverty levels follow expected patterns, where lower education percentages and higher poverty rates correlate with higher crash risks. The percentage of college graduates was excluded from the DEA models due to computational constraints; thus, higher education here refers to graduate degree holders, while lower education reflects those with less than a high school diploma or only a high school degree. The male-to-female ratio maintains a negative association across models. Additional results from the sensitivity analysis indicate that a higher proportion of communities that are classified as experiencing social vulnerability have an increased crash risk when considering both road miles and total population of the area (Appendix L).

The models show structural consistency despite their different input specifications (i.e., road miles versus population). Unemployment rates show positive coefficients in both models, potentially indicating areas with better employment infrastructure may experience higher traffic exposure. Racial composition variables exhibit particularly strong effects, with White population percentages showing the largest negative coefficients among all demographic factors. The graduate education variable demonstrates the strongest negative association among socioeconomic indicators, which may be partly explained by Arizona's higher than average urban population (Berman, 2019), where over 86% of crashes occur (Arizona Department of Transportation [ADOT], 2023) and where individuals with higher education levels are more likely to reside (Carlsen et al., 2016).

Maryland. The results from DEA models for Maryland are presented in Table 4. These results reveal distinct sociodemographic patterns associated with crash risks, showing both similarities and differences compared to the Arizona findings.

Table 4: Results from the DEA models for Maryland.

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	−9611.44*	−22548.69	−21333.78	−8661.29*	−19505.90	−18637.08
Road Miles				691.65*	800.07	3595.74
Population	−21563.05*	−42400.66	−39168.25			
Unemployment Rate	−26974.08*	−52928.33	−50753.48	−22992.73*	−45164.20	−38847.32
Male-to-Female Ratio	−285.59*	−658.27	−474.06	−250.23*	−621.44	−376.29
% White	10677.22*	19908.19	21474.70	16680.02*	29080.10	32869.54
% Black	−86905.52*	−169350.20	−161789.50	−75247.32*	−149608.33	−142031.09
% Native American	−6819.43*	−13523.44	−12575.04	−6008.76*	−12016.67	−10314.63
% Asian	−26374.91*	−50751.62	−46778.40	−23737.41*	−46954.02	−39897.44
% Pacific Islander	−1806.20*	−3737.05	−3219.01	−1593.49*	−3405.63	−2366.04
% Other Race	−11226.21*	−21582.62	−19500.63	−9940.56*	−19748.68	−17041.00
% Two or More Race	−26678.81*	−51693.81	−48136.61	−22938.33*	−45218.21	−36673.49
% Hispanic	−23922.32*	−46351.96	−43040.73	−21163.20*	−42010.77	−37107.73
% Education Less than High School	−23773.80*	−46440.40	−43898.34	−20116.08*	−39943.83	−35846.47
% High School Graduate	−31501.17*	−62160.31	−59376.47	−24789.06*	−48670.48	−42162.97
% Graduate Degree	−36037.56*	−69509.75	−64721.11	−30373.08*	−59889.23	−53005.84
% Below Poverty	−23160.70*	−45348.51	−43298.31	−19559.42*	−38512.32	−33254.86

** Indicates statistical significance at the 95% confidence level*

Both models (mile and population) consistently demonstrate that census tracts with higher proportions of Black, Asian, Hispanic, and multiracial populations tend to have elevated crash risks, as indicated by their negative coefficients. Areas with higher White population percentage shows a positive association, contrasting with most other racial/ethnic groups. The male-to-female ratio maintains a negative relationship with safety outcomes, while unemployment rates show a negative correlation. The sensitivity analysis indicates that both communities experiencing social vulnerability and lower activity diversity, based on road miles, are more likely to experience higher crash risks whereas no significance was found based on total population (Appendix L).

The models further highlight education and poverty as significant predictors of crash risks, with all education level variables and poverty measures showing substantial negative coefficients. This suggests that areas with lower educational attainment and higher poverty concentrations experience significantly worse traffic safety outcomes. The consistency between the mile-based and population-based models reinforces the robustness of these findings, though the population model generally shows slightly reduced effect sizes.

Oregon. The results from DEA models for Oregon are presented in **Error! Not a valid bookmark self-reference.**. The population-based DEA analysis for Oregon identified several noteworthy sociodemographic patterns in crash risk distribution.

Table 5: Results from the DEA models for Oregon.

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	−114.33*	−2024.61	−1181.97	−197.59*	−4725.48	−3092.25
Road Miles				−399.82*	−1591.19	−257.42
Population	−3716.53	−3912.34	5489.31			
Unemployment Rate	−1064.91	−1127.01	1604.42	−2183.59*	−4305.76	−2586.61
Male-to-Female Ratio	5296.50	−6348.10	5629.26	8871.97*	14400.63	17826.93
% White	−5869.39	−6222.58	8908.85	−11589.12*	−21620.47	−15436.70
% Black	2258.09	−3150.59	2383.38	3831.50*	4699.80	7407.10
% Native American	−137.11	−163.88	126.77	−243.60	−668.79	1156.98
% Asian	−1226.30	−1308.40	1690.90	−2305.35*	−4583.94	−2855.74
% Pacific Islander	540.98	−898.09	558.22	922.98*	1020.69	2111.80
% Other Race	−544.89	−598.71	767.63	−1108.73*	−2369.76	−911.63
% Two or More Race	−1880.38	−2004.25	2569.64	−3597.96*	−6757.61	−4816.56
% Hispanic	−935.27	−986.59	1531.35	−1950.68*	−3873.53	−2315.56
% Education Less than High School	1167.64	−1259.12	1259.03	1768.35*	2433.34	3704.46
% High School Graduate	−984.12	−1131.75	1621.84	−2381.86*	−4753.65	−3258.14
% Graduate Degree	−3553.14	−3796.27	5015.08	−6628.92*	−12255.99	−7396.21
% Below Poverty	1024.78	−1102.69	1105.50	1509.15*	1790.13	3296.81

** Indicates statistical significance at the 95% confidence level*

The model shows higher crash risks in census tracts with higher percentages of White, Asian, Hispanic, and multiracial residents, as evidenced by their negative coefficients. Conversely, areas with greater Black and Pacific Islander populations appear associated with reduced crash likelihoods. An unexpected positive relationship emerges for the male-to-female ratio, diverging from Arizona's and Maryland's results. Educational attainment presents complex associations, with both higher education levels and areas containing more residents without high school diplomas correlating with different risk patterns.

Poverty rates demonstrate an inverse relationship with crash risk, suggesting potentially unique socioeconomic dynamics in Oregon's traffic safety outcomes. The road mile-based DEA model did not produce statistically significant predictors for Oregon. A possible explanation for why this occurred could be due to the high concentration of roadway miles within a small area of the state, known as the Willamette Valley, that comprises approximately 3.5% of the total area of the state and contains around 75% of the total population. Areas within the state that have lower diversity rates and have higher unemployment are rural or frontier counties that typically do not have many roadways running through them. When considering the sensitivity analysis there was no indication that either the active diversity or social vulnerability index impacted communities (Appendix L).

North Carolina. The North Carolina DEA model results analysis is shown in

. It is noteworthy that North Carolina's models are slightly different from the other three states as the model only considers fatal and serious injury outcome due to constraints regarding the availability of location data.

Table 6: Results from the DEA models for North Carolina.

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	−6715.73*	−17134.90	−15434.46	−4103.31*	−16947.29	−13105.05
Road Miles				−17104.39*	−16927.16	−5211.06
Population	54914.35*	99722.41	108526.11			
Unemployment Rate	−27145.87*	−53450.03	−48960.86	−32718.53*	−61949.76	−57785.23
Male-to-Female Ratio	−1533.91*	−3035.81	−2265.77	−2391.19*	−4133.13	−3264.25
% White	−83459.18*	−163811.30	−141823.70	−108639.30*	−197712.26	−174282.56
% Black	−16208.19*	−31820.99	−28017.23	−24942.78*	−45775.17	−37409.74
% Native American	−6405.45*	−13488.67	−11079.57	−7374.85*	−14671.89	−12220.55
% Asian	−398.39	−3323.91	194.54	−2138.04*	−3393.76	−966.50
% Pacific Islander	−3322.41*	−6825.71	−5701.93	−3808.26*	−7731.47	−6703.66
% Other Race	−14302.26*	−29287.12	−27453.19	−17346.19*	−33622.36	−30962.44
% Two or More Race	−14640.64*	−29136.97	−26667.21	−19243.41*	−35482.94	−31611.80
% Hispanic	−782.74*	−3168.59	−1099.48	−5071.14*	−7634.24	−3037.77
% Education Less than High School	−6399.66*	−12235.59	−9003.12	−10444.48*	−18769.01	−14060.58
% High School Graduate	−37379.81*	−73405.46	−65224.96	−47451.30*	−87969.99	−79159.16
% Graduate Degree	−12710.70*	−25226.21	−22606.39	−17340.15*	−31018.37	−27132.94
% Below Poverty	−6711.33*	−12680.69	−8394.64	−11827.17*	−20551.69	−15102.27

** Indicates statistical significance at the 95% confidence level*

Both the mile-based and population-based DEA models reveal consistent sociodemographic patterns associated with severe crash outcomes in North Carolina. The models show strong negative coefficients for all racial/ethnic groups with the highest risks seen in communities with higher White, Black, and multiracial population percentages, indicating these groups face heightened risks of fatal/serious injuries. There was evidence of an association with education level, with areas containing more high school graduates or higher showing particularly high crash risks. Poverty rates demonstrate a negative association in both models, suggesting economically disadvantaged areas experience worse traffic safety outcomes.

The male-to-female ratio shows negative relationship in both models while unemployment rates show a negative correlation indicating census tracts with higher unemployment rate are more prone to fatal or serious injury risks. While most racial/ethnic groups follow similar patterns across both models, the Hispanic population shows a weaker association in the mile-based specification compared to the population model. The consistent findings across both model types strengthen confidence in these crash risks across sociodemographic groups. Additionally, communities with a lower ADI are more likely to experience higher crash rates whereas communities with a higher SVI are less likely to experience higher crash rates when considering road miles with full results available in Appendix L.

The mile-based and population-based DEA models for North Carolina consistently showed negative coefficients across nearly all sociodemographic variables. This pattern occurs because two-stage DEA models measure how effectively census tracts minimize severe crashes relative to their population or road infrastructure. A negative coefficient means that as a given variable increases (e.g., poverty rates or racial/ethnic population shares), the likeliness of fatal and serious injury crashes per capita or per mile also rises. The universal negativity of these coefficients suggests that none of the included sociodemographic characteristics are associated with lower crash rates as their proportions increase. Instead, areas with higher poverty levels, lower educational attainment, or larger proportions of all racial and ethnic groups consistently show higher rates of fatal or serious injury crashes as their proportions increase.

Data Envelopment Analysis: Selected Findings

National

- Higher Crash Risks: Associated with poverty, lower education, and higher male-to-female ratios.
- Elevated Risk: White-majority, Native American, and Black communities.
- Lower Risk: Asian and Hispanic-majority areas show protective effects.

Arizona

- Increased crash risks in White, Black, and Hispanic communities.
- Reduced risks in Native American areas.
- Strong link between low education, poverty, and higher crash rates.

Maryland

- Black, Asian, Hispanic, and multiracial communities face higher crash risks.
- Poverty and low education strongly correlate with worse safety outcomes.

Oregon

- Higher crash risks in White, Asian, Hispanic, and multiracial areas.
- Black and Pacific Islander communities show lower risks.

North Carolina

- All racial/ethnic groups face high fatal/serious injury risks.
- Poverty and unemployment linked with worse outcomes.

Summary

Poverty & Education: Consistently linked to higher crash risks nationwide.

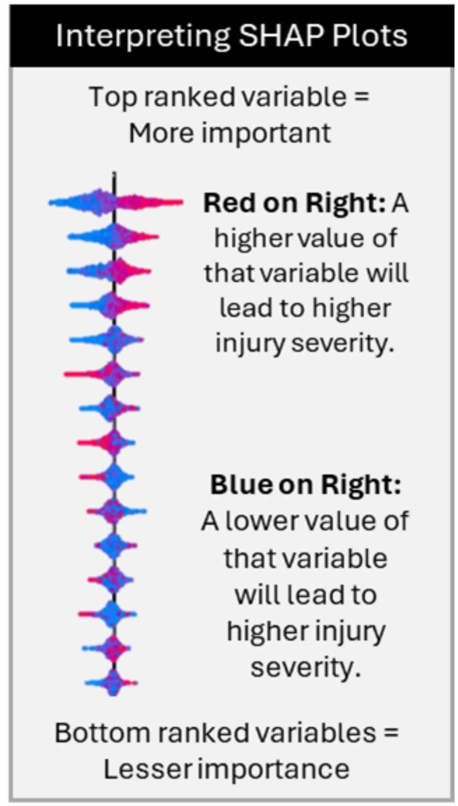
Racial Inequities: Crash risks vary significantly by race/ethnicity and location.

State Variations: Local demographics and infrastructure shape unique risk profiles.

Machine Learning Models: National Perspective

One machine learning model was analyzed identifying factors related to higher fatal crash counts across counties. **Error! Reference source not found.** presents the results from the XGBoost model with SHAP values, which provide valuable insights into the factors influencing fatality counts across census tracts nationally. In SHAP results figures, each dot represents a county's data point and is colored according to the factor's value, with red for high values and blue for low values (see box: Interpreting SHAP Plots). For example, if the factor is total population, a county with a large population is red, while a small-population county is blue. The horizontal axis shows the SHAP value, which indicates whether the factor increases or decreases predicted fatal crashes. Dots to the right indicate an increase in predicted crashes, and dots to the left indicate a decrease.

When more red dots appear on the right, it indicates that more counties with high values of the factor generally have higher predicted crashes. For example, a large-population county appearing as a red dot on the right suggests that high population increases crash risk. When more red dots appear on the left, it shows that high values reduce predicted crashes, such as a highly populated county with effective traffic safety measures. Similarly, when more blue dots appear on the right, it indicates that more counties with low values of the factor experience higher predicted crashes, for example, more small rural counties with few residents and more dangerous roads. When more blue dots appear on the left, it shows that low values reduce predicted crashes, such as a smaller counties with few residents and safe roads.



The bulge, or area where most dots cluster, represents the typical effect of the factor for most counties. A bulge toward the right or left shows whether the factor generally increases or decreases predicted crashes. The spread, or the full horizontal range of the dots, indicates how much the factor's effect varies across counties. For example, if red dots are widely spread in the left for total population, it suggests that higher population generally leads to more crashes, but the strength of the effect differs across counties. When there is a spread without a clear bulge, it indicates that the factor consistently affects counties in one direction, though the intensity varies. The number of dots reflects how many counties the factor influences, with more dots indicating broader relevance.

The analysis illustrated in Figure 15 reveals that certain sociodemographic factors were strongly associated with higher fatality counts. Specifically, an increase in the population of the county, as well as a higher proportion of residents aged 65+, were both linked to a higher number of fatalities. Additionally, counties with a higher male-to-female ratio and those with a larger percentage of individuals with a high school diploma or less also show a higher likelihood of increased fatality counts. The presence of higher percentages of American Indian and Pacific Islander populations within a county was similarly associated with a higher number of fatalities.

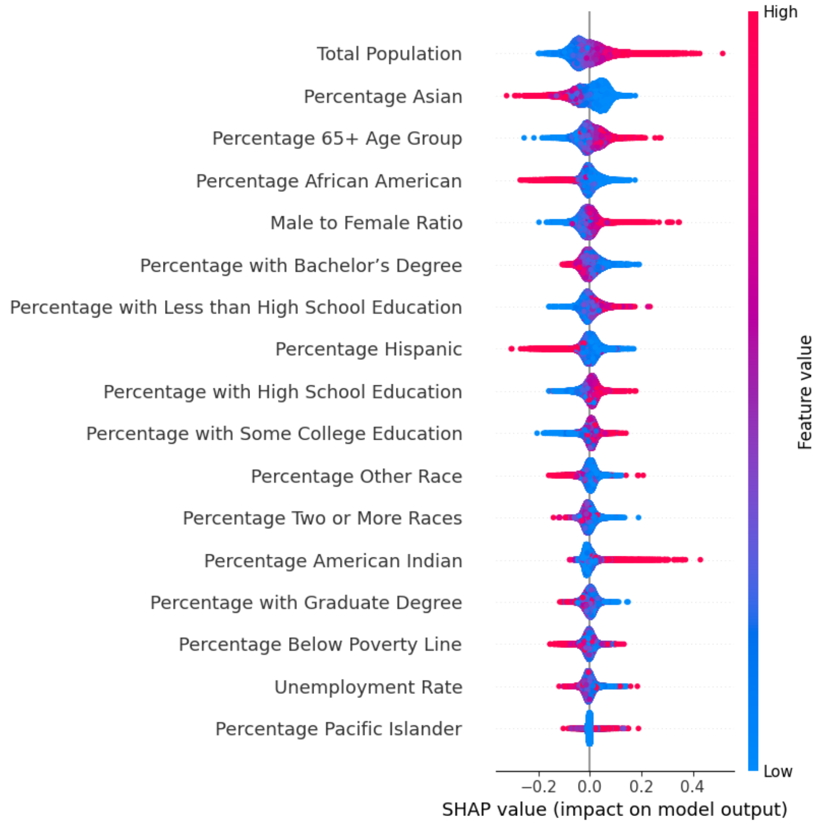


Figure 15: SHAP results for the fatality count and sociodemographic factors across counties.

On the other hand, counties with higher proportions of Asian, Black, or Hispanic populations tend to exhibit lower fatality counts. This suggests that these demographic groups may have different risk profiles or contribute to factors that reduce fatality rates. The impact of socioeconomic variables, such as the percentage of people living below the poverty line and the unemployment rate, is more complex. These factors show mixed results, indicating that their influence on fatality counts is not straightforward and may vary depending on other contextual variables within each census tract.

Machine Learning Models: Case Study—States.

The results from the machine learning models are explained in two subsections corresponding to the two types of analysis conducted. The first analysis depicts how likeliness of higher injury severity varies across where the crash occurred. This analysis is done at the crash level. The second analysis indicates how crash costs of a census tract are related to the sociodemographic composition of that census tract.

Injury Severity Models. Figure 18 through Figure 18 depict the results from the injury severity model for the three states. North Carolina's analysis for this model was not possible due to non-availability of less severe injury data.

The SHAP analysis of Arizona crash data revealed distinct sociodemographic associations with injury severity. Census tracts with higher percentages of older residents (65+), Native American populations, individuals without high school diplomas, and those below the poverty line show increased severe injury likelihood. Areas with greater male representation also demonstrate higher severity risks. Conversely, tracts with higher proportions of Asian or Pacific Islander populations, higher overall population, and higher percentages of graduate degree holders tend to experience lower injury severity. Unemployment rates showed no clear effect on the models.

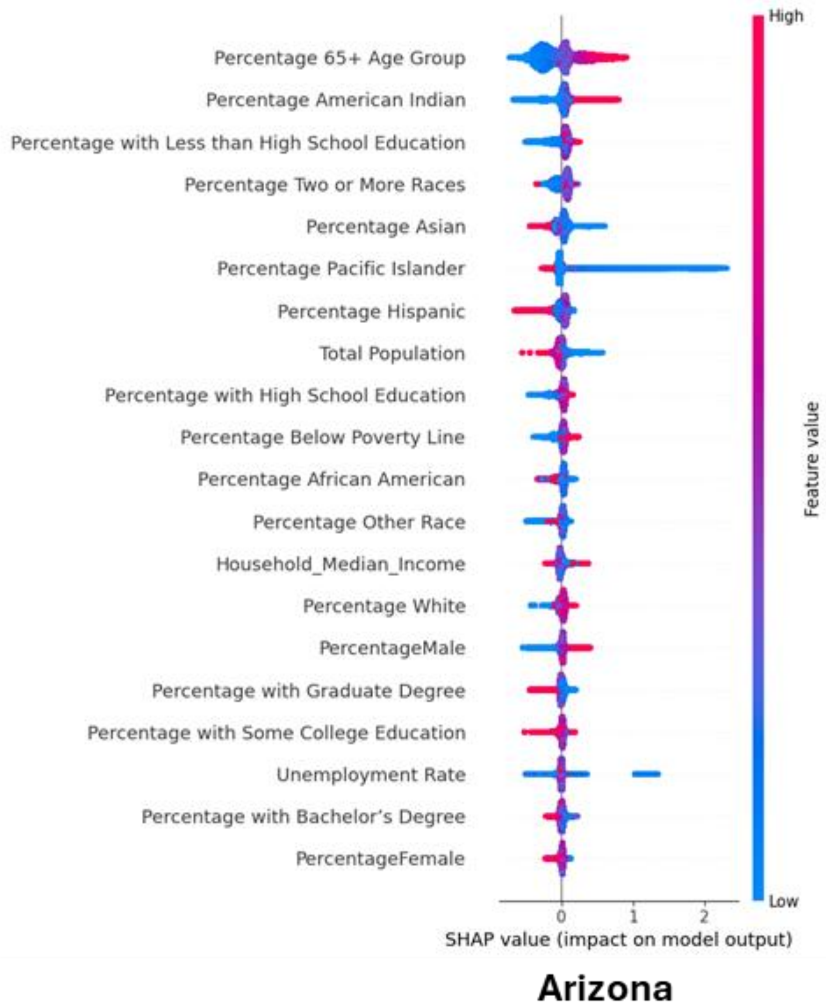


Figure 16: SHAP results identifying how sociodemographic factors may be associated with high injury severity across census tracts for Arizona.

Maryland's injury severity model produced different patterns, with higher severity linked to tracts containing greater proportions of White, Hispanic, and American Indian populations, along with higher unemployment rates and areas with higher poverty rates. Only higher percentages of high school graduates show a protective effect against severe injuries. Most other variables display ambiguous relationships with injury outcomes.

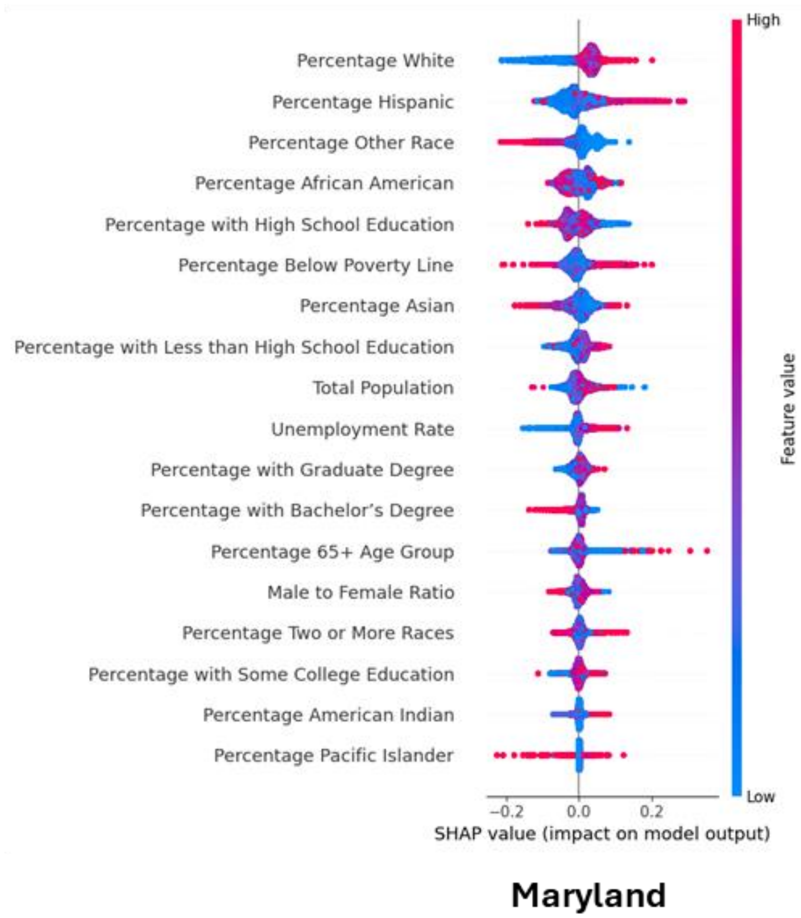


Figure 17: SHAP results identifying how sociodemographic factors may be associated with high injury severity across census tracts for Maryland.

Oregon's SHAP analysis identified education level and race as key severity predictors. Tracts with more high school/some college-educated residents and higher Asian or Hispanic populations correlate with increased severity, as did areas with higher median incomes and population. In contrast, predominantly White tracts and those with more bachelor or graduate degree holders show reduced severity. Unemployment rates demonstrate mixed effects without clear directional trends. These state-specific analyses collectively demonstrate that while certain patterns appear consistent, the sociodemographic drivers of crash severity vary substantially by region.

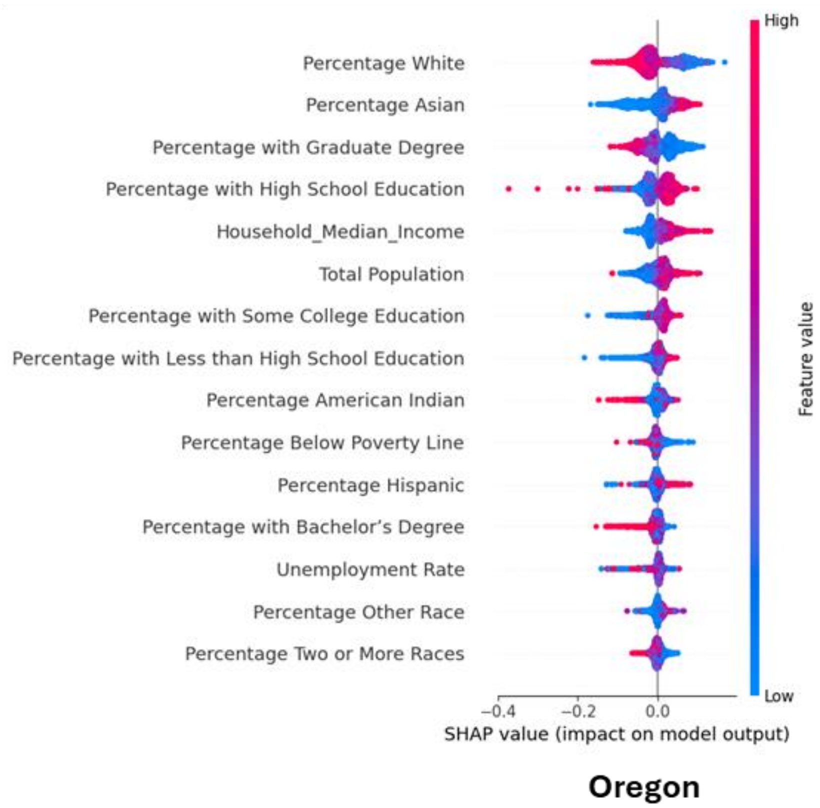


Figure 18: SHAP results identifying how sociodemographic factors may be associated with high injury severity across census tracts for Oregon.

Cost of Injury Models. Figure 19 presents the results identifying how the demographic composition of a census tract is related to the cost incurred by the census tracts. The SHAP results revealed distinct state-specific patterns in how sociodemographic factors correlate with crash-related costs.

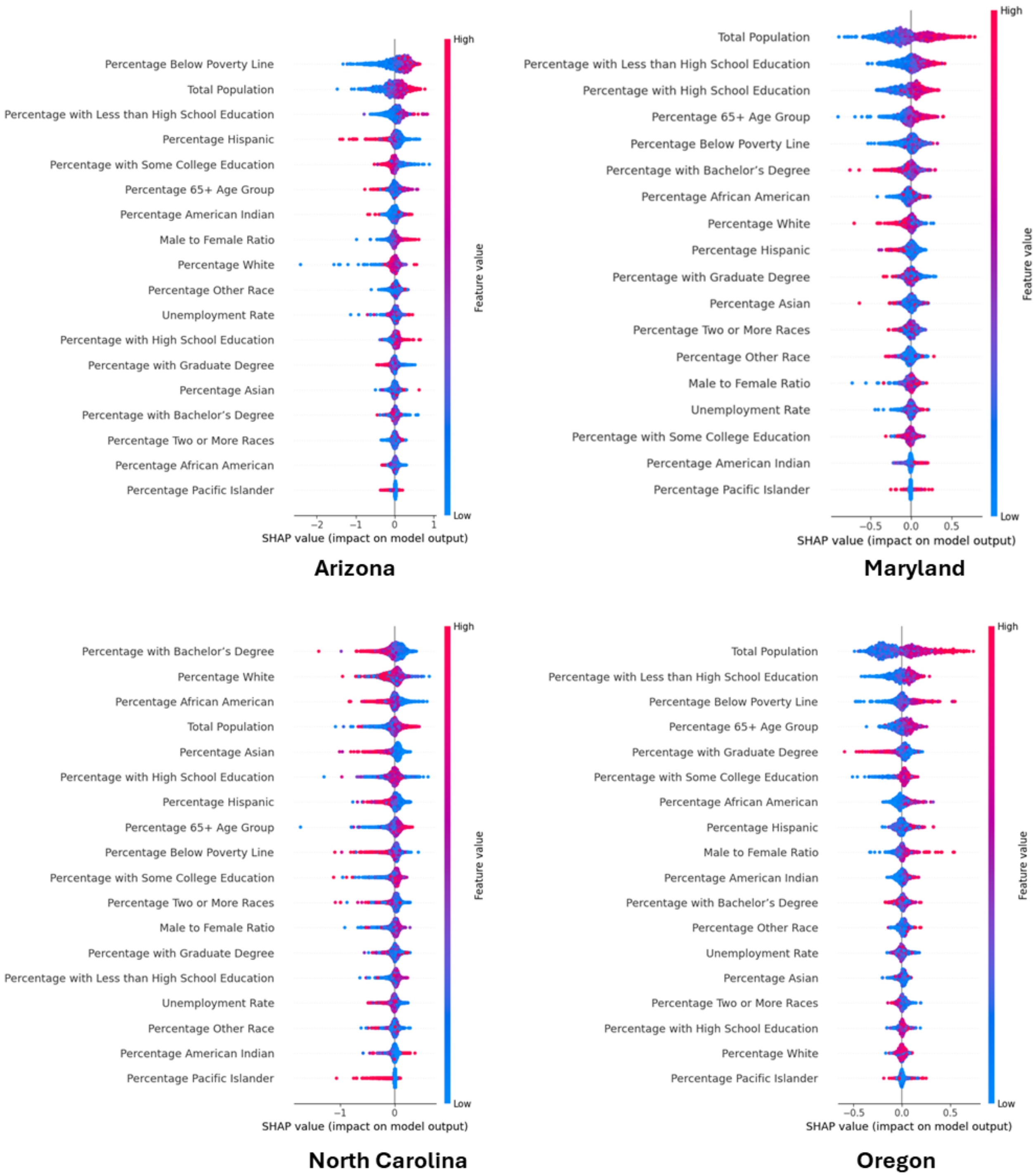


Figure 19: SHAP results identifying sociodemographic factors within census tracts that are highly correlated with higher and lower injury costs to that census tract.

In Arizona, census tracts with higher poverty rates, larger populations, larger male-to-female ratios, and greater proportions of high school-educated residents tended to incur significantly higher injury costs.

Maryland's analysis showed that areas with larger populations, more elderly residents (65+), higher percentages of individuals with only high school education, and greater American Indian or Pacific Islander populations were associated with increased crash costs. Conversely, tracts with more White or Hispanic residents and higher graduate degree attainment demonstrated lower financial impacts from crashes.

North Carolina's injury cost model (limited to fatal/severe crashes) found that more populous tracts and those with higher American Indian representation correlated with greater crash costs. Areas with higher unemployment rates and more educated populations showed reduced cost burdens.

Oregon's results indicated strong cost correlations with population, poverty levels, and sex distribution, with higher male percentages linked to greater costs. Tracts with more American Indian, Black, or Hispanic residents showed increased crash costs, while Asian populations were associated with lower costs. These findings collectively demonstrate that while population size consistently predicts higher crash costs across states, other sociodemographic factors like education, race, and poverty show varying state-specific relationships.

Qualitative Analysis Findings: Key Themes from Expert Interviews

The study engaged 27 participants representing diverse transportation organizations, including state, local, and federal agencies, as well as academic institutions and industry organizations. Following the methodology outlined in the qualitative analysis methodology section, all interview transcripts were processed through a systematic coding procedure to identify and categorize recurring themes. The following section presents the key thematic findings that emerged from this rigorous qualitative analysis.

*[**Note**: The names of interviewees and specific references to report titles, and agency names have been generalized to focus on substantive issues while protecting sources from potential professional consequences. This anonymization allows for open discussion of these important planning challenges without jeopardizing individuals or agencies.]*

Data Gaps in Tribal Communities

At a national level, those who identify as Native American are at higher crash frequency and severity risks despite reports indicating lower crash rates in state level analyses. Participants were asked to clarify what factors might be contributing to these crash rate differences. Transportation and public health officials attributed persistent challenges in obtaining comprehensive crash data from tribal communities and existing infrastructure as meaningful contributions to the disparities.

At the state level, the Arizona Department of Transportation (ADOT) has worked to support data sharing with tribes by offering access to the Traffic and Criminal Software system and funding for recording equipment. However, at present, only one of Arizona's twenty-two tribes regularly submits crash data to ADOT. Factors impacting the decision of tribal communities to participate in these collection efforts were attributed to sovereignty concerns and long-standing trust issues leading to a "blind spot" in understanding safety disparities on tribal lands, making it challenging to address traffic safety issues effectively.

Other state departments of transportation in the country have chosen to approach the issue through the construction of new roadway infrastructure. This is due to tribal communities' challenges with speeding and emergency medical service response times. Working together with tribal communities to incorporate traffic calming measures such as roundabouts has seen some success in reducing crash frequency and severity; however, there is still a need to ensure that the concerns of each individual community are addressed in a way that is most beneficial to them. It was consistently noted that higher crash rates may be associated with income levels in different tribal communities, as well as the fact that many residents often walk to their destinations along roadways that, while not necessarily designed for high-speed travel, are frequently used as such.

While progress has been made in fostering collaboration between tribal communities and government agencies to improve data collection and roadway infrastructure, lingering mistrust remains. This mistrust is shaped by historical injustices, including broken treaties, displacement, and exclusion from decision making processes that have impacted tribal lands and communities. This creates a barrier to collecting critical information, such as citation and health data. As noted by participants, it will require sustained effort working with these communities and their elders to build trust and confidence that transportation agencies are seeking to help and not harm.

Equity vs. Data-driven Approach Focus

Interviewees were asked about steps taken to integrate equity into safety plans and how this consideration aligns with data-driven decision-making in traffic safety planning. The discussions revealed a tension between prioritizing locations with the highest fatality and serious injury rates and addressing the needs of underserved communities through equity-focused approaches.

At the state level, Arizona has continued to approach addressing high fatal and serious injury crashes using traffic volume and crash data, focusing on targeting hotspot locations where crash frequency and/or severity are overrepresented in relation to comparison sites. There is a desire to focus on funding projects by hotspot analysis rather than by some version of equity score. An interviewee from Massachusetts also indicated that the focus is more on using a data-driven approach, but that many of the same locations highlighted were consistent with environmental justice communities. In contrast to the data driven approach, Maryland has focused on the Justice40 initiative to help with analyzing the number of fatalities and serious injuries occurring in census tracts that have been identified as transportation disadvantaged. Through the use of this approach, the state is able to refine its use of equity metrics leading to an eventual outcome of 40 percent of funding or efforts being directed toward transportation disadvantaged areas. The state of Washington includes an equity approach into their decision-making processes through a Vulnerable Road User Characteristics Index, in which projects are graded on a zero to ten scale, with higher levels indicating that a greater number of socioeconomic characteristics are being met through the delivery of a particular project. By overlaying this with existing crash data analysis, it addresses both current and potential crash issues, while taking into consideration social indicators such as lower income communities having inadequate infrastructure and higher speeds.

Motorist Prioritization in Transportation Policy

When asked about policy changes, the interviewees echoed the need for policies that caters to all road users. The interviews revealed deep-seated institutional preferences for motorists in current transportation planning practices, with several experts calling for fundamental policy reforms to create a more balanced approach that prioritizes the safety and needs of all road users including pedestrians, cyclists, and drivers equally.

One interviewee in North Carolina noted that the North Carolina Department of Transportation (NCDOT) has traditionally prioritized driver safety, which is often justified by citing traffic volume data as an indicator of higher exposure to risk for drivers. NCDOT seeks to counter this by bringing into focus that while drivers are protected by a vehicle, vulnerable road users do not have the same safety protection. Arizona is also a state that has a vehicle-orientated design culture in which wider roads encourage higher speeds, and a lack of separated pedestrian infrastructure creates inherently dangerous conditions for non-motorists. Oregon noted that the state Department of Transportation was originally founded as the Highway Division and as such, has been dominated by a highway-focused culture. Over the years, it has increased its focus on all modes of transportation by creating divisions focusing on non-vehicle alternatives indicating that there is some movement away from prioritizing vehicles. Experts agree that transportation agencies need to move beyond motorist-centered approaches. However, this shift is often constrained by long-standing practices, vehicle-oriented engineering standards, historical infrastructure investments focused primarily on motor vehicles under the premise of maximizing efficient mobility, and funding structures that continue to prioritize vehicular travel.

Transportation Inequities in Low-Income Communities

Interviewees were asked about the reason why high poverty areas consistently ranked as disproportionally unsafe throughout all states analyzed and nationally. The interviews revealed consistent patterns linking poverty, transportation mode choice, and increased crash vulnerability. Multiple experts highlighted how economically disadvantaged populations face compounded risks due to inadequate infrastructure and limited transportation options.

In North Carolina, lower-income urban residents lack vehicle access which led to a reliance on walking, biking, and taking transit in areas with inadequate supporting walking and biking infrastructure such as sidewalks and bicycle lanes for these modes of transportation. As such, this led to a significant increase in crash exposure and injury severity potential. Similarly, in Arizona, the lack of vehicle access led to vulnerable travel patterns as individuals traveled longer distances to reach jobs leading to a greater exposure to crash outcomes.

Conversations with those in other states, such as Washington and Massachusetts, noted the lack of available or safe infrastructure for those taking local transit to their destinations. One interviewee noted that plans, which appear effective on paper, may not be accessible in reality due to a failure to consider those within the community who might have concerns about mobility issues, safety issues, or limited access to reliable infrastructure needed to reach transit facilities. Additionally, many lower-income neighborhoods with inadequate infrastructure are also located in areas with higher speeds, which when combined with walking or biking leads to a greater risk of high-severity and fatal crashes. Those in Oregon and Washington noted that with gentrification happening in larger cities such as Portland and Seattle, many people are being priced out of housing located in walkable communities.

The interviews collectively reveal a pattern in which transportation disadvantage compounds safety risks for low-income populations. As most experts noted, lack of vehicle access forces residents to rely on walking, biking, and public transit, all modes that immediately classify them as vulnerable road users. This creates a dangerous paradox: where communities least equipped to withstand transportation injuries are systematically funneled into the riskiest travel modes across poorly established surface transportation infrastructure. Interview data suggests this is not coincidental, but rather a structural feature of how transportation systems have evolved. Economically disadvantaged neighborhoods frequently suffer from double jeopardy where they contain the highest proportions of resident’s dependent more on vulnerable modes, while simultaneously having the most outdated and dangerous infrastructure to support those modes.

Authentic Community Engagement in Transportation Planning

Interviewees were asked how their agencies incorporate diverse communities into their processes and what challenges they face in doing so. The interviews revealed unanimous agreement about the necessity and current shortcomings of meaningful community involvement in transportation safety initiatives.

Those working at state agencies emphasized engaging in active conversation with communities to ensure that their input is meaningfully considered in planning processes. Interviewees in Maryland elaborated that current practice spans the gamut between a superficial outreach approach and genuine engagement seeking an active incorporation of community input during planning processes. One recently adopted approach to increase access has included making public meetings available both virtually and in-person. In Oregon, those running public meetings have noted the issue of timing and financial strain to attending these meetings, which might be held during work hours. To facilitate the inclusion of all members of the community, a reimbursement structure has been created to ensure that barriers from participating in these meetings are removed. This includes compensating individuals for their time, covering travel costs such as mileage, and providing meal reimbursements. These measures are intended to ensure that individuals from underserved or low-income backgrounds are not excluded due to financial constraints. The Oregon Department of Transportation has also provided training to ensure that those working on projects are able to recognize biases that might be unintentional to ensure that all voices are heard.

However, substantial barriers to equitable participation remain, particularly for marginalized groups. In Arizona, obstacles have been identified at the cultural level that prevent many Hispanic and disadvantaged communities from engaging with those at transportation agencies. Individuals from more privileged backgrounds, including those in wealthier neighborhoods, are often more likely to engage with agencies and advocate for improvements. In contrast, underserved communities may be less likely to engage, in part due to longstanding mistrust, past experiences of being overlooked or excluded from decision making, or a lack of access to resources such as time to participate. Policymaking has also been identified as an area where there is often a disconnect between decision-makers and the daily realities of the communities they serve. Policies may be implemented that overlook or inadequately address on-the-ground needs due to a lack of consideration for lived experiences of local road users.

Experts highlighted key principles for effective community-driven approaches, emphasizing the need for ongoing, adaptive engagement that aligns with community norms and includes multiple levels of involvement. However, substantial barriers remain, including resource disparities, cultural and language challenges, and historical distrust in government institutions. Overcoming these requires a sustained commitment to building trust, providing equitable resources, and fostering inclusive outreach that goes beyond superficial efforts.

Expanding Accessibility

Interviewees were asked about programs focused on educating diverse communities on traffic safety while addressing cultural or linguistic barriers. The interviews revealed growing but uneven efforts to create transportation safety materials that serve diverse linguistic communities. Several experts shared insights into their agencies' efforts to ensure that safety education reaches underrepresented communities, with a focus on both language and cultural considerations.

Multiple participants brought up the provision of driver's manuals being made available in multiple languages, representing an important step in accommodating non-English speakers. While some agencies might primarily focus on translating official documents, others are looking to provide comprehensive safety communication strategies. The Maryland Department of Transportation has incorporated educational materials that also consider those with lower literacy levels and include diverse imagery to ensure that community members can comprehend the content.

Those in the State of Washington noted the use of translator services to communicate with immigrant communities, noting that all written documents are translated into the eight major languages to ensure greater accessibility. Oregon has built on this approach as well with the mindset that educational documents regarding safety might be the only source of information available to certain groups. These documents are formatted to be accessible to those who might read at a lower grade level and have been translated into 41 different languages.

Intersection of Rural Living and Transportation Safety for White Communities

When asked about the reasons for communities with higher percentages of White residents being more vulnerable to transportation-related risks, the interviewees noted that these groups tend to live in more rural areas and have fewer socioeconomic opportunities. This geographic isolation, combined with long commutes, raises the risk of being involved in crashes. Cultural factors were also mentioned, including a tendency among individuals in more rural areas to be less likely to wear seatbelts. In some cases, this may stem from the belief that driving inherently involves risk and that such risks are simply part of daily life. In other instances, resistance to seatbelt use may be tied to perceptions of government enforcement interfering with their freedom of choice.

Local and Federal Influence on Equity

Through these interviews, it was found that many states have different approaches to incorporating equity into their transportation policies both at the state and local levels. For Arizona, while equity has not been a primary focus in transportation policies, several local and regional initiatives have incorporated elements of equity into their safety plans, largely due to federal mandates and the initiatives of individual agencies. In contrast, the State of Washington has passed a variety of legislation that incorporate equity within all executive state branches. King County, Washington, which includes the City of Seattle and is home to nearly 30 percent of the state's population, passed the "Fair and Just Ordinance" in 2010. This ordinance requires that equity-focused reforms be implemented across all county agencies and departments, not just at the executive level.

At the state level, many agencies have incorporated equity into their Strategic Highway Safety Plan with varying levels of success. Due to national pushbacks, some states have reduced emphasizing the inclusion of equity within their plans reflecting the broader challenges in making equity a central pillar in statewide safety strategies. Others have noted their gradual success in the inclusion of equity and that at the end of each three-year cycle, a review is held to ensure that underrepresented groups are being included as well as utilizing annual public opinion surveys to ensure that drivers of these groups feel that their voices are being heard. Overall, in some states, while broader transportation policies may not heavily emphasize equity, several cities and counties have proactively integrated equity components into their safety action plans, driven by federal guidance and local leadership.

Shifts in Equity-Focused Safety Planning

As the current federal administration advances major changes in the transportation sector, interviewees noted a noticeable shift in how transportation agencies are approaching equity within safety planning efforts. While some agencies continue to maintain their stance on incorporating equity into the framework of their projects and decision-making policies, there are others who fear the repercussions certain terminology might have on their agencies. At the state level, a transportation official described carefully modifying planning documents in response to new directives. The agency has systematically removed or replaced specific terminology related to equity from their materials, operating under the assumption that reviewers may evaluate documents based on the presence of certain keywords rather than substantive content.

Interviews: Key Themes

Data Gaps in Tribal Communities: Native American communities face high crash risks but remain underrepresented in state crash data due to sovereignty concerns and mistrust.

Equity vs. Data Dilemma: Hotspot focused states (e.g., Arizona) prioritize crash data, while others (e.g., Maryland, Washington) integrate equity metrics (e.g., Justice40, VRUCI scores).

Car-Centric Culture: DOTs still favor drivers; multimodal shifts are slow but growing.

Poverty = Higher Crash Risks: Low-income communities face dangerous conditions: inadequate infrastructure, high-speed roads, and forced reliance on unsafe modes.

Rural White Communities at Risk: Geographic isolation, long commutes, and cultural resistance to safety measures (e.g., seatbelts) increase crash severity.

Equity Progress Uneven: Some states (e.g., Washington, Maryland) mandate equity; others retreat due to politics.

Discussion

This study identifies factors associated with increasing crash risks across sex, age, race, and other socioeconomic and sociodemographic factors. The crash rates across these sociodemographic groups were presented, followed by the results of the DEA analysis and machine learning models. Finally, interviews were conducted to understand the underlying pattern of inequities across sociodemographic groups. The findings highlight critical disparities in serious injury and fatality patterns across demographic groups and geographic regions, reinforcing existing literature while providing new insights into state-specific risk factors.

Males were found to be consistently overrepresented in fatal and serious injury crashes in alignment with previously identified trends (Al-Balbissi, 2003; Amarasingha & Dissanayake, 2014). Similar results were found in census tracts where male representation was high. Literature often cites behavioral and exposure differences amongst males and females contributing to increased crash and injury risks among males (Cullen et al., 2021; Turner & McClure, 2003). This study supports those findings and further highlights that, on a per capita basis, males experience higher rates of injury. However, it is important to note that this analysis did not differentiate by crash type or injury type, as previous research suggests these factors may result in higher injury risk for women in certain crash scenarios (Kelley-Baker & Romano, 2010; Ryan & Knodler, 2022). Without segmentation by crash or injury type, the results of this study indicate that males experience higher overall crash risk and injury severity across all sociodemographic and user groups examined, indicating that sex-based differences in crash outcomes may be universal.

Age-related risks in literature have been very mixed. Some research indicates younger age groups to be more prone to serious injury crash risks (Mafi et al., 2019), other studies identified mid-age and older age groups to be more prone to serious injuries (Kocatepe et al., 2019; Mafi et al., 2019). The crash rates obtained in the present study indicate that mid-aged individuals (25–44 years of age) were the most risk prone to severe injuries. For bicyclists, older age groups were the most vulnerable. Although the age composition of census tracts and counties were not considered in DEA models, they were considered in SHAP analysis, where areas with a higher proportion of older road users were prone to higher injury severity as well as higher crash costs. Scant literature was identified associating age characteristics of a geographic area with crash risks, presenting an opportunity for future research.

When considering racial characteristics, the results varied widely across different geographic areas. Crash rates indicate Native Americans were the most vulnerable racial group for all types of road users. Previous research often identifies Native Americans as the most vulnerable racial group in terms of crash frequency and injury severity (Oh et al., 2017), often linking these disparities to behavioral factors prevalent among Native

American drivers, such as lower restraint use and higher rates of alcohol impairment (Grossman et al., 1997). Beyond these behaviors, their increased vulnerability is also driven by lower vehicle ownership, leading to greater reliance on more dangerous travel modes, longer average travel distances, and residence in rural, low-income areas with limited infrastructure and emergency services (Blumenberg et al., 2007). The DEA results indicate that although these communities have higher vulnerability as described by national data, they were found to be safer communities in Arizona when normalized against road miles or population. This contradicts previous documented results describing these communities to be generally more vulnerable (James & Russo, 2019; Piontkowski et al., 2015). Interviews with Arizona officials indicated data limitations affecting tribal communities with only one of Arizona's twenty-two tribes reporting crash data to the Arizona Department of Transportation, a possible contributor to the inconsistency. More consistent with previous findings (Iragavarapu et al., 2015; Vachal, 2020), interviews revealed that longstanding mistrust, jurisdictional complexity, and sovereignty-related concerns continue to hinder the collection of reliable crash data in these regions. These data limitations generate systemic gaps in safety reporting at state, and thus, correspondingly, national levels. When transportation agencies base funding decisions solely on these partial datasets, underrepresented communities may be excluded from critical safety improvements. This problem aligns with the concept of "equity biases" (Ricord & Wang, 2023) where systematic data deficiencies can disproportionately affect marginalized groups and may perpetuate disparities.

The results across Arizona, Maryland, and Oregon reveal both consistent and divergent patterns in how sociodemographic characteristics shape traffic safety outcomes, offering both support for and extensions to prior research (Balakrishnan et al., 2019; Sagar et al., 2021). A key takeaway is that racial and ethnic composition plays a variable role across states. For instance, in Arizona, higher proportions of White, Black, and Hispanic populations are linked to increased crash risks, while areas with more Native American residents appear safer. In contrast, Maryland shows elevated risks in tracts with higher Black, Asian, Hispanic, and multiracial populations, while higher White population percentages are associated with safer outcomes. Oregon presents yet another pattern where higher crash risks are found in areas with more White, Asian, Hispanic, and multiracial residents, while Black and Pacific Islander populations show a protective association. These patterns support previous research showing that traffic safety outcomes are deeply shaped by local context and the intersection of race with spatial inequality, infrastructure quality, and mobility patterns (Karner et al., 2020; Spray et al., 2022; Weiwu, 2024). This variation underscores the need to interpret racial and ethnic disparities in crash risk within the unique context of each location's urban design, infrastructure, and socioeconomic conditions. It further emphasizes that elevated crash risk is not inherently linked to an individual's racial or ethnic identity. Instead, these disparities arise from the intersection of race and locational factors, where structural factors such as uneven temporal and spatial exposure to hazardous environments and disparities in access to quality infrastructure shape observed differences in crash outcomes.

Across all the states analyzed, areas with higher Hispanic populations are consistently associated with elevated crash risks. This pattern may be partially explained by behavioral and structural factors often cited in prior research, including lower rates of seat belt use and higher incidences of speeding, unlicensed driving, and alcohol involvement (Harper et al., 2000; Romano et al., 2006). Additionally, Hispanic drivers are more likely to own older vehicles (Harper et al., 2000), which may lack modern safety features, further increasing vulnerability in the event of a crash. Further, results indicated that Black drivers and pedestrians had higher fatal crash rates. This corresponds with previous literature where numerous behavioral and cultural factors were attributed to such outcomes. The factors included drinking and driving, aggressive and reckless driving, and inconsistent seat belt use (Cordy et al., 2002). Possible explanations to consider also include systemic underinvestment in pedestrian and cycling infrastructure in communities of color, disparities in emergency response, variations in quality of care and outcomes, limited access to medical insurance, and economic constraints (Raifman & Choma, 2022).

Census tracts and counties with a higher proportion of White population were found to have high crash and injury severity risks nationally, as well as in three of the four states analyzed. Interviews indicated that this might be attributed to the fact that a lot of counties and census tracts with larger White populations are rural areas where residents drive longer distances and other behavioral and infrastructure factors constrain individual safety factors. Literature regarding rural areas indicate lack of sidewalks, lower use of traffic control devices, less seatbelt compliance, as well as frequency of driving under influence, as major factors behind increased risk in rural roads (Ossenbruggen et al., 2001; Rakauskas et al., 2009).

Areas with higher poverty rates were consistently associated with elevated crash risk and injury severity across three of the four states analyzed, as well as at the national level. This pattern aligns with extensive literature documenting the strong correlation between socioeconomic disadvantage and transportation safety outcomes (Li et al., 2022; Males, 2009). Lower-income communities often lack critical infrastructure such as sidewalks, crosswalks, and adequate lighting, making them more dangerous for all road users, particularly pedestrians and cyclists. These areas also tend to be located along high-speed arterial roads where traffic volume and severity of crashes are elevated (Dumbaugh et al., 2022). The interviews highlighted that economically disadvantaged neighborhoods frequently suffer from double jeopardy, where the highest proportions of residents depend on vulnerable modes, while simultaneously having the most outdated and inadequate infrastructure to support those modes. Literature also often points to the fact that drivers in these communities drive older vehicles that are less safe (Haddad et al., 2024).

Pedestrian fatalities in this study followed similar demographic patterns, with comparably higher risks in Arizona. This aligns with earlier research highlighting increased pedestrian fatality rates among Native American populations in the state (Campos-Outcalt et al., 2002). These disparities have often been attributed to alcohol-related factors and the prevalence of rural areas with inadequate pedestrian infrastructure (Campos-Outcalt et al., 2002). The current analysis further reveals higher pedestrian fatality risks among Black pedestrians, particularly at the national level. These results point to persistent structural and environmental inequities that disproportionately affect vulnerable communities and emphasize the need for targeted pedestrian safety improvements.

The present study responds to calls in the literature (Patwary et al., 2024) for more holistic approaches that account for both spatial analysis and community-specific needs analysis. The findings support previous work showing that crash risks are not evenly distributed across space (Ziakopoulos & Yannis, 2020) or populations (Merlin et al., 2020) and that standard, uniform safety interventions are often inadequate (Li et al., 2022). The study further reinforces the importance of combining technical analysis with community engagement. Modeling alone can identify where disparities occur, but understanding the underlying causes requires engagement with the communities affected. This dual approach reflects the discussions of Linovski and Baker (2023), who emphasize that lived experience is critical to designing effective and equitable transportation policies. Addressing disparities in transportation safety will require both better tools and better relationships with the communities most at risk.

The qualitative interviews highlighted both existing policy frameworks and emerging needs in transportation equity. Traditional data-driven approaches, while emphasizing efficiency and measurable outcomes, often perpetuate disparities by prioritizing high-volume corridors over systemic inequities. As Karner and Marcantonio (2018) argue, standard public engagement processes tend to marginalize underserved communities, limiting their influence over transportation decisions. Their recommendation to establish dedicated funding mechanisms for priority community needs offers a more bottom-up approach that aligns with equity initiatives such as Maryland's Justice40 program, where solutions are shaped by local priorities.

The persistent prioritization of motorists over vulnerable road users in transportation policies, as seen in the interviews, reflects a deeply rooted institutional bias in transportation planning. Norton (2011) documented how mid-20th-century transportation policy entrenched car-centric infrastructure at the expense of other modes. This legacy continues to disadvantage low-income and marginalized groups, who often experience unsafe environments and restricts mobility, conditions that Bullard et al. (2004) describe as transportation racism. Similarly, the elevated crash risks observed in rural White communities and discussed in interviews align with prior research linking geographic isolation, longer travel distances, and cultural resistance to safety measures with increased fatality rates (Adeyemi et al., 2022; Rakauskas et al., 2009).

Limitations and Future Work

This study has several limitations that should be considered when interpreting the results. First, the analysis examined driver-level risk factors and community-level risk factors separately across demographic categories including sex, age, and race. Although demographic-specific crash rates were calculated and both DEA and SHAP analyses identified key community characteristics linked to higher injury severity, these two levels of analysis were derived from different data sources and are not inherently aligned. The drivers involved in crashes may not accurately represent the demographic composition of the communities where crashes occurred, necessitating caution when interpreting combined individual-level and area-level results. Second, limitations in race data reliability for serious injury cases, particularly in Maryland, may affect the accuracy of race-specific comparisons for crash rates, and this constraint should be acknowledged when drawing conclusions from these findings.

Furthermore, the study's findings should be interpreted considering certain methodological limitations. The analysis could not account for variations in crash reporting practices across different jurisdictions and demographic groups, particularly potential underreporting of non-fatal crashes, which may bias the calculated rates and obscure true disparities. Additionally, while population and road mileage served as exposure metrics, these proxies fail to capture more direct measures of risk exposure such as vehicle miles traveled, time spent on roadways, or trip frequency, factors that vary across communities and demographic groups. The absence of direct exposure data restricts the precision of the rate calculations and may affect interpretation of risk disparities. Finally, the interview sample was limited to 28 interviewees and spanned multiple jurisdictions, resulting in limited representation within each geographic and institutional context. This small sample design precludes definitive conclusions but aligns with exploratory qualitative research aimed at identifying thematic patterns rather than generalizable truths.

Future research should pursue several important directions to build upon this work. First, investigations should examine the intersection between driver demographics and community characteristics in crash risk assessment. Analyzing whether drivers of particular demographic groups experience different risk profiles across different communities could reveal meaningful contextual patterns in safety outcomes. This line of inquiry would extend beyond the current focus on community characteristics to incorporate driver-community interactions.

Second, expanding the range of intermediate variables in safety models represents a critical research need. While this study concentrated on sociodemographic factors, future models should incorporate behavioral metrics such as typical speeds, environmental conditions including weather and lighting, and vehicle characteristics to provide more comprehensive risk assessments. Such multidimensional modeling could better capture the complex interactions that shape crash outcomes.

Third, enhancing DEA models with additional input variables would improve their precision and practical applicability. Incorporating behavioral exposure metrics like average miles driven, trip purpose, or vehicle age could yield more accurate efficiency measurements. These refinements would help account for variations in mobility patterns when evaluating community-level safety performance, leading to more targeted and effective interventions.

Conclusions

This study used a mixed-methods framework combining quantitative and qualitative approaches to examine traffic safety disparities. The research identifies unequal safety outcomes across communities and users while investigating the underlying factors contributing to these disparities through stakeholder interviews. This integrated methodology provides both statistical evidence of transportation inequities and contextual understanding of their systemic causes. Interpretation of the mixed method results indicates some actionable strategies for stakeholders interested in improving equity in traffic safety (see Box on page 70), including improving data collection and reporting, prioritizing equitable infrastructure, shifting agency culture, and advocating for locally appropriate solutions, equity impact assessments, and policies that address the root causes of disparities.

The analysis reveals significant disparities in crash rates across demographic groups and geographic regions. Male road users, middle-aged individuals, and Native American populations experience disproportionately high crash impacts nationwide. Geographic variations in these patterns are also present, with North Carolina exhibiting consistently higher crash rates across all sociodemographic groups compared to the other three states analyzed. However, the state demonstrates more balanced sex-related disparities in fatal crashes compared to other regions. State-specific analyses uncover distinct risk profiles with Maryland showing the most substantial sex-related disparity; male fatalities occur nearly four times more frequently than female fatalities in Maryland. Arizona emerges as dangerous for vulnerable road users, recording the highest rates of pedestrian fatality and bicycle fatality across all age and sex groups.

National data indicates that Black road users face elevated fatality rates; however, the DEA models show lower fatality rates in communities with higher Black populations. This contrast may reflect differences between where people live and where crashes occur. The SHAP analysis also suggests that while Black individuals are disproportionately involved in crashes nationwide, their neighborhoods often have comparatively better traffic safety outcomes. These patterns highlight the likelihood that crash risk is shaped more by conditions along travel routes and travel patterns than by residential demographic and infrastructure characteristics. However, this was not explicitly explored in this investigation, and could be explored in future work to more fully understand these relationships. These findings reinforce the need to consider both community context and broader travel networks when addressing traffic safety disparities.

Native American communities experienced some of the highest crash rates both nationally and across the four states analyzed. These communities tend to be safer in Arizona and Oregon, two states with a higher population of Native Americans in this study. However, this apparent contradiction indicates a more complex reality. Interviews with transportation and public health professionals revealed that these discrepancies are, in part, the result of persistent challenges in collecting comprehensive crash data from tribal lands. Only one of Arizona's twenty-two tribes regularly submits crash data to the Arizona Department of Transportation. This limited participation is influenced by sovereignty concerns and longstanding mistrust, creating a "blind spot" in safety data that hinders understanding and therefore intentionally targeted interventions.

Asian communities were consistently found to have the lowest fatality rates nationally as well as across all the four states reviewed, with both the DEA and SHAP models indicating that communities with a higher percentage of Asian residents are among the safest nationally. Educational attainment also plays a role, with communities that had higher levels of education generally experiencing lower crash rates. Notably, this trend varies by state.

Interviews revealed a consistent and concerning link between poverty, transportation mode choice, and increased crash vulnerability across all states. The quantitative analysis consistently identified higher poverty rate areas as more prone to higher crash risks across all areas. Experts noted that economically disadvantaged communities often face compounded risks due to limited transportation options and outdated infrastructure. Lack of vehicle access forces residents to rely on walking or biking, often in environments that are ill-equipped to support these modes, leading to heightened crash exposure and injury severity. Gentrification in cities is also pushing lower-income residents into less walkable, higher-speed environments. The collective insight highlights a structural disadvantage faced by low-income communities, where residents who rely on the most vulnerable modes of travel are often required to navigate the most hazardous conditions. This double jeopardy, high exposure combined with poor infrastructure, is a systemic outcome of inequitable transportation planning.

Transportation experts in Oregon and Arizona emphasized how cultural factors shape both institutional practices and community engagement in safety planning. The Oregon Department of Transportation's legacy as a Highway Division has created a persistent vehicle-centric culture within the agency, where even recent multimodal initiatives sometimes struggle against entrenched norms. Simultaneously, cultural barriers prevent meaningful participation from Hispanic and immigrant communities in transportation discussions, resulting in planning processes that overlook their safety needs.

In terms of equity initiatives, agencies across several states have launched programs to embed equity into traffic safety efforts. These include translating driver manuals and safety materials into multiple languages, adapting content for low-literacy audiences, and incorporating culturally relevant visuals. Maryland and Oregon have led in language accessibility, while Washington has implemented statewide equity mandates. In King County, Washington, the "Fair and Just Ordinance" requires equity practices across all departments. Local and regional plans also reflect these efforts, supported by federal guidance and agency leadership.

Interviewees highlighted several key policy solutions to improve transportation safety equity. Building trust with American Indian communities through sustained engagement with tribal elders was seen as essential for improving data sharing. Experts further emphasized the need for transportation agencies to shift from a motorist-first mindset to one focused on equity of use, ensuring safety for all road users. Some interviewees also cautioned that future policy changes may deprioritize or intentionally sideline equity, highlighting the need to ensure it remains a core focus in planning and decision-making.

The present study also demonstrates that traffic safety risks vary substantially across different communities and geographic regions, as evidenced by the DEA model results. These variations reveal that traditional standardized approaches to safety interventions are often inadequate, as different populations face distinct challenges shaped by local conditions and sociodemographic factors. To effectively address these disparities, transportation agencies must combine advanced analytical methods with meaningful community engagement. Analytical tools help identify localized risk patterns, while direct engagement uncovers the contextual factors behind these disparities. Through this integrated approach agencies develop solutions that meet the specific safety needs of diverse communities across different regions.

Moving forward, transportation agencies may consider adopting a more balanced approach that integrates equity metrics with data-driven analysis, prioritizes infrastructure improvements in high-risk areas, and fosters authentic and sustained community engagement. By centering the voices of marginalized populations and addressing structural barriers, policymakers can develop targeted interventions that enhance safety for all road users. The insights from this study provide a foundation for actionable recommendations, urging stakeholders to bridge the gap between equity goals and on-the-ground implementation.

Actionable Strategies

Improve Data Collection & Reporting

- Build trust with Native American communities to improve crash data reporting from tribal lands.
- Ensure consistent and inclusive data collection across race, income, sex and other socioeconomic and sociodemographic factors.

Prioritize Equitable Infrastructure

- Focus safety improvements in low-income and high-crash neighborhoods.
- Mitigate displacement-related risks by retrofitting unsafe routes in areas where low-income residents are relocated.

Shift Agency Culture & Planning

- Move beyond car-centric planning to prioritize all modes equally.
- Formalize equity criteria in funding decisions.

Policy & Advocacy

- Design interventions based on community context
- Require equity impact assessments for transportation projects.
- Push for policies that address root causes.

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References

Adeyemi, O. J., Paul, R., & Arif, A. (2022). An assessment of the rural-urban differences in the crash response time and county-level crash fatalities in the United States. *The Journal of Rural Health*, *38*(4), 999–1010. https://doi.org/10.1111/jrh.12627

Al-Balbissi, A. H. (2003). Role of Gender in Road Accidents. *Traffic Injury Prevention*, *4*(1), 64–73. https://doi.org/10.1080/15389580309857

Allen, B., McDermott, R., Clark, J., Daubs, G., Vashon, T., Elliott, I., Daubs, M., & Maitra, S. (2022). Traumatic spinal injury patterns of on vs. Off-road motorcycle crashes. *Traffic Injury Prevention*, *25*, 85–90. https://doi.org/10.1080/15389588.2023.2259530

Alnawmasi, N., & Mannering, F. (2023). An analysis of day and night bicyclist injury severities in vehicle/bicycle crashes: A comparison of unconstrained and partially constrained temporal modeling approaches. *Analytic Methods in Accident Research*, *40*. https://doi.org/10.1016/j.amar.2023.100301

Amarasingha, N., & Dissanayake, S. (2014). Gender differences of young drivers on injury severity outcome of highway crashes. *Journal of Safety Research*, *49*, 113–120. https://doi.org/10.1016/j.jsr.2014.03.004

Anderson, K. F., & Galaskiewicz, J. (2021). Racial/ethnic residential segregation, socioeconomic inequality, and job accessibility by public transportation networks in the United States. *Spatial Demography*, *9*(3), 341–373. https://doi.org/10.1007/s40980-021-00093-8

Arizona Department of Transportation. (2023). *Arizona Motor Vehicle Crash Facts | Department of Transportation*. https://azdot.gov/planning/traffic-safety/arizona-motor-vehicle-crash-facts

Avni, A., Burley, P., Casey, P., Cherney, J., Christiansen, L., Daly, J. S., Evans, R., Jared, D., Landgraf, G., Meier, A., Minotti, J., Post, B., Sandstedt, B., Sarmiento, R., Sillick, S., Sweet, B. Wendt, M., Winter, K., & Yu, H. (2015). *Literature Searches and Literature Reviews for Transportation Research Projects, How to Search, Where to Search, and How to Put It All Together: Current Practices*. Transportation Research Board.

Babaei, M., Hasanzadeh, S., Pirnejad, H., Mohebbi, I., Hoseini, R., & Niazkhani, Z. (2022). Socioeconomic status and severity of traffic accident injuries: A cross-sectional study. *Iran Occupational Health Journal, 19*(1), 380–392. https://doi.org/10.52547/ioh.19.1.380

Balakrishnan, S., Moridpour, S., & Tay, R. (2019). Sociodemographic Influences on Injury Severity in Truck-Vulnerable Road User Crashes. *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part A: Civil Engineering*, *5*(4), 04019015. https://doi.org/10.1061/AJRUA6.0001023

Berman, D. R. (2019). *Revisiting the Urban-Rural Relationship in Arizona*. Arizona State University, Morrison Institute for Public Policy. https://morrisoninstitute.asu.edu/sites/g/files/litvpz841/files/urban-rural_relationship.pdf

Blumenberg, E., Donahue, M., Handy, S., Lovejoy, K., Rodier, C., Shaheen, S., & Volker, J. (2007). *Travel of Diverse Populations: Literature Review*. UC Berkeley: California Partners for Advanced Transportation Technology. https://escholarship.org/uc/item/0b68h9cq

Braun, L. M., Le, H. T. K., Voulgaris, C. T., & Nethery, R. C. (2021). Healthy for whom? Equity in the spatial distribution of cycling risks in Los Angeles, CA. *Journal of Transport & Health*, *23*.. https://doi.org/10.1016/j.jth.2021.101227

Bullard, R. D., Johnson, G. S., & Torres, A. O. (2004). *Highway Robbery: Transportation Racism & New Routes to Equity*. South End Press.

Campos-Outcalt, D., Bay, C., Dellapenna, A., & Cota, M. K. (2002). Pedestrian fatalities by race/ethnicity in Arizona, 1990–1996. *American Journal of Preventive Medicine*, *23*(2), 129–135. https://doi.org/10.1016/s0749-3797(02)00465-8

Carlsen, F., Rattsø, J., & Stokke, H. E. (2016). Education, experience, and urban wage premium. *Regional Science and Urban Economics*, *60*, 39–49. https://doi.org/10.1016/j.regsciurbeco.2016.06.006

Chai, H., Zhang, Z., Xue, J., & Hu, H. (2022). A quantitative traffic performance comparison study of bicycles and E-bikes at the non-signalized intersections: Evidence from survey data. *Accident Analysis & Prevention*, *178*. https://doi.org/10.1016/j.aap.2022.106853

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research*, *2*(6), 429–444. https://doi.org/10.1016/0377-2217(78)90138-8

Chimba, D., Musinguzi, A., & Kidando, E. (2018). Associating pedestrian crashes with demographic and socioeconomic factors. *Case Studies on Transport Policy*, *6*(1), 11–16. https://doi.org/10.1016/j.cstp.2018.01.006

Cordellieri, P., Baralla, F., Ferlazzo, F., Sgalla, R., Piccardi, L., & Giannini, A. M. (2016). Gender Effects in Young Road Users on Road Safety Attitudes, Behaviors and Risk Perception. *Frontiers in Psychology*, *7*. https://doi.org/10.3389/fpsyg.2016.01412

Cordy, S., Raines, K., Singletary, J., & Tillery-Larkin, R. (2002). *Highway safety in Black/African-American communities: Issues and strategies*. U.S. Department of Transportation: National Highway Traffic Safety Administration. https://doi.org/10.21949/1525614

Cullen, P., Möller, H., Woodward, M., Senserrick, T., Boufous, S., Rogers, K., Brown, J., & Ivers, R. (2021). Are there sex differences in crash and crash-related injury between men and women? A 13-year cohort study of young drivers in Australia. *SSM-Population Health*, *14*, 100816. https://doi.org/10.1016/j.ssmph.2021.100816

Dadashova, B., Park, E. S., Mousavi, S. M., Dai, B., & Sanders, R. (2022). Assessment of inequity in bicyclist crashes using bivariate Bayesian copulas. *Journal of Safety Research*, *82*, 221–232. https://doi.org/10.1016/j.jsr.2022.05.013

Das, S., Tamakloe, R., Zubaidi, H., Obaid, I., & Rahman, M. A. (2023). Bicyclist injury severity classification using a random parameter logit model. *International Journal of Transportation Science and Technology*, *12*, 1093–1108. https://doi.org/10.1016/j.ijtst.2023.02.001

Dong, C., Khattak, A. J., Shao, C., & Xie, K. (2019). Exploring the factors contribute to the injury severities of vulnerable roadway user involved crashes. *International Journal of Injury Control and Safety Promotion*, *26*, 302–314. https://doi.org/10.1080/17457300.2019.1595665

Duddu, V. R., Pulugurtha, S. S., & Kukkapalli, V. M. (2020). Variable categories influencing single-vehicle run-off-road crashes and their severity. *Transportation Engineering*, *2*. https://doi.org/10.1016/j.treng.2020.100038

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*. https://doi.org/10.1016/j.trip.2022.100696

Dumbaugh, E., Li, Y., Saha, D., & Merlin, L. (2020). *The Influence of the Built Environment on Crash Risk in Lower-Income and Higher-income Communities*. Federal Highway Administration. https://www.roadsafety.unc.edu/wp-content/uploads/2020/11/SB_R11-Final-Report_20201111.pdf

Dumbaugh, E., Stiles, J., Mitsova, D., & Saha, D. (2024). The Most Vulnerable User: Examining the Role of Income, Race, and the Built Environment on Pedestrian Injuries and Deaths. *Transportation Research Record*, *2678*, 743–752. https://doi.org/10.1177/03611981231175888

Edwards, M., & Leonard, D. (2022). Effects of large vehicles on pedestrian and pedalcyclist injury severity. *Journal of Safety Research*, *82*, 275–282. https://doi.org/10.1016/j.jsr.2022.06.005

Fry, C., Graff, S., & Hadwin, A. (2020). *Public infrastructure for an equitable future*. http://onsidepartners.org/wp-content/uploads/2020/08/OnsidePartners_Equitable_Infrastructure_August-2020.pdf

Gehrke, S. R., Russo, B. J., Huff, M. P., & Smaglik, E. J. (2023). Multiscale spatial analysis of macro-level determinants of bicycle crash frequencies in the Phoenix metro region. *Journal of Transportation Safety & Security, 16*(3). https://doi.org/10.1080/19439962.2023.2201176

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.

González-Iglesias, B., Gómez-Fraguela, J. A., & Luengo-Martín, M. Á. (2012). Driving anger and traffic violations: Gender differences. *Transportation Research Part F: Traffic Psychology and Behaviour*, *15*(4), 404–412. https://doi.org/10.1016/j.trf.2012.03.002

Grossman, D. C., Sugarman, J. R., Fox, C., & Moran, J. (1997). Motor-vehicle crash-injury risk factors among American Indians. *Accident Analysis & Prevention*, *29*(3), 313–319. https://doi.org/10.1016/S0001-4575(96)00085-1

Gu, X., Abdel-Aty, M., Lee, J., Xiang, Q., & Ma, Y. (2022). Identification of contributing factors for interchange crashes based on a quasi-induced exposure method. *Journal of Transportation Safety & Security*, *14*, 671–692. https://doi.org/10.1080/19439962.2020.1812783.

Guerra, E., Dong, X., Lin, L., & Guo, Y. (2020). Temporal Analysis of Predictors of Pedestrian Crashes. *Transportation Research Record*, *2674*, 252–263. https://doi.org/10.1177/0361198120920633

Haddad, A., Mondal, A., Eluru, N., & Bhat, C. R. (2024). A novel integrated approach to modeling and predicting crash frequency by crash event state. *Analytic Methods in Accident Research*, *41*. https://doi.org/10.1016/j.amar.2024.100319

Haggerty, B., Hamberg, A., McGee, C., & Campbell, A. (2021). *Multnomah County REACH Transportation Crash and Safety Report: At the Intersection of Transportation, Health, Race and Justice*. PSU Transportation Seminars. https://multco.us/file/95327/download

Harmon, T., Bahar, G. B., & Gross, F. B. (2018). *Crash Costs for Highway Safety Analysis* (FHWA-SA-17-071). Federal Highway Administration Office of Safety. https://rosap.ntl.bts.gov/view/dot/42858

Harper, J. S., Marine, W. M., Garrett, C. J., Lezotte, D., & Lowenstein, S. R. (2000). Motor vehicle crash fatalities: A comparison of hispanic and non-hispanic motorists in colorado. *Annals of Emergency Medicine*, *36*(6), 589–596. https://doi.org/10.1067/mem.2000.111058

Haule, H. J., Sando, T., Kitali, A. E., & Richardson, R. (2019). Investigating proximity of crash locations to aging pedestrian residences. *Accident Analysis & Prevention*, *122*, 215–225. https://doi.org/10.1016/j.aap.2018.10.008

Hossain, A., Sun, X., Thapa, R., Hossain, Md. M., & Das, S. (2023). Exploring association of contributing factors to pedestrian fatal and severe injury crashes under dark-no-streetlight condition. *IATSS Research*, *47*(2), 214–224. https://doi.org/10.1016/j.iatssr.2023.03.002

Hossain, A., Sun, X., Zafri, N. M., & Codjoe, J. (2023). Investigating pedestrian crash patterns at high-speed intersection and road segments: Findings from the unsupervised learning algorithm. *International Journal of Transportation Science and Technology, 14,* 186–201. https://doi.org/10.1016/j.ijtst.2023.04.007

Hossain, M. M., Zhou, H., Sun, X., Hossain, A., & Das, S. (2024). Crashes involving distracted pedestrians: Identifying risk factors and their relationships to pedestrian severity levels and distraction modes. *Accident Analysis & Prevention*, *194*. https://doi.org/10.1016/j.aap.2023.107359

Hosseini, S. H., Davoodi, S. R., & Behnood, A. (2022). Bicyclists injury severities: An empirical assessment of temporal stability Author links open overlay panel. *Accident Analysis & Prevention*, *168*. https://doi.org/10.1016/j.aap.2022.106616

Hurwitz, D., Woodside, J., Jashami, H., Chang, K., Young, R., & Campos, A. R. (2023). *Impact of bicycle rolling stop laws on safety-relevant behaviors in the pacific northwest*. Pacific Northwest Transportation Consortium (PacTrans)(UTC). https://rosap.ntl.bts.gov/view/dot/66729

Iragavarapu, V., Carlson, P., & Schertz, G. (2015). Review of Tribal Transportation Safety. *Transportation Research Record: Journal of the Transportation Research Board*, *2531*(1), 153–160. https://doi.org/10.3141/2531-18

James, E., & Russo, B. J. (2019). Analysis of Factors Affecting Injury Severity in Traffic Crashes on Arizona Tribal Lands. *Transportation Research Record: Journal of the Transportation Research Board*, *2673*(9), 345–354. https://doi.org/10.1177/0361198119847613

Jashami, H., Anderson, J. C., Mohammed, H. A., Cobb, D. P., & Hurwitz, D. S. (2023). Contributing factors to right-turn crash severity at signalized intersections: An application of econometric modeling. *International Journal of Transportation Science and Technology, 13,* 243–257. https://doi.org/10.1016/j.ijtst.2023.02.004

Johnson, N. K., Johnson, B. M., Denning, G. M., & Jennissen, C. A. (2019). Adult moped-related injuries treated in U.S. emergency departments. *Traffic Injury Prevention*, *20*, 813–819. https://doi.org/10.1080/15389588.2019.1665650

Kahane, C. J. (2013). *Injury vulnerability and effectiveness of occupant protection technologies for older occupants and women (DOT HS 811 766)*. National Highway Traffic Safety Administration. https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/811766.pdf

Kakhani, A., Jalayer, M., Kidando, E., Roque, C., & Patel, D. (2024). Identifying contributing factors and locations of pedestrian severe crashes using hazard-based duration model. *Accident Analysis & Prevention*, *198*. https://doi.org/10.1016/j.aap.2024.107500

Karner, A., London, J., Rowangould, D., & Manaugh, K. (2020). From Transportation Equity to Transportation Justice: Within, Through, and Beyond the State. *Journal of Planning Literature*, *35*(4), 440–459. https://doi.org/10.1177/0885412220927691

Karner, A., & Marcantonio, R. A. (2018). Achieving Transportation Equity: Meaningful Public Involvement to Meet the Needs of Underserved Communities. *Public Works Management & Policy*, *23*(2), 105–126. https://doi.org/10.1177/1087724X17738792

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

Kelley-Baker, T., & Romano, E. (2010). Female involvement in U.S. nonfatal crashes under a three-level hierarchical crash model. *Accident Analysis & Prevention*, *42*(6), 2007–2012. https://doi.org/10.1016/j.aap.2010.06.010

Kocatepe, A., Ulak, M. B., Ozguven, E. E., & Horner, M. W. (2019). Who might be affected by crashes? Identifying areas susceptible to crash injury risk and their major contributing factors. *Transportmetrica A: Transport Science*, *15*, 1278–1305. https://doi.org/10.1080/23249935.2019.1581854

Lee, J., Abdel-Aty, M., & Cai, Q. (2020). Investigation of Safety-in-Numbers for Pedestrians and Bicyclists at a Macroscopic Level with Various Exposure Variables. *Transportation Research Record*, *2674*, 568–580. https://doi.org/10.1177/0361198120953795

Li, X., Yu, S., Huang, X., Dadashova, B., Cui, W., & Zhang, Z. (2022). Do underserved and socially vulnerable communities observe more crashes? A spatial examination of social vulnerability and crash risks in Texas. *Accident Analysis & Prevention*, *173*, 106721. https://doi.org/10.1016/j.aap.2022.106721

Li, Y., & Fan, W. (David). (2022). Mixed logit approach to modeling the severity of pedestrian-injury in pedestrian-vehicle crashes in North Carolina: Accounting for unobserved heterogeneity. *Journal of Transportation Safety & Security*, *14*(5), 796–817. https://doi.org/10.1080/19439962.2020.1821850

Lin, Z., & Fan, W. (David). (2021a). Cyclist injury severity analysis with mixed-logit models at intersections and nonintersection locations. *Journal of Transportation Safety & Security*, *13*(2), 223–245. https://doi.org/10.1080/19439962.2019.1628140

Lin, Z., & Fan, W. (David). (2021b). Exploring bicyclist injury severity in bicycle-vehicle crashes using latent class clustering analysis and partial proportional odds models. *Journal of Safety Research*, *76*, 101–117. https://doi.org/10.1016/j.jsr.2020.11.012

Linovski, O., & Baker, D. M. (2023). Community-Designed Participation: Lessons for Equitable Engagement in Transportation Planning. *Transportation Research Record: Journal of the Transportation Research Board*, *2677*(6), 172–181. https://doi.org/10.1177/03611981221145131

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*. https://doi.org/10.1016/j.aap.2023.107375

Liu, J., Jones, S., Adanu, E. K., & Li, X. (2021). Behavioral pathways in bicycle-motor vehicle crashes: From contributing factors, pre-crash actions, to injury severities. *Journal of Safety Research*, *77*, 229–240. https://doi.org/10.1016/j.jsr.2021.02.015

Liu, J., Khattak, A. J., Li, X., Nie, Q., & Ling, Z. (2020). Bicyclist injury severity in traffic crashes: A spatial approach for geo-referenced crash data to uncover non-stationary correlates. *Journal of Safety Research*, *73*, 25–35. https://doi.org/10.1016/j.jsr.2020.02.006

Lombardi, L. R., Pfeiffer, M. R., Metzger, K. B., Myers, R. K., & Curry, A. E. (2022). Improving identification of crash injuries: Statewide integration of hospital discharge and crash report data. *Traffic Injury Prevention*, *23*, S130–S136. https://doi.org/10.1080/15389588.2022.2083612

Lu, W., Liu, J., Fu, X., Yang, J., & Jones, S. (2022). Integrating machine learning into path analysis for quantifying behavioral pathways in bicycle-motor vehicle crashes. *Accident Analysis & Prevention*, *168*. https://doi.org/10.1016/j.aap.2022.106622

Mafi, S., AbdelRazig, Y., Amirinia, G., Kocatepe, A., Ulak, M. B., & Ozguven, E. E. (2019). Investigating exposure of the population to crash injury using a spatiotemporal analysis: A case study in Florida. *Applied Geography*, *104*, 42–55. https://doi.org/10.1016/j.apgeog.2019.02.001

Mahmoud, N., Abdel-Aty, M., Cai, Q., & Zheng, O. (2021). Vulnerable road users' crash hotspot identification on multi-lane arterial roads using estimated exposure and considering context classification. *Accident Analysis & Prevention*, *159*. https://doi.org/10.1016/j.aap.2021.106294

Mahmoudi, J., Xiong, C., Yang, M., & Luo, W. (2023). Modeling the Frequency of Pedestrian and Bicyclist Crashes at Intersections: Big Data-driven Evidence From Maryland. *Transportation Research Record*, *2677*, 1245–1260. https://doi.org/10.1177/03611981221122776

Males, M. A. (2009). Poverty as a determinant of young drivers' fatal crash risks. *Journal of Safety Research*, *40*(6), 443–448. https://doi.org/10.1016/j.jsr.2009.10.001

Massachusetts Department of Transportation (n.d.). *Top crash locations and maps | Mass.gov*. Retrieved June 13, 2025. https://www.mass.gov/info-details/top-crash-locations-and-maps

Merlin, L. A., Guerra, E., & Dumbaugh, E. (2020). Crash risk, crash exposure, and the built environment: A conceptual review. *Accident Analysis & Prevention*, *134*. 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

Morris, E. A., Blumenberg, E., & Guerra, E. (2020). Does lacking a car put the brakes on activity participation? Private vehicle access and access to opportunities among low-income adults. *Transportation Research Part A: Policy and Practice*, *136*, 375–397. https://doi.org/10.1016/j.tra.2020.03.021

National Highway Traffic Safety Administration. (2024). *Fatality Analysis Reporting System (FARS): 2023 traffic fatalities* [Dataset]. https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars

Nickkar, A., Pourfalatoun, S., Miller, E. E., & Lee, Y.-J. (2024). Applying the heteroskedastic ordered probit model on injury severity for improved age and gender estimation. *Traffic Injury Prevention*, *25*, 202–209. https://doi.org/10.1080/15389588.2023.2286429

Norton, P. (2011). *Fighting Traffic: The Dawn of the Motor Age in the American City*. MIT Press. https://mitpress.mit.edu/9780262516129/fighting-traffic/

Oh, S. A., Liu, C., & Pressley, J. C. (2017). Fatal pediatric motor vehicle crashes on us native american indian lands compared to adjacent non-indian lands: Restraint use and injury by driver, vehicle, roadway and crash characteristics. *International Journal of Environmental Research and Public Health*, *14*(11), 1287. https://doi.org/10.3390/ijerph14111287

Okaidjah, D., Haddad, M., Day, C., & Das, B. (2023). Spatial Analysis of Relationships Between Intersection Safety, the Urban Built Environment, and Average Income Level: A Case Study of Des Moines. *Transportation Research Record*, *2677*, 803–817. https://doi.org/10.1177/03611981221108392

Ossenbruggen, P. J., Pendharkar, J., & Ivan, J. (2001). Roadway safety in rural and small urbanized areas. *Accident Analysis & Prevention*, *33*(4), 485–498. https://doi.org/10.1016/S0001-4575(00)00062-2

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., & Grimshaw, J. M. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *International Journal of Surgery*, *88*. https://doi.org/10.1016/j.ijsu.2021.105906

Pareschi, G., Küng, L., Georges, G., & Boulouchos, K. (2020). Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data. *Applied Energy*, *275*, 115318. https://doi.org/10.1016/j.apenergy.2020.115318

Patwary, A. L., Haque, A. M., Mahdinia, I., & Khattak, A. J. (2024). Investigating transportation safety in disadvantaged communities by integrating crash and Environmental Justice data. *Accident Analysis & Prevention*, *194*. https://doi.org/10.1016/j.aap.2023.107366

Pereira, R. H. M., Schwanen ,Tim, & and Banister, D. (2017). Distributive justice and equity in transportation. *Transport Reviews*, *37*(2), 170–191. https://doi.org/10.1080/01441647.2016.1257660

Piontkowski, S. R., Peabody, J. S., Reede, C., Velascosoltero, J., Tsatoke, G., Shelhamer, T., & Hicks, K. R. (2015). Reducing motor vehicle-related injuries at an Arizona Indian reservation: Ten years of application of evidence-based strategies. *Global Health: Science and Practice*, *3*(4), 619–629. https://doi.org/10.9745/ghsp-d-15-00249

Raifman, M. A., & Choma, E. F. (2022). Disparities in Activity and Traffic Fatalities by Race/Ethnicity. *American Journal of Preventive Medicine*, *63*, 160–167. https://doi.org/10.1016/j.amepre.2022.03.012

Rakauskas, M. E., Ward, N. J., & Gerberich, S. G. (2009). Identification of differences between rural and urban safety cultures. *Accident Analysis & Prevention*, *41*(5), 931–937. https://doi.org/10.1016/j.aap.2009.05.008

Rebentisch, H., Wasfi, R., & Daniel P. Piatkowski, K. M. (2019). Safe Streets for All? Analyzing Infrastructural Response to Pedestrian and Cyclist Crashes in New York City, 2009–2018. *Transportation Research Record*, *2673*, 672–685. https://doi.org/10.1177/0361198118821672

Ricord, S., & Wang, Y. (2023). Investigation of Equity Biases in Transportation Data: A Literature Review Synthesis. *Journal of Transportation Engineering, Part A: Systems*, *149*(11), 03123004. https://doi.org/10.1061/JTEPBS.TEENG-7791

Roberts, S. C., Zhang, F., Fisher, D., & Vaca, F. E. (2021). The effect of hazard awareness training on teen drivers of varying socioeconomic status. *Traffic Injury Prevention*, *22*, 455–459. https://doi.org/10.1080/15389588.2021.1940984

Rolison, J. J., & Moutari, S. (2018). Risk-Exposure Density and Mileage Bias in Crash Risk for Older Drivers. *American Journal of Epidemiology*, *187*(1), 53–59. https://doi.org/10.1093/aje/kwx220

Romano, E. O., Tippetts ,A. Scott, & and Voas, R. B. (2006). Language, Income, Education, and Alcohol-Related Fatal Motor Vehicle Crashes. *Journal of Ethnicity in Substance Abuse*, *5*(2), 119–137. https://doi.org/10.1300/J233v05n02_07

Rosenfeld, R., Rojek, J., & Decker, S. (2012). Age Matters: Race Differences in Police Searches of Young and Older Male Drivers. *Journal of Research in Crime and Delinquency*, *49*(1), 31–55. https://doi.org/10.1177/0022427810397951

Ryan, A., Ai, C., Fitzpatrick, C., & Knodler, M. (2022). Crash proximity and equivalent property damage calculation techniques: An investigation using a novel horizontal curve dataset. *Accident Analysis & Prevention*, *166*, 106550. https://doi.org/10.1016/j.aap.2021.106550

Ryan, A., Barchers, C., Christofa, E., & Knodler, M. (2021). Equitable resource allocation for municipal safety: A data envelopment analysis. *Transportation Research Part D: Transport and Environment*, *97*, 102926. https://doi.org/10.1016/j.trd.2021.102926

Ryan, A., & Knodler, M. (2022). Influential crash conditions leading to injury differences experienced by female and male drivers. *Journal of Transport & Health*, *24*, 101293. https://doi.org/10.1016/j.jth.2021.101293

Ryan, A., Tainter, F., Fitzpatrick, C., Gazzillo, J., Riessman, R., & Knodler, M. (2022). The impact of sex on motor vehicle crash injury outcomes. *Journal of Transportation Safety & Security*, *14*(5), 818–842. https://doi.org/10.1080/19439962.2020.1834478

Sagar, S., Stamatiadis, N., & Stromberg, A. (2021). Effect of Socioeconomic and Demographic Factors on Crash Occurrence. *Transportation Research Record: Journal of the Transportation Research Board*, *2675*. https://doi.org/10.1177/03611981211027887

Schell, C. J., Dyson, K., Fuentes, T. L., Des Roches, S., Harris, N. C., Miller, D. S., Woelfle-Erskine, C. A., & Lambert, M. R. (2020). The ecological and evolutionary consequences of systemic racism in urban environments. *Science*, *369*(6510), eaay4497. https://doi.org/10.1126/science.aay4497

Schwebel, D. C., Johnston, A., McDaniel, D., & McClure, L. A. (2024). Child pedestrian safety training in virtual reality: How quickly do children achieve adult functioning and what individual differences impact learning efficiency? *Journal of Safety Research, 89,* 135–140. https://doi.org/10.1016/j.jsr.2024.01.012

Shah, N. R., Aryal, S., Wen, Y., & Cherry, C. R. (2021). Comparison of motor vehicle-involved e-scooter and bicycle crashes using standardized crash typology. *Journal of Safety Research*, *77*, 217–228. https://doi.org/10.1016/j.jsr.2021.03.005

Siddiqui, C., & Abdel-Aty, M. (2012). Nature of Modeling Boundary Pedestrian Crashes at Zones. *Transportation Research Record*, *2299*(1), 31–40. https://doi.org/10.3141/2299-04

Simar, L., & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Smith, M. R., Tillyer, R., Lloyd, C., & Petrocelli, M. (2021). Benchmarking Disparities in Police Stops: A Comparative Application of 2nd and 3rd Generation Techniques. *Justice Quarterly*, *38*(3), 513–536. https://doi.org/10.1080/07418825.2019.1660395

Soto, G. W., Whitfield, G. P., Webber, B. J., Omura, J. D., Chen, T. J., Zaganjor, H., & Rose, K. (2022). Traffic as a barrier to walking safely in the United States: Perceived reasons and potential mitigation strategies. *Preventive Medicine Reports*, *30*. https://doi.org/10.1016/j.pmedr.2022.102003

Spray, J., Witten, K., Wiles, J., Anderson, A., Paul, D., Wade, J., & Ameratunga, S. (2022). Inequitable mobilities: Intersections of diversity with urban infrastructure influence mobility, health and wellbeing. *Cities & Health*, *6*(4), 711–725. https://doi.org/10.1080/23748834.2020.1827881

Tokey, A. I., Shioma, S. A., & Uddin, M. S. (2023). Assessing the effectiveness of built environment-based safety measures in urban and rural areas for reducing the non-motorist crashes. *Heliyon*, *9*(3). https://doi.org/10.1016/j.heliyon.2023.e14076

Turner, C., & McClure, R. (2003). Age and gender differences in risk-taking behaviour as an explanation for high incidence of motor vehicle crashes as a driver in young males. *Injury Control and Safety Promotion*, *10*(3), 123–130. https://doi.org/10.1076/icsp.10.3.123.14560

Ulak, M. B., Asadi, M., & Geurs, K. T. (2025). Examining the nonlinear effects of traffic and built environment factors on the traffic safety of cyclist from different age groups. *Accident Analysis & Prevention*, *211*, 107872. https://doi.org/10.1016/j.aap.2024.107872

Vachal, K. (2020). *Encouraging Tribal Community Crash Reporting*. Mountain-Plains Consortium. https://rosap.ntl.bts.gov/view/dot/61627

Weiwu, L. (2024). *Unequal Access: Racial Segregation and the Distributional Impacts of Interstate Highways in Cities*. MIT: Job Market Paper. https://economics.stanford.edu/events/unequal-access-racial-segregation-and-distributional-impacts-interstate-highways-cities

Yocum, R. L., & Gayah, V. V. (2022). County-level crash prediction models for Pennsylvania accounting for income characteristics. *Transportation Research Interdisciplinary Perspectives*, *13*. https://doi.org/10.1016/j.trip.2022.100562

Younes, H., Noland, R. B., Hagen, L. A. V., & Meehan, S. (2023). Pedestrian- and bicyclist-involved crashes: Associations with spatial factors, pedestrian infrastructure, and equity impacts. *Journal of Safety Research*, *86*, 137–147. https://doi.org/10.1016/j.jsr.2023.05.005

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*, 136–149. https://doi.org/10.1177/0739456X18807759

Zhu, C., Brown, C. T., Dadashova, B., Ye, X., Sohrabi, S., & Potts, I. (2023). Investigation on the driver-victim pairs in pedestrian and bicyclist crashes by latent class clustering and random forest algorithm. *Accident Analysis & Prevention*, *182*. https://doi.org/10.1016/j.aap.2023.106964

Ziakopoulos, A., & Yannis, G. (2020). A review of spatial approaches in road safety. *Accident Analysis & Prevention, 135*. https://doi.org/10.1016/j.aap.2019.105323

Appendix A: Interview Questions

Question 1

Primary Question

How does your agency collect and analyze data to identify safety disparities among different demographic groups?

Probing Questions

1. What types of data are primarily collected?
2. What types of analysis are performed to identify disparities?
3. Are there any groups that may be underrepresented in your data collection process?
4. How do you define and measure “safety disparities” among different groups?

Question 2

Primary Question

What steps has your agency taken to consider equity when developing and implementing safety plans?

Probing Questions

1. What are the primary equity-related data currently considered?
2. How do sociodemographic factors influence investment decisions in the development of safety-focused investment plans?
    a. Are equity metrics incorporated into project prioritization processes? How are they tracked? What tools are used to monitor or report metrics?
    b. How is success defined for equity-focused initiatives? Who determines these standards?
    c. How does your agency involve disadvantaged communities in decision-making processes for transportation safety projects?
    d. Are there specific programs to address infrastructure gaps in high-risk/low-income neighborhoods?
    e. Are there programs aimed at educating diverse communities on traffic safety while addressing cultural or linguistic barriers?
3. What are the barriers to considering sociodemographic factors?
4. Has your approach to integrating equity into safety plans changed recently?

Question 3

Primary Question

Our preliminary findings suggests that communities with a higher proportion of American Indian and Alaska Native residents tend to have the highest fatal crash risks. Given your professional expertise, what factors might contribute to this observation?

Probing Questions

1. Have you seen this disparity in your state? If so, in what contexts?
2. Is this occurrence more associated with behavioral factors or community-related factors or both? (Behavioral factors indicate that driver behavior may increase or decrease crash risk while community-related factors might indicate infrastructure or other social constructs impact crash risks) Given your professional expertise, why is this the case?

1. Has your state implemented any measures to improve the safety of this community?
    a. Which measures have been more effective in decreasing this disparity?
    b. What have been some of the challenges in implementing these measures?
    c. Which measures have been less effective?
    d. What barriers have you faced in identifying and implementing strategies to mitigate this disparity?

Question 4

Primary Question

Our preliminary finding suggests that communities with a higher proportion of White residents have the second-highest fatal crash risk, following communities with a higher proportion of American Indian and Alaska Native residents. Given your professional expertise, what factors might contribute to this observation?

Probing Questions

1. Have you seen this disparity in your state? In what contexts?
2. Is this occurrence more associated with behavioral factors or community-related factors or both? (Behavioral factors indicate that driver behavior may increase or decrease crash risk while community-related factors might indicate infrastructure or other social constructs impact crash risks.) Given your professional expertise, why is this the case?
3. Has your state implemented any measures to improve the safety of this community?
    a. Which measures have been more effective in decreasing this disparity?
    b. What have been some of the challenges in implementing these measures?
    c. Which measures have been less effective?
    d. What barriers have you faced in identifying and implementing strategies to mitigate this disparity?

Question 5

Primary Question

Our preliminary findings suggest that communities with higher poverty rates tend to experience higher crash risks. Given your professional expertise, what factors might contribute to this observation?

Probing Questions

1. Have you seen this disparity in your state? In what contexts?
2. Is this occurrence more associated with behavioral factors or community-related factors or both? (Behavioral factors indicate that driver behavior may increase or decrease crash risk while community-related factors might indicate infrastructure or other social constructs impact crash risks.) Given your professional expertise, why is this the case?
3. Has your state implemented any measures to improve the safety of this community?
   a. Which measures have been more effective in decreasing this disparity?
   b. What have been some of the challenges in implementing these measures?
   c. Which measures have been less effective?
   d. What barriers have you faced in identifying and implementing strategies to mitigate this disparity?

Question 6

Primary Question

What are the key traffic safety inequities you have observed in your state?

Probing Questions

1. What do you think is contributing to these inequities (probe: behavioral patterns, infrastructure investments, other)?
2. What are examples of policy changes that are required to address these inequities?
3. Do you have any examples of policy changes that you were able to successfully enact? What were some of the barriers and how did you overcome them?
4. Are there policies you would like to enact? What are the barriers to implementation?

Appendix B: Suspected serious injury rates of drivers across sexes

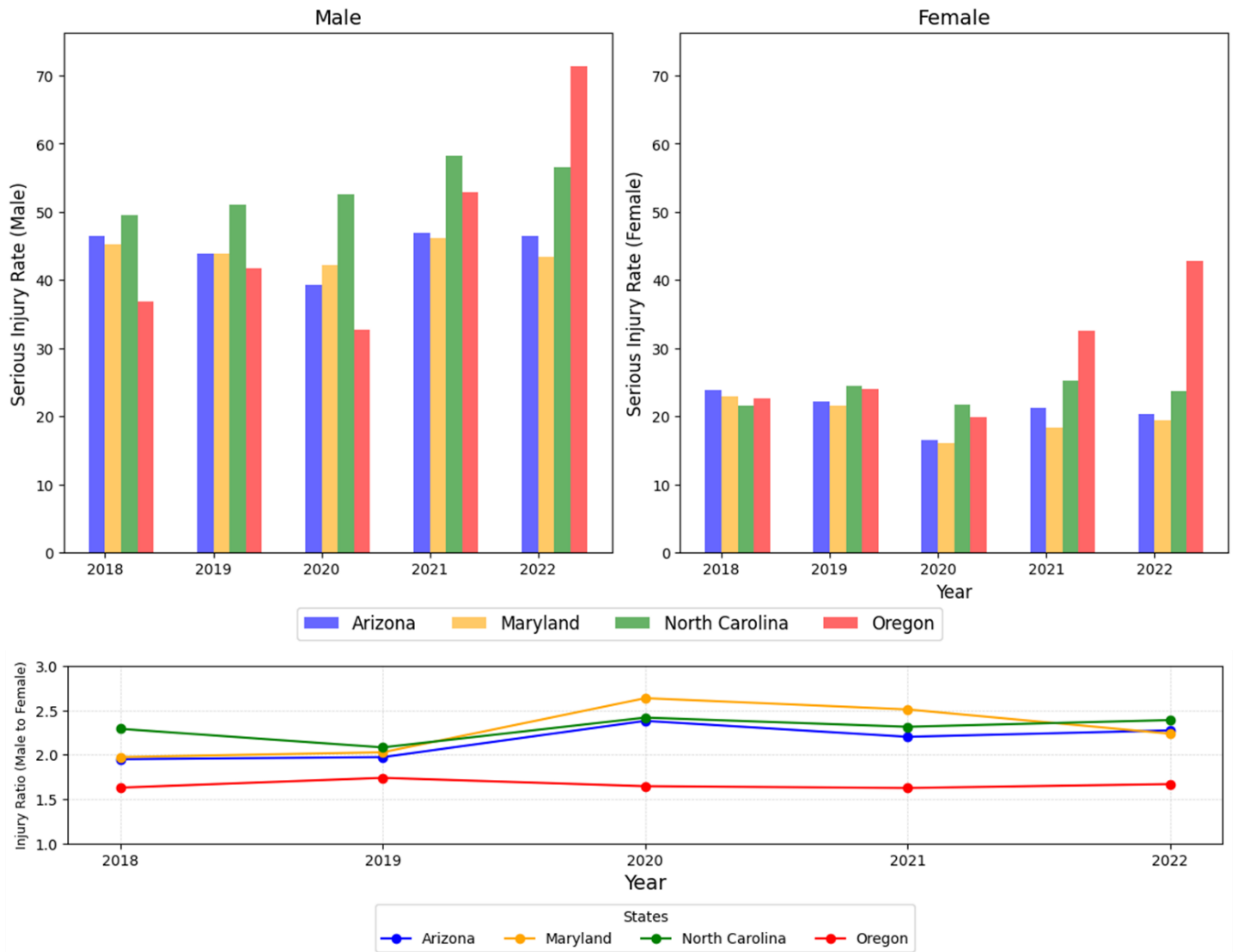


Figure A1: Male-to-female driver suspected serious injury rates and ratios (per 100,000 people)

Figure A1 depicts the suspected serious injury rates of male and female drivers across the four states from 2018 to 2022. These rates represent the number of suspected serious injuries per 100,000 people, highlighting the disparities between male and female drivers involved in serious injury incidents. In all states examined, the ratios indicate that male drivers were at a higher risk of suspected serious injuries compared to their female counterparts; however, the difference is lower than that seen in fatal outcome cases. Maryland consistently exhibited the highest male-to-female suspected serious injury ratio throughout the five-year period; the same was also seen in fatal outcome cases. In contrast, Oregon had the lowest ratio among the states analyzed, with ratios hovering around 1.6 to 1.7, indicating a smaller difference in serious injury risk between male drivers and female drivers. Notably, Oregon was one of the states exhibiting higher differences for fatal outcome cases. Arizona and North Carolina displayed stable ratios, with minor fluctuations over the years, but both remained above 2, suggesting a significant risk for male drivers compared to females.

For male drivers, most states displayed stable injury rates over the observed years. Arizona’s rates fluctuated between 39.3 and 46.9, while Maryland maintained a consistent range of 42.2 to 46.2. North Carolina showed a notable increase, reaching 58.27 in 2021, indicating growing concerns for male driver safety. In contrast, Oregon exhibited considerable variability, with male driver injury rates rising sharply from 36.88 in 2018 to 71.31 in 2022, reflecting an increasing risk for male drivers.

Similarly, female driver rates remained stable across most states. Arizona’s rates ranged from 16.5 to 23.8, and Maryland’s fluctuated between 16.0 and 22.9, showing little overall change. North Carolina’s female rates peaked at 25.17 in 2021, while Oregon’s rates demonstrated significant variability, increasing from 19.90 to 42.72 during the same period. This consistent increase in both male and female driver injury rates in Oregon are notable in the context of relative stability observed/examined observed in other states, underscoring a growing concern for driver safety in that region.

Appendix C: Suspected serious injury rates across age groups

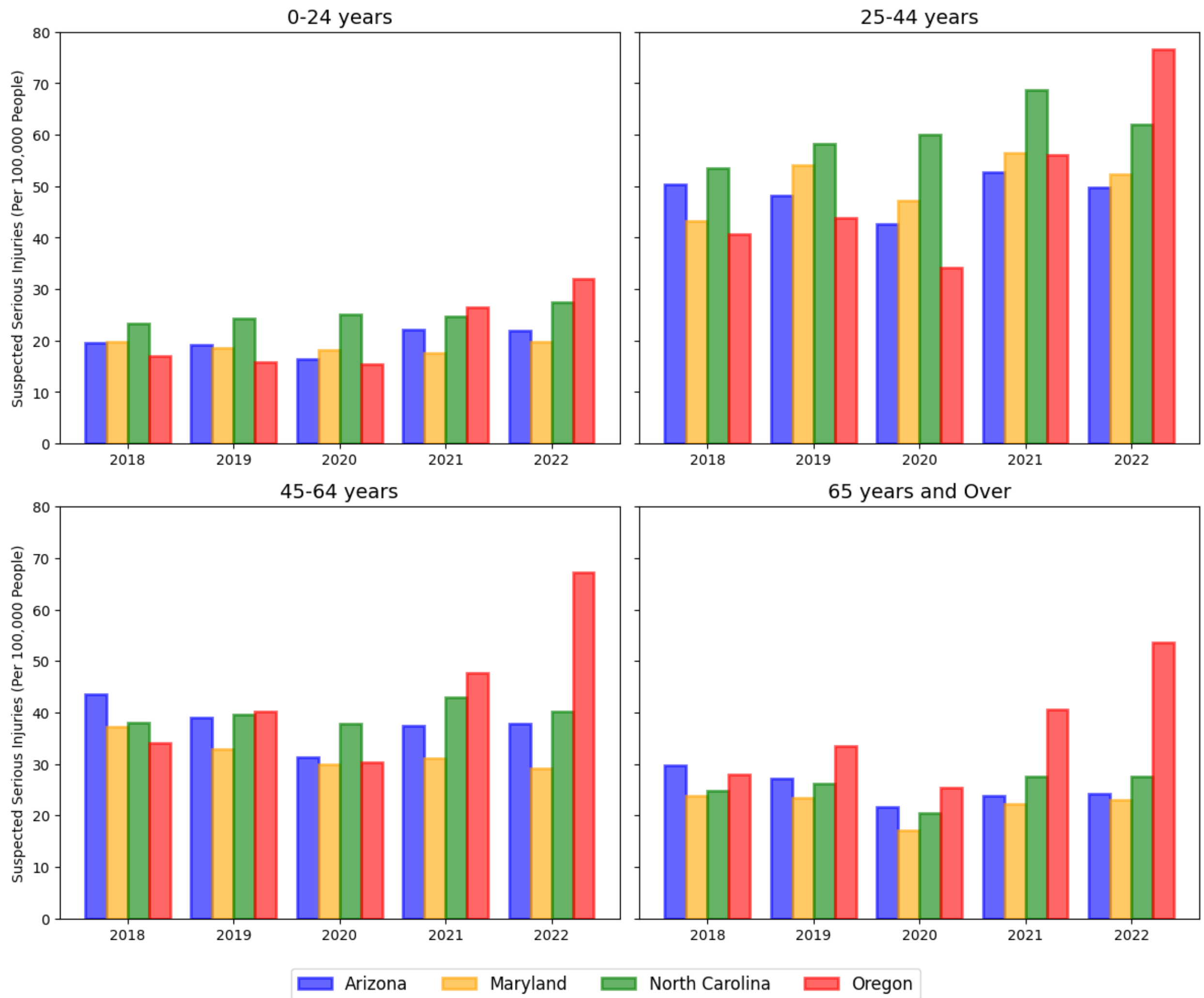


Figure A2: Suspected serious injury rate across age groups by state (per 100,000 people)

The distribution of suspected serious injuries across different age groups and states reveals significant differences as shown in Figure A2. Working-age adults aged 25–44 years consistently bore the highest burden of injuries across all examined states. In Oregon, the suspected serious injury rates in this age group reached as high as 76.6 per 100,000 in 2021, indicating a substantial risk for this demographic. Maryland and North Carolina also show elevated rates in the 25–44 age group, though North Carolina's rates peaked at 69.4 driver serious injuries per 100,000 people. Arizona's rates for this age group fluctuated but typically remained less than the other three states.

Oregon demonstrated a troubling upward trajectory in injury rates across all age groups, with particularly stark increases in recent periods. This trend is especially pronounced in the 25–44 and 45–64 age groups, where Oregon's rates have escalated to double those of comparable populations in other states. For the 45–64 age group, Oregon's rates reached 34.5 serious injuries per 100,000 people, while North Carolina's rates also reflect significant concerns at 38.7 serious injuries per 100,000 people.

The data shows that younger populations (ages 0–24) experienced lower injury rates compared to other age groups, with rates consistently falling below 30 serious injuries per 100,000 people in most states. However, North Carolina had higher rates for this age group, peaking at 27.53 serious injuries per 100,000 people in the most recent year of data. In contrast, Maryland and Arizona maintained lower rates for the 0–24 age group, typically ranging from 19 to 22 serious injuries per 100,000 people.

Older adults (65+ years old) exhibit varying vulnerability patterns across states. Arizona and Maryland report stable and lower rates for this age group, with figures ranging between 23 and 30 serious injuries per 100,000 people, although Arizona has seen a decline in serious injuries in recent years. Conversely, Oregon's elderly population (65+ years old) has experienced a concerning increase in injury rates, reaching 53.5 serious injuries per 100,000 people in 2022. North Carolina also reports elevated rates for older adults, at 27.5 serious injuries per 100,000 people, consistently surpassing the figures observed in Maryland and Arizona across all age groups.

Appendix D: Traffic Stop Rates: Arizona

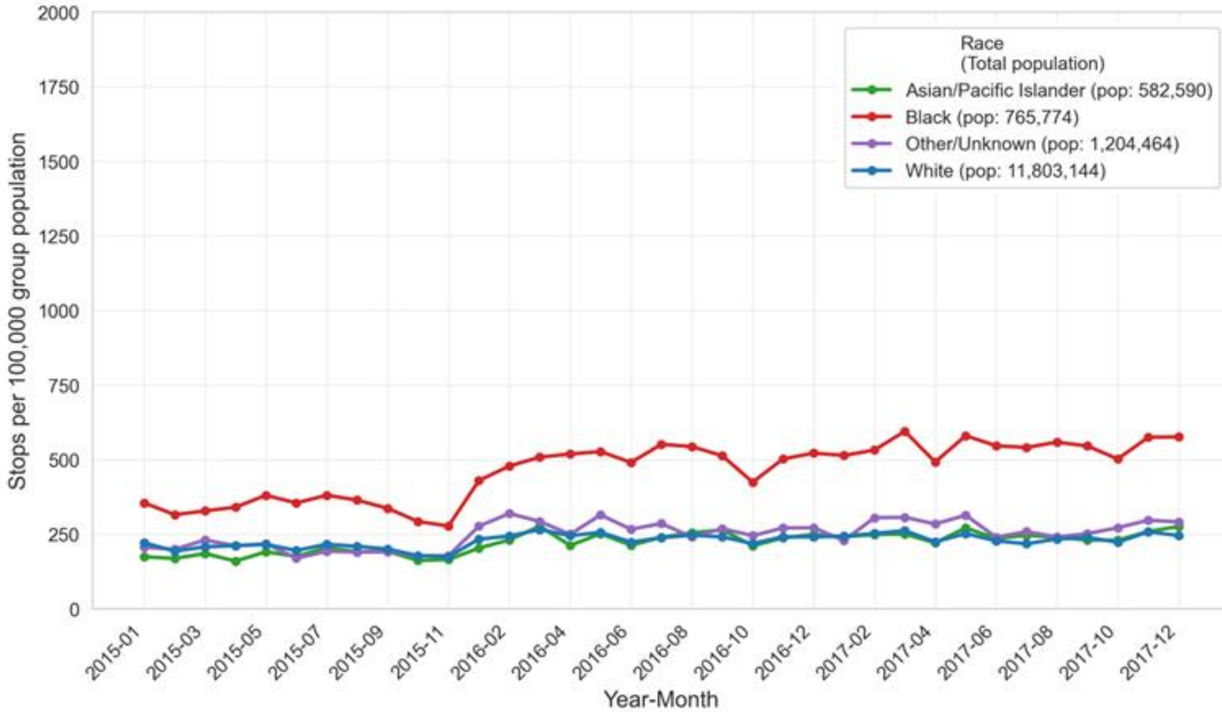


Figure A3: Traffic stop rate by race for Arizona (2015–2017)

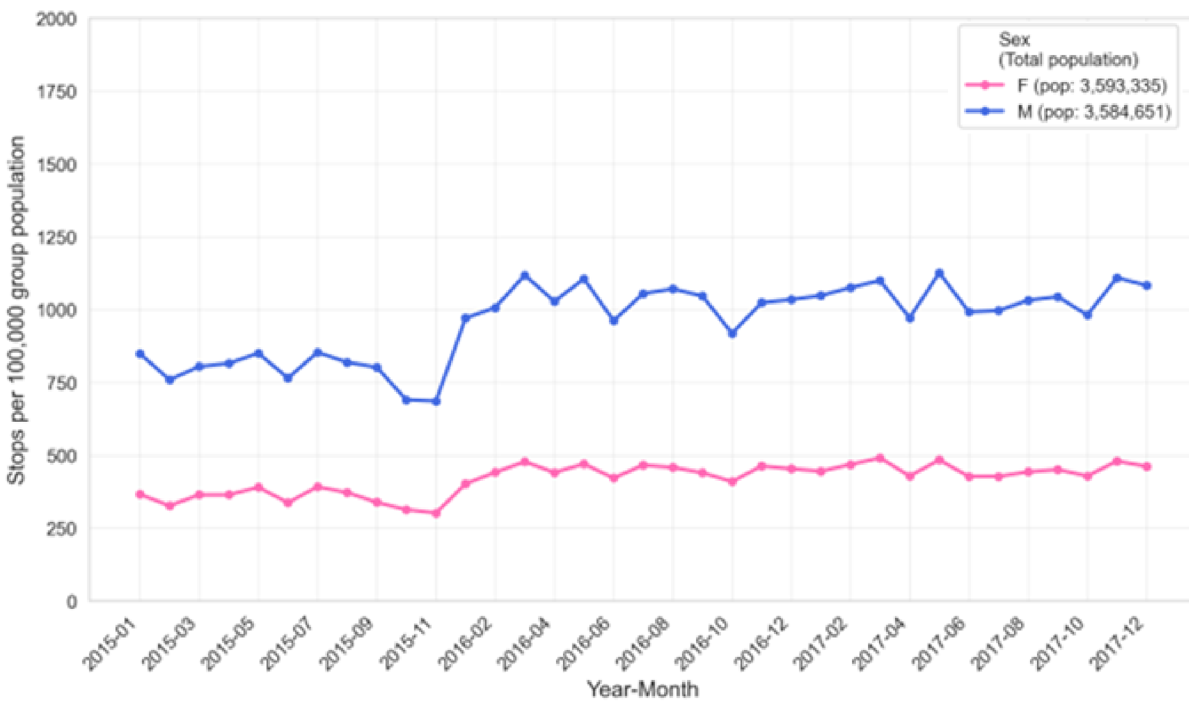


Figure A4: Traffic stop rate by sex for Arizona (2015–2017)

Appendix E: Traffic Stop Rates: Maryland

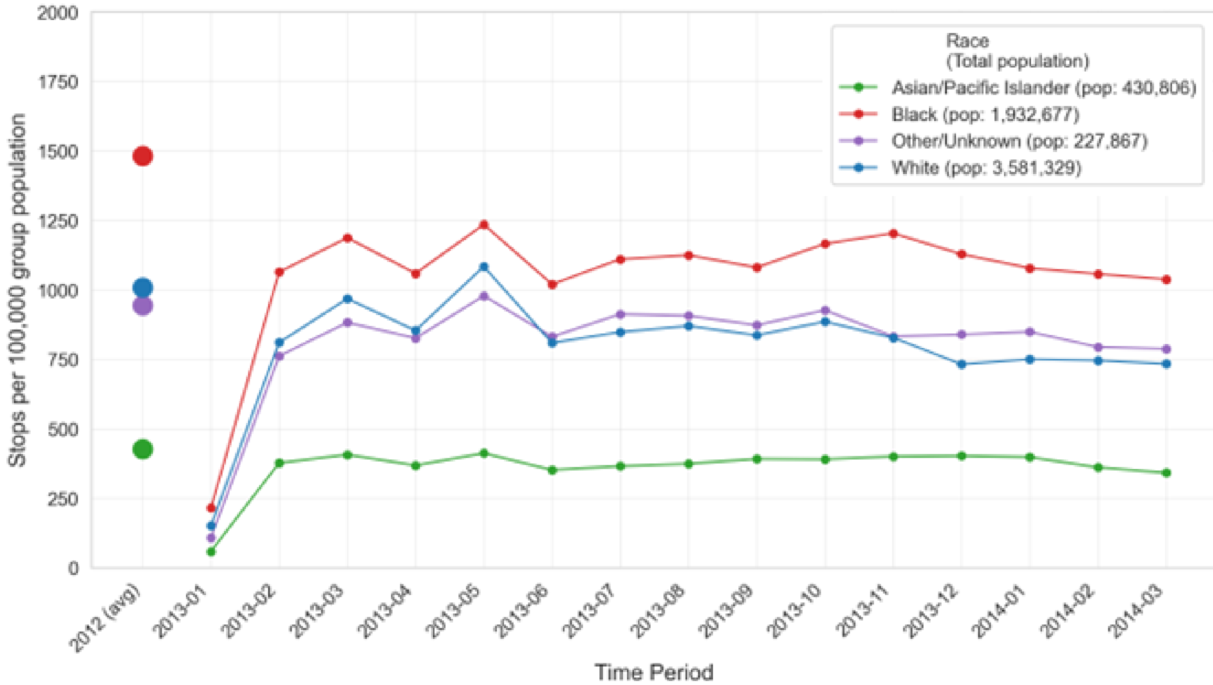


Figure A5: Traffic stop rate by race in Maryland (2012–2014)

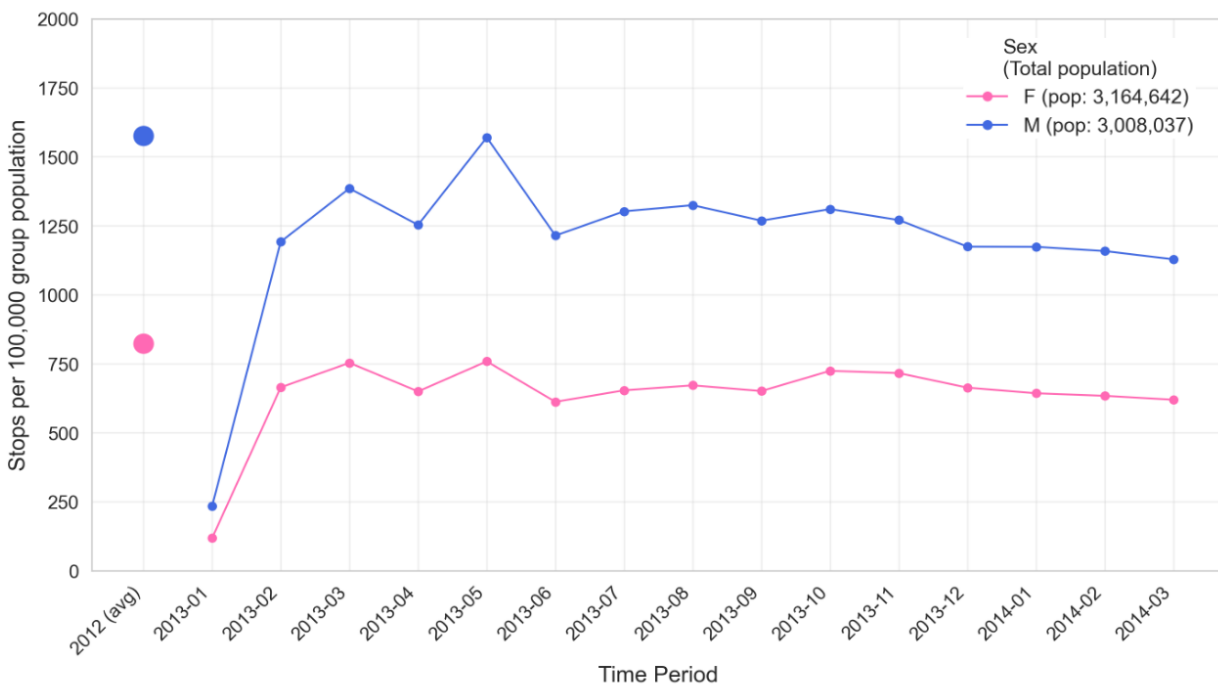


Figure A6: Traffic stop rate by sex in Maryland (2012–2014)

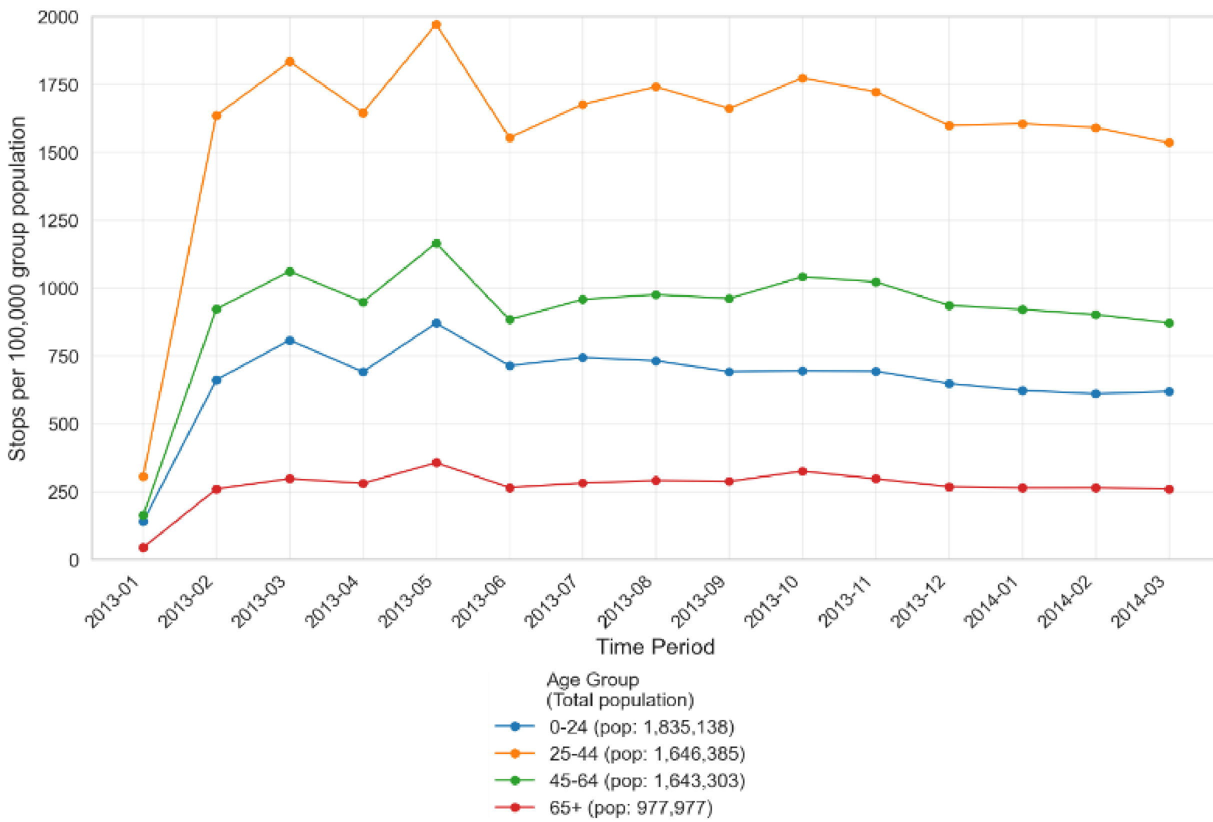


Figure A7: Traffic stop rate by age in Maryland (2012–2014)

Appendix F: Traffic Stop Rates: North Carolina

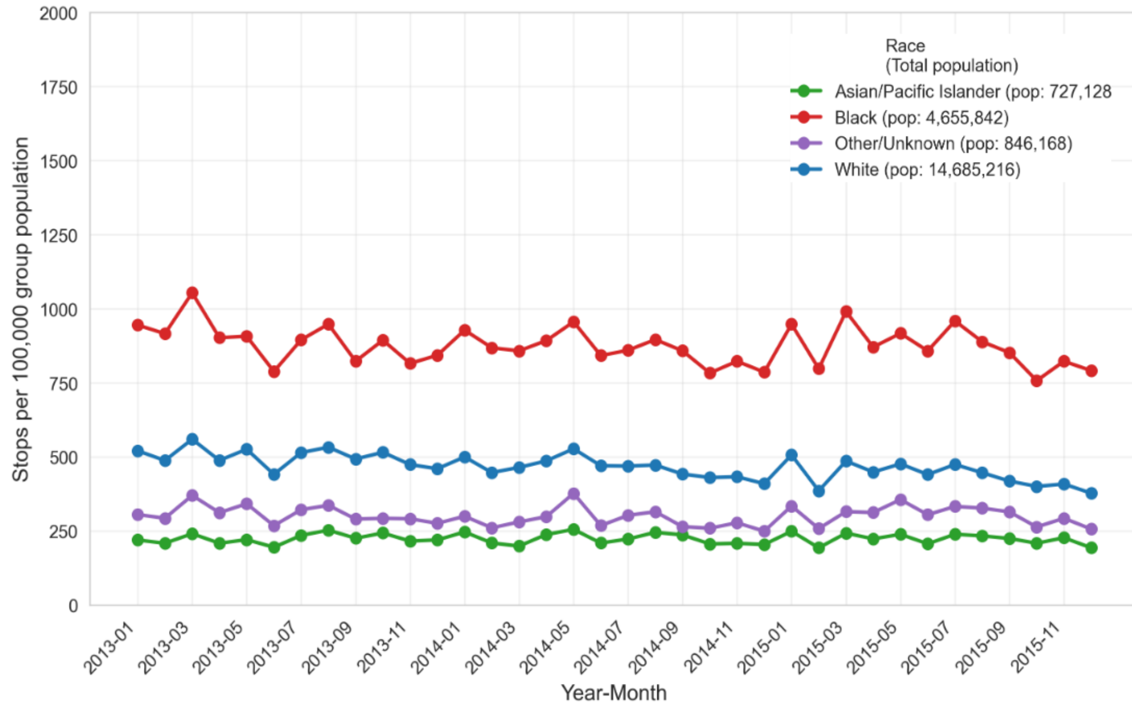


Figure A8: Traffic stop rate by race in North Carolina (2013–2015)

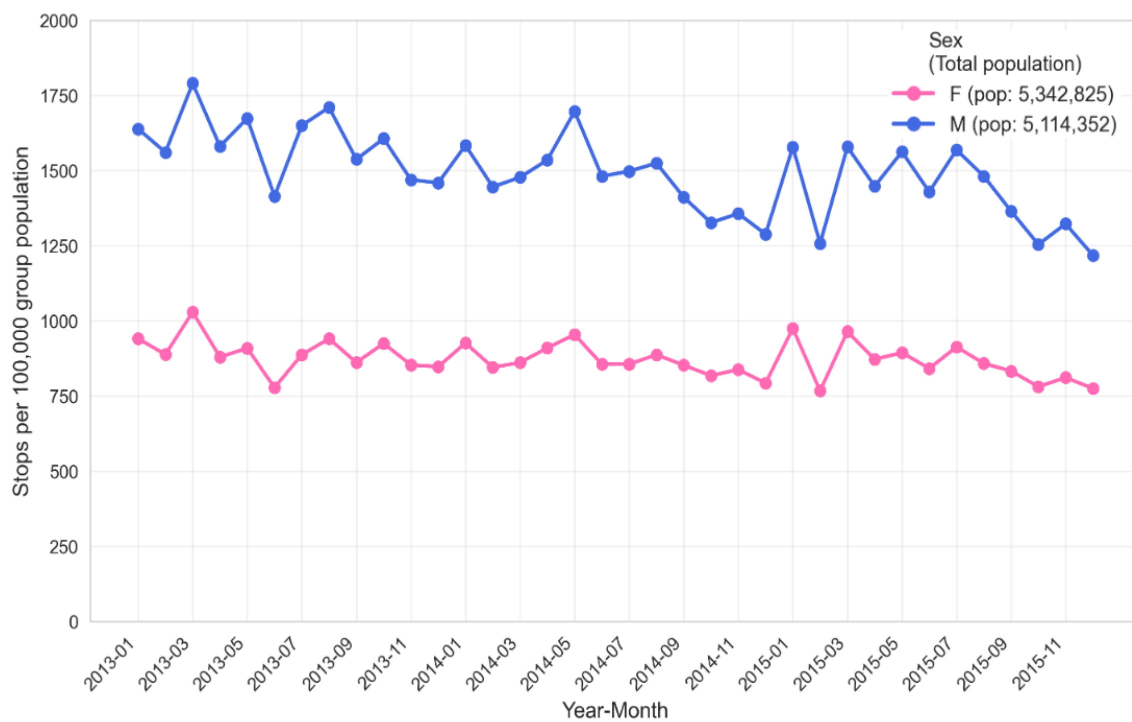


Figure A9: Traffic stop rate by sex in North Carolina (2013–2015)

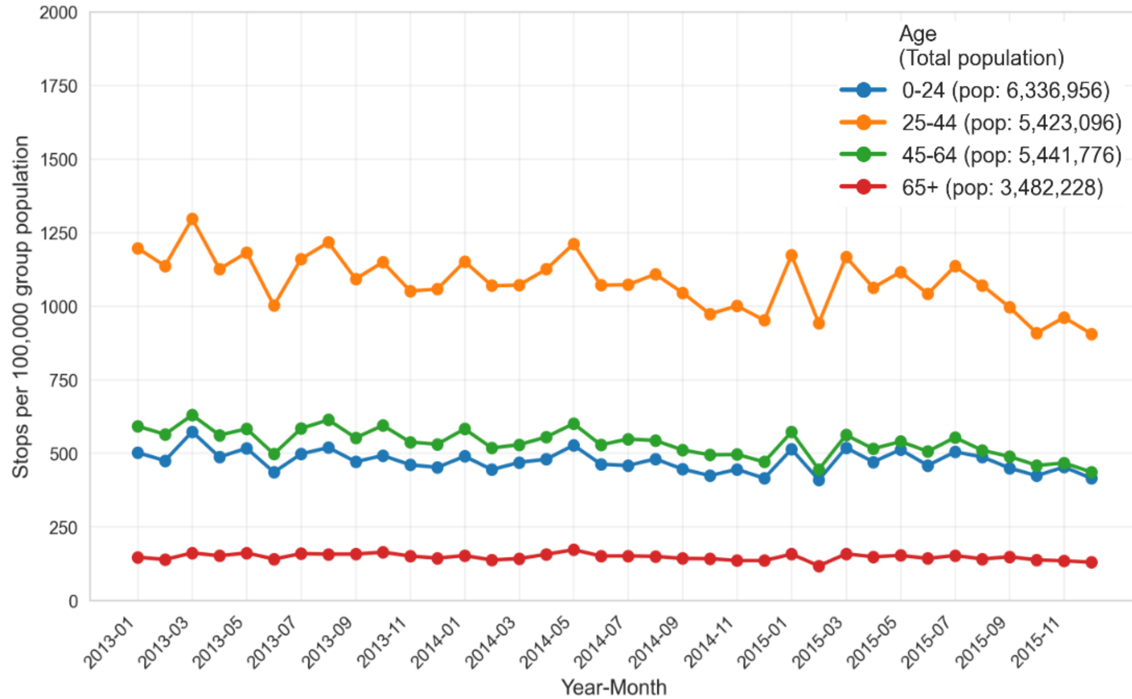


Figure A10: Traffic stop rate by age in North Carolina (2013–2015)

Analysis of traffic stop data from Arizona (2015–2017), Maryland (2012–2014), and North Carolina (2013–2015) reveals persistent and substantial disparities in traffic stop rates across demographic groups. The data, reported per 100,000 individuals and broken down by race, sex, and where available, age, show clear and consistent patterns. In each state, Black individuals were stopped at significantly higher rates than White individuals. Males were also stopped more frequently than females. Furthermore, where age data was available (Maryland and North Carolina), drivers in the 25–44 age group had the highest stop rates.

These patterns are consistent with prior research. Studies have frequently documented racial and ethnic disparities in stop rates, with minority groups, particularly Black individuals, often being stopped at disproportionately higher rates than White individuals, even after controlling for factors like driving behavior (Pareschi et al., 2020; Rosenfeld et al., 2012). Similarly, research often indicates that males are stopped more frequently than females, which can be attributed to a combination of factors including driving patterns, risk-taking behavior, and targeted enforcement (Cordellieri et al., 2016; González-Iglesias et al., 2012). Age-related patterns similarly reflect legitimate exposure differences, with working-age adults representing peak driving activity years when travel distance per trip and overall mileage are highest, naturally resulting in increased enforcement encounters (Rolison & Moutari, 2018).

Appendix G: Male and Female Crash Rates across Census Tracts

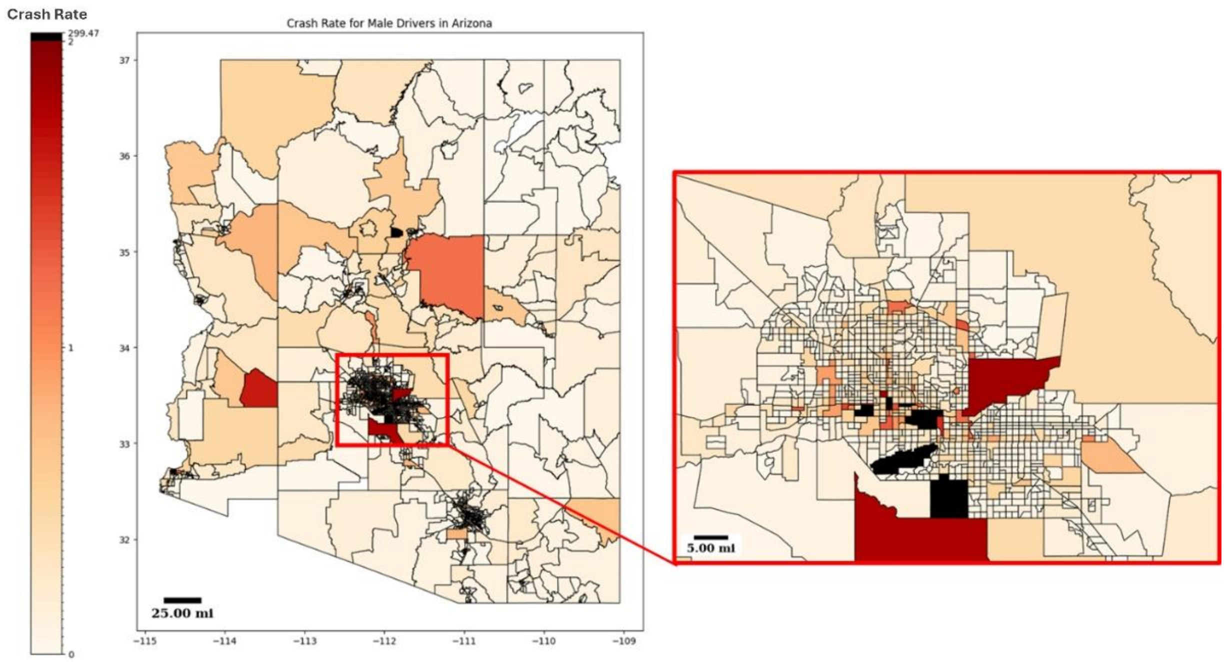


Figure A11: Weighted crash rates for male drivers in Arizona

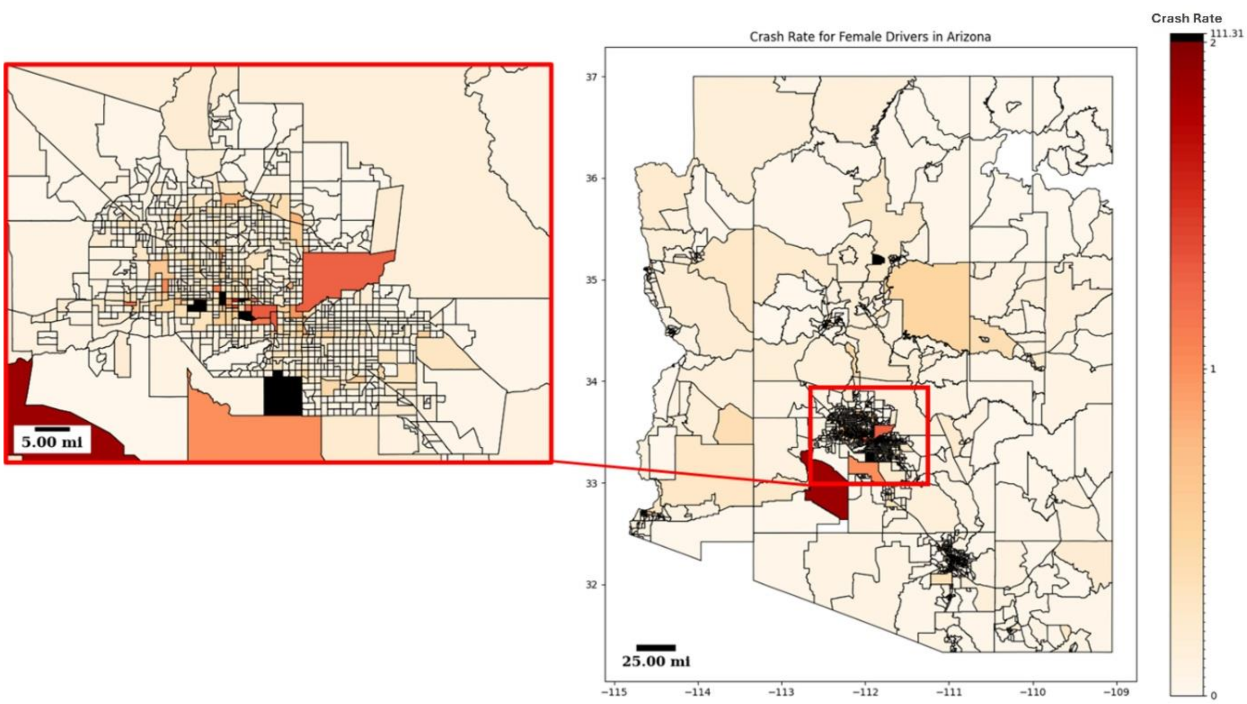


Figure A12 Weighted crash rates for female drivers in Arizona

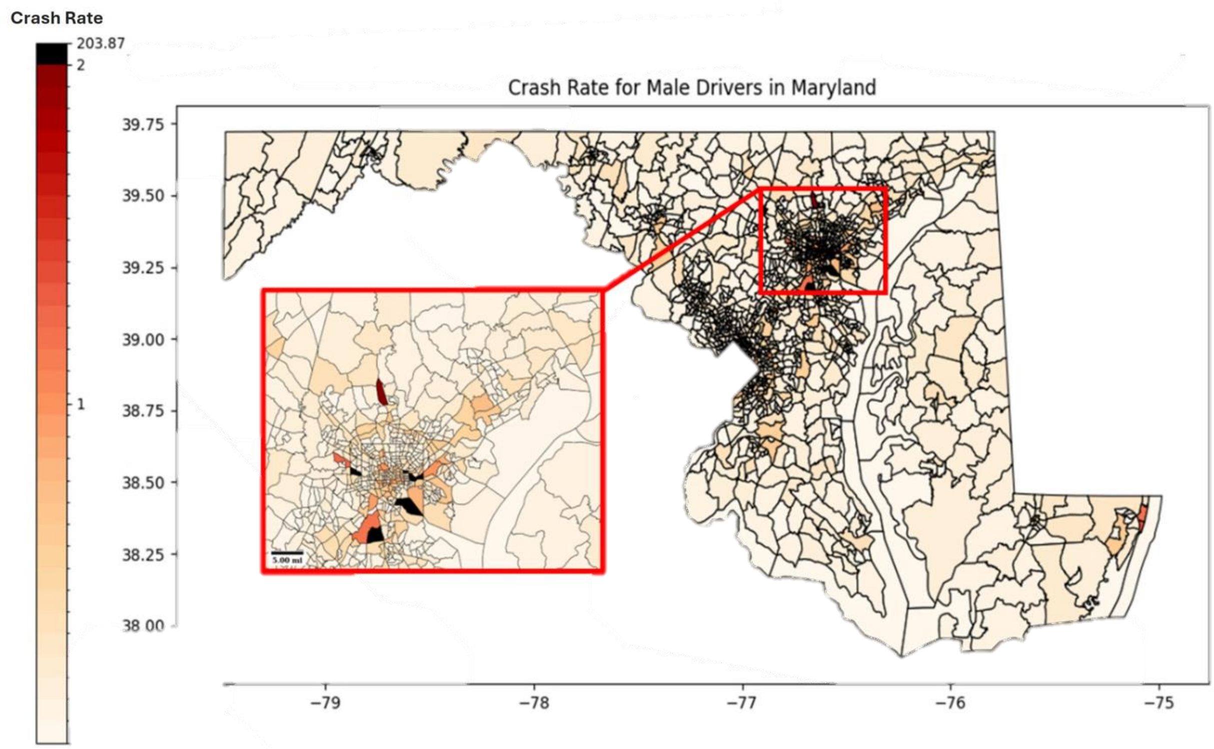


Figure A13: Weighted crash rates for male drivers in Maryland

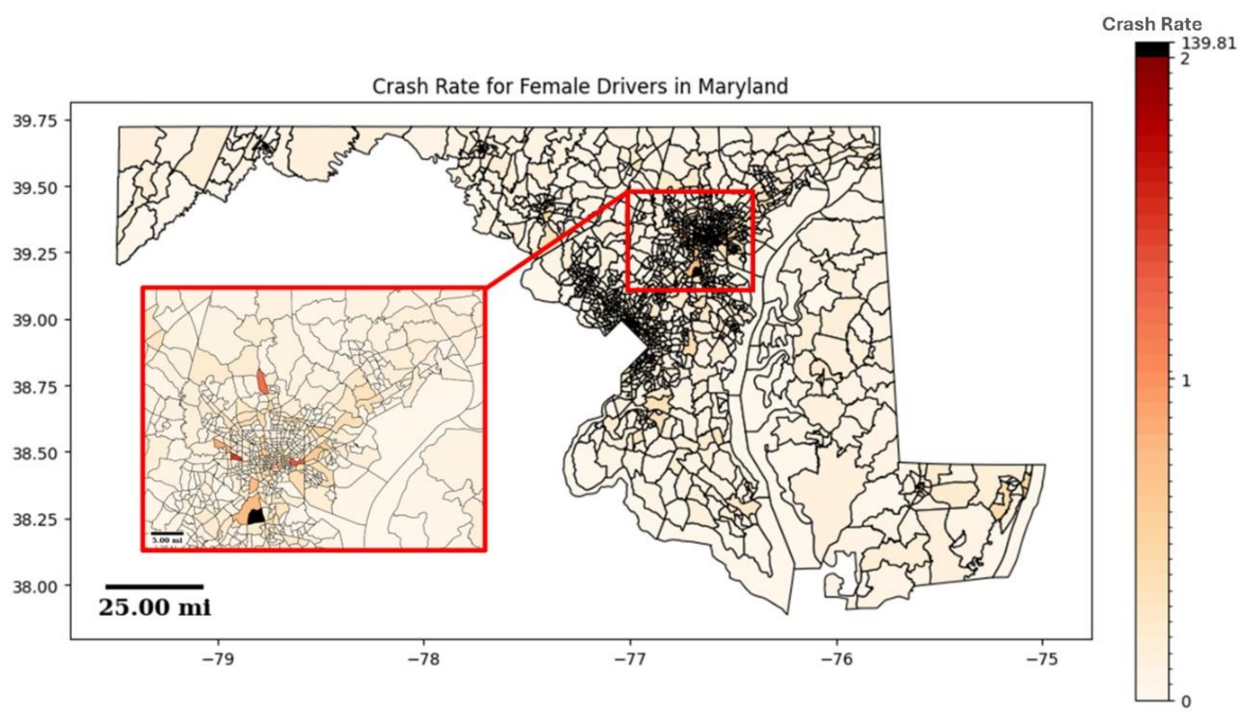


Figure A14: Weighted crash rates for female drivers in Maryland

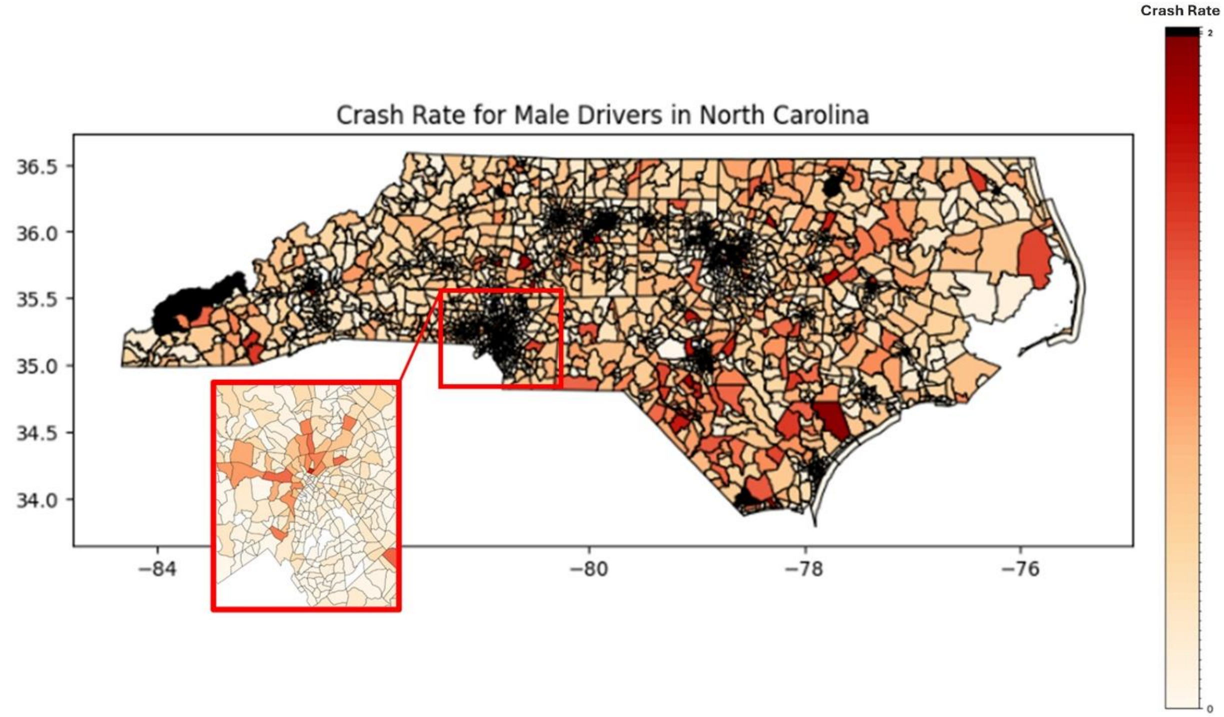


Figure A15: Weighted crash rates for male drivers in North Carolina (fatal and serious injuries only)

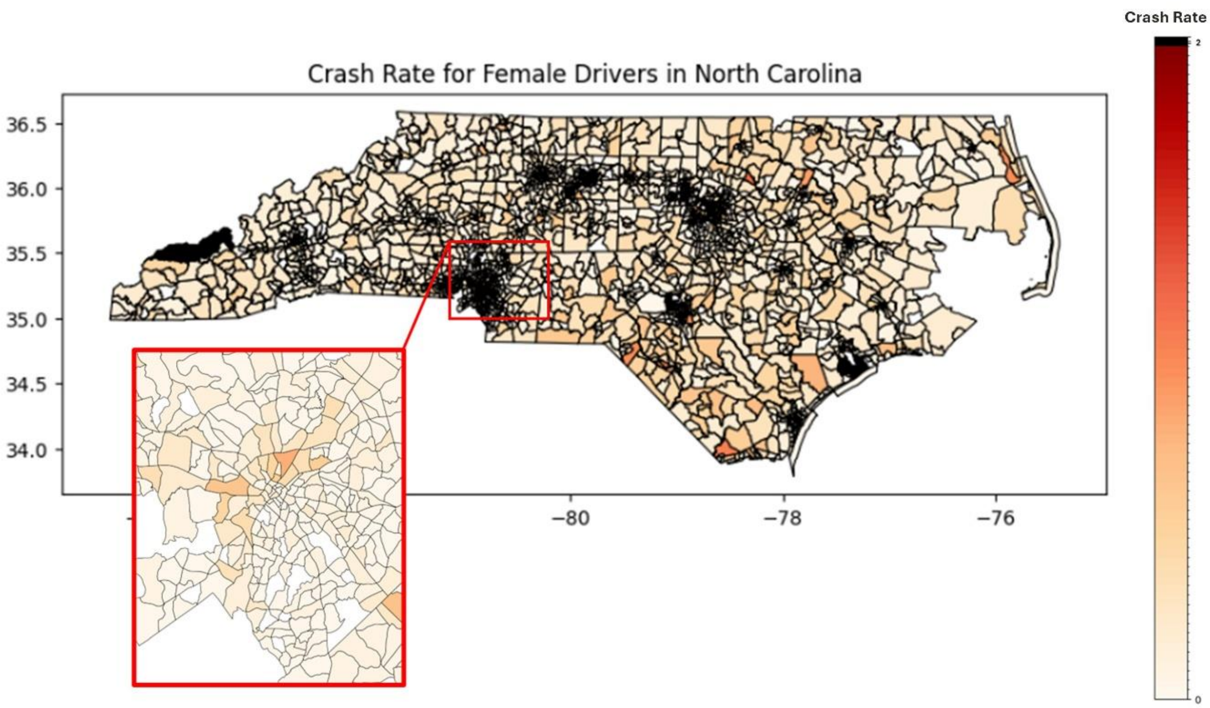


Figure A16: Weighted crash rates for female drivers in North Carolina (fatal and serious injuries only)

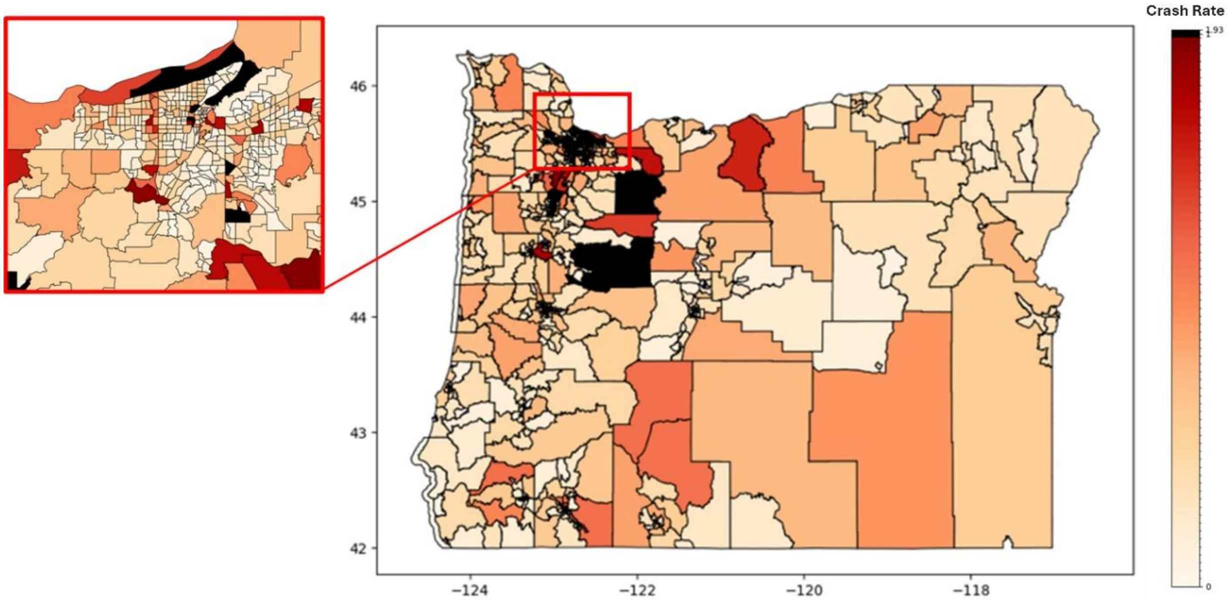


Figure A17: Weighted crash rates for male drivers in Oregon

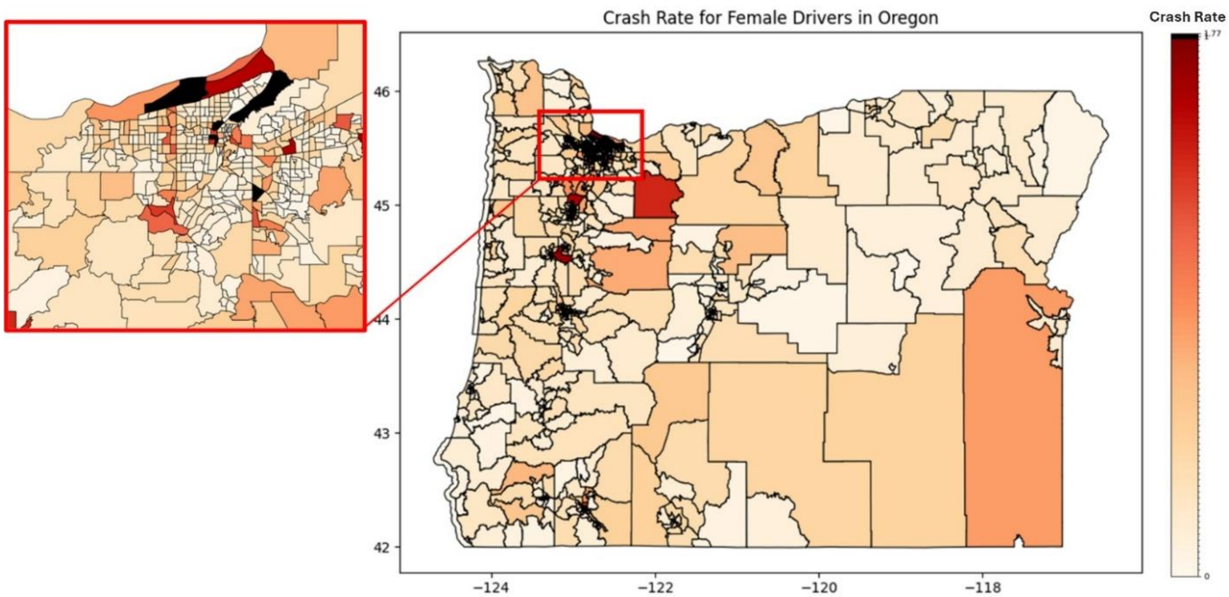


Figure A18: Weighted crash rates for female drivers in Oregon

Appendix H: National EMS Analysis

The data from National Emergency Medical Services Information System (NEMSIS) was summarized to understand how primary symptoms and Chief Anatomic Location differs across different sociodemographic groups. Age, race, and gender were considered.

Chief Complain Anatomic Location across Gender, Race, and Age Group

Figure A19 displays the distribution of chief complaint anatomic locations in EMS-responsive crashes across gender, race, and age groups. The percentages represent the proportion of reported chief complaint anatomic locations for each demographic subgroup, relative to the total number of incidents within that subgroup.

The plots reveal several trends in how the chief complaint anatomic location varies across sociodemographic groups involved in traffic crashes. Males were more likely to sustain injuries to the head, upper extremities, and lower extremities, while females were more likely to experience injuries to the neck, abdomen, and head. In terms of age, younger individuals were more prone to head, abdomen, and lower extremity injuries compared to older age groups, who tend to suffer more chest injuries. Race-based differences show that individuals identifying as Native American were more likely to experience head and lower extremity injuries. In contrast, Black individuals were more likely to sustain back and lower extremity injuries. Asian individuals were more likely to have chest and neck injuries compared to other racial groups.

Primary Symptoms Across Gender, Race, and Age Groups

Figure A20 illustrates the distribution of primary symptoms for EMS-responsive crashes across gender, race, and age groups. The percentages represent the proportion of a specific primary symptom reported within a sociodemographic subgroup, relative to the total injuries reported by that subgroup.

The analysis highlights distinct trends in how primary symptoms vary across sociodemographic groups involved in traffic crashes. Males were found to be more likely to report symptoms related to pain, head injuries, and multiple injuries, while females were more likely to report back pain, cervicalgia, and chest pain.

Age-wise, individuals aged 65+ were more likely to report chest pain as a primary symptom compared to other age groups. Among racial groups, individuals identifying as White were more likely to report head injuries, while Asians were more likely to report chest injuries. Similarly, individuals identifying as Black or African American were more likely to report back pain as their primary symptom compared to other racial groups.

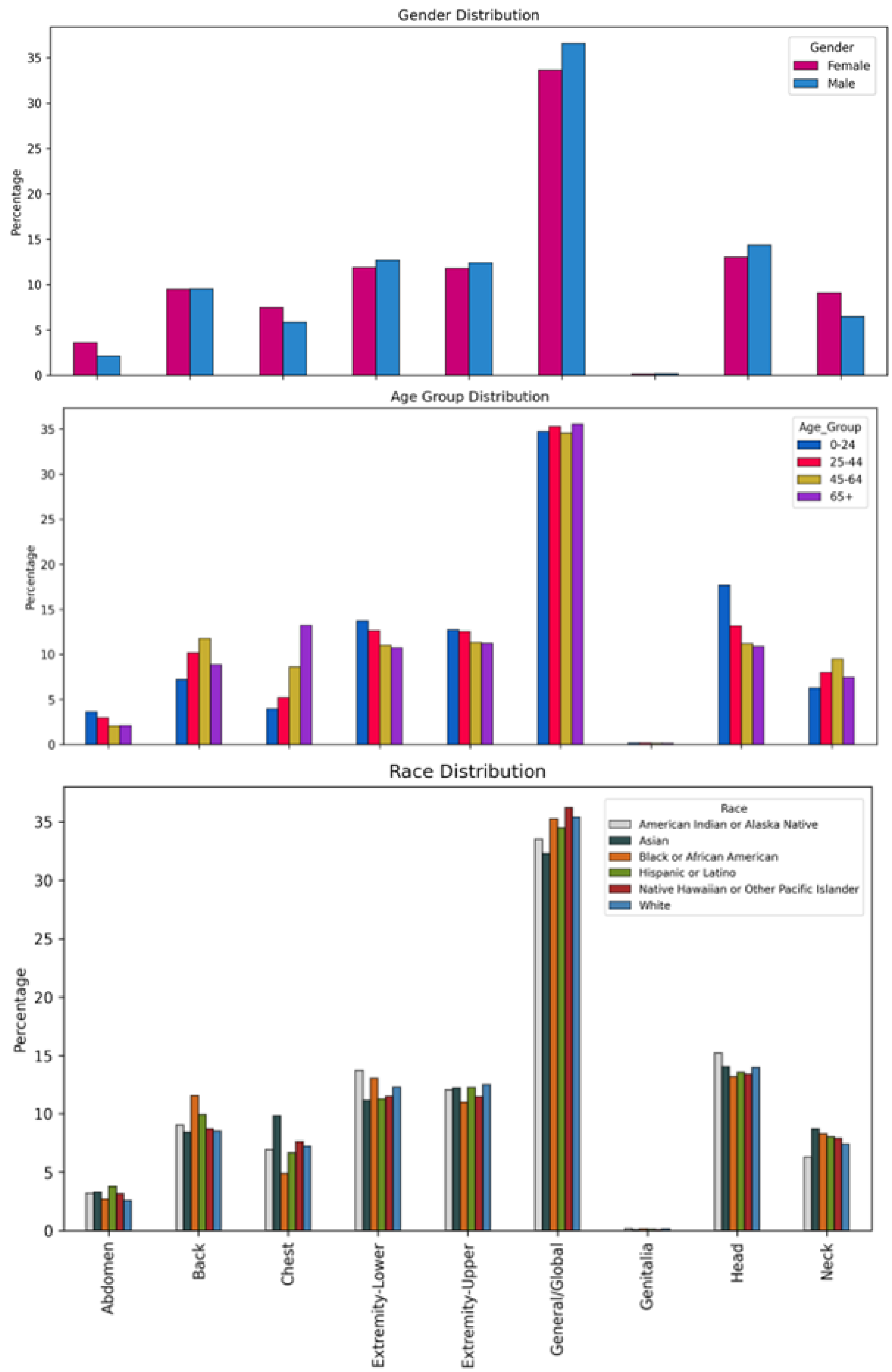
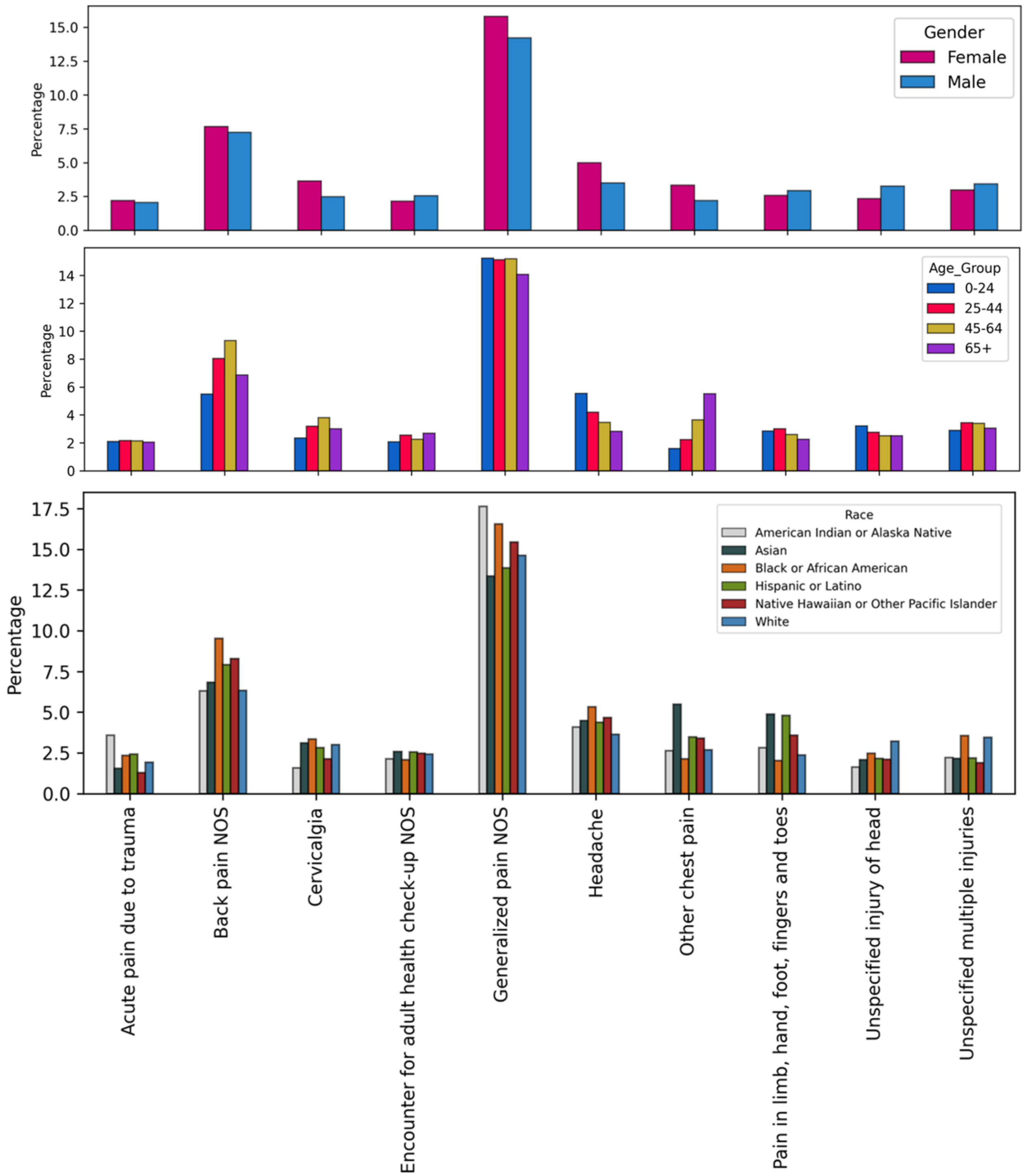


Figure A19: Chief complaint anatomic location across gender, race, and age groups for individuals in EMS-responsive crashes



(NOS = Not Otherwise Specified)

Figure A20: Primary symptoms across gender, race, and age groups for individuals in EMS-responsive crashes

Appendix I: Maryland EMS Data

The Maryland EMS data was obtained from the Maryland Institute for Emergency Medical Services Systems and analyzed to assess differences in primary symptoms and chief anatomic location across sociodemographic groups, including age, race, and gender. While the NEMSIS dataset lacks state-level identifiers, preventing state-specific analysis, the Maryland EMS dataset follows a similar format but is limited to cases within Maryland.

Chief Complain Anatomic Location

Figure A21 displays the distribution of chief complaint anatomic locations in EMS-responsive crashes across gender, race, and age groups for Maryland. The percentages represent the proportion of reported chief complaint anatomic locations for each demographic subgroup, relative to the total number of incidents within that subgroup.

Key patterns emerge in how injury locations differ across sociodemographic groups. Consistent with national data, males in Maryland showed higher rates of head, upper extremity, and lower extremity injuries, while females more frequently sustained neck, abdomen, and chest injuries. Unlike national trends, however, Maryland males were more likely than females to report back injuries. Age-related differences mirrored national findings, with younger individuals more prone to head, abdomen, and lower extremity injuries, while older groups experienced more chest injuries. Racial disparities also aligned with broader trends: Native American individuals had higher rates of head and lower extremity injuries, Black or African American individuals more often sustained back and lower extremity injuries, and Asian individuals showed greater likelihood of chest and neck injuries compared to other racial groups. These results closely parallel to national-level observations.

Primary Symptoms

Figure A22 illustrates the distribution of primary symptoms for EMS-responsive crashes across gender, race, and age groups. The percentages represent the proportion of a specific primary symptom reported within a sociodemographic subgroup, relative to the total injuries reported by that subgroup.

The analysis highlights distinct trends in how primary symptoms vary across sociodemographic groups involved in traffic crashes. Males were found to be more likely to report symptoms related to head injuries, and altered mental status, while females were more likely to report general pain in injury-related cases.

Age-wise, individuals aged 65+ were more likely to report altered mental status as a primary symptom compared to other age groups. Among racial groups, individuals identifying as White were more likely to report head injuries, while individuals identifying as Black or African American were more likely to report acute pain as their primary symptom compared to other racial groups.

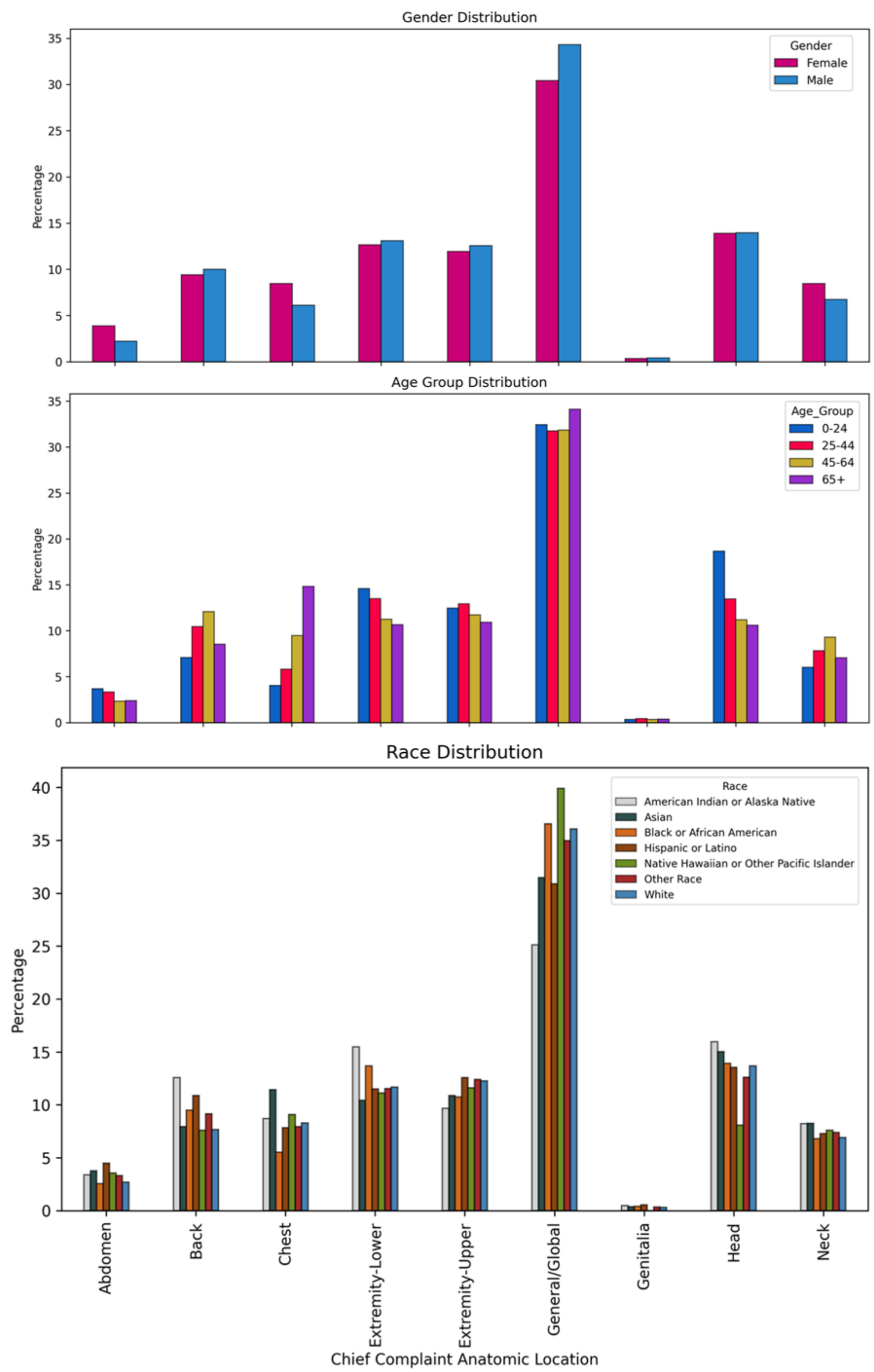


Figure A21: Chief complaint anatomic location for people involved in EMS-responsive crashes in Maryland

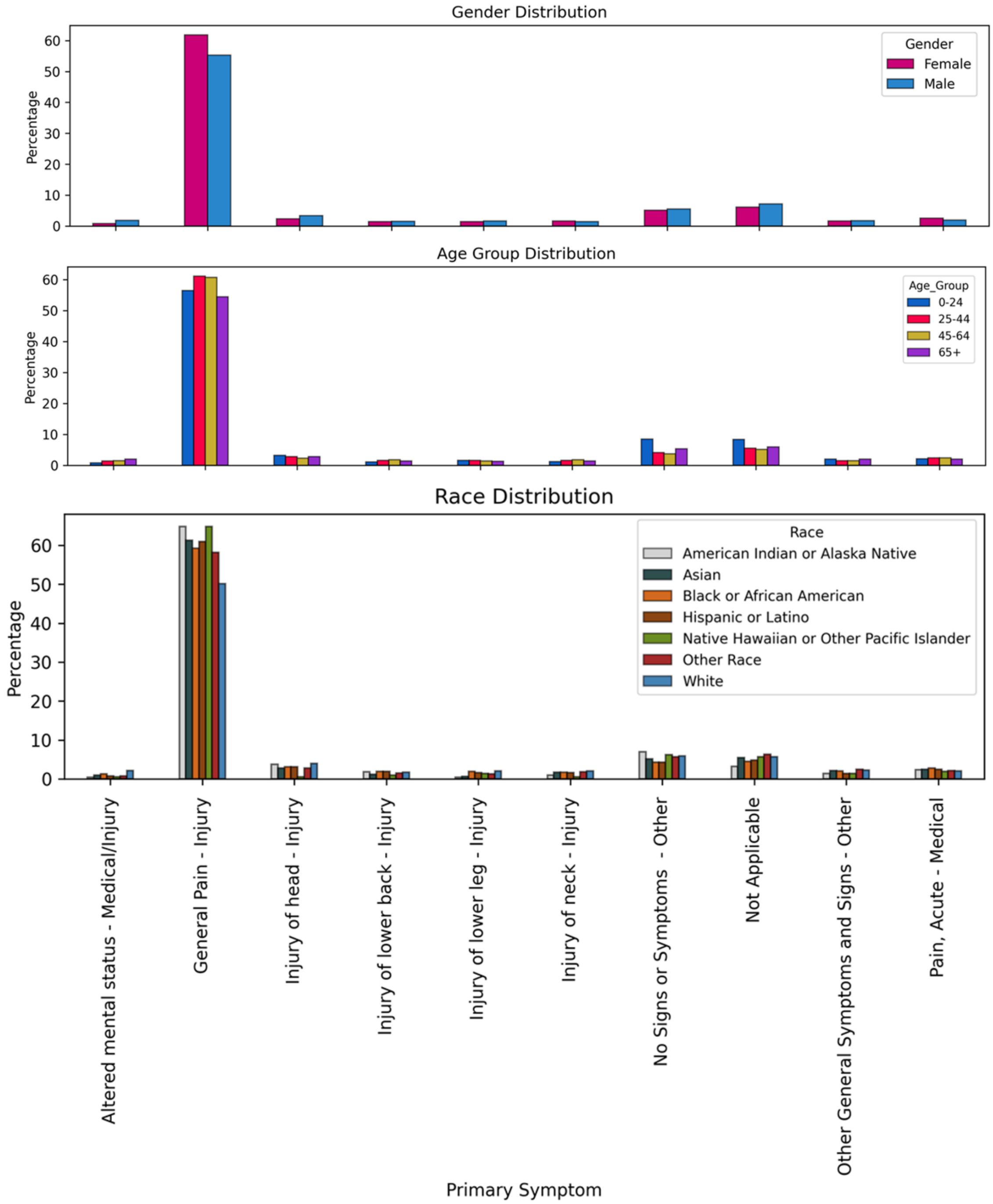


Figure A22: Primary injury outcome for people involved in EMS-responsive crashes in Maryland

Appendix J: Crash Rates across Age groups

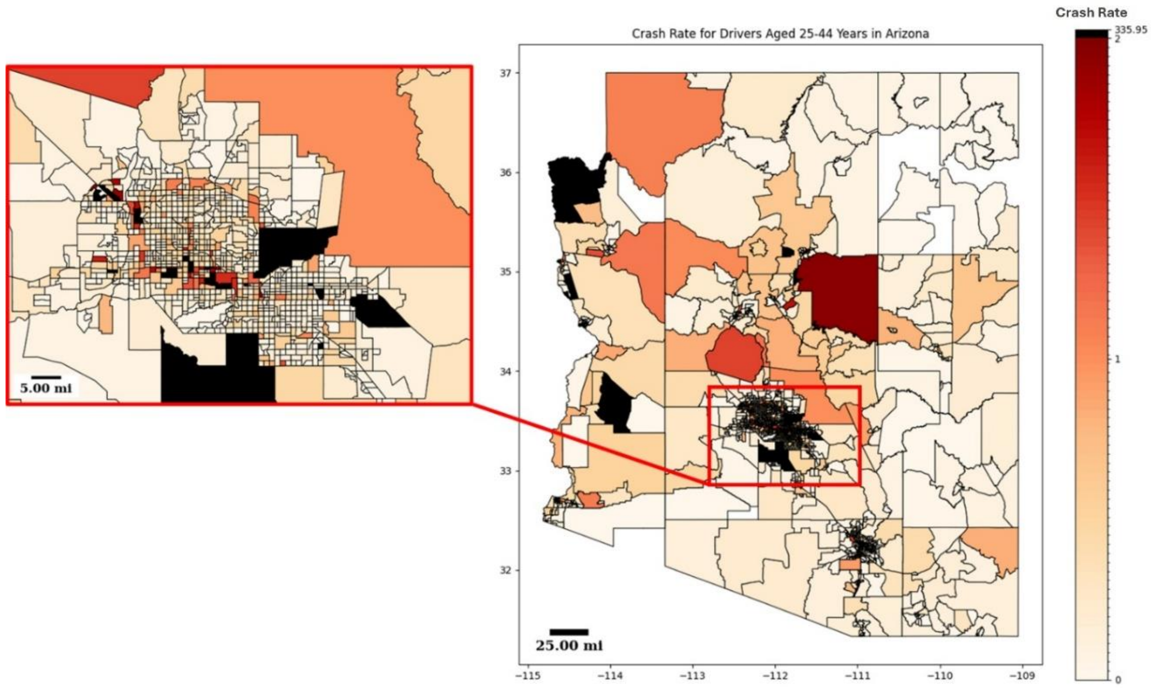


Figure A23: Weighted crash rate for drivers aged 25–44 years in Arizona

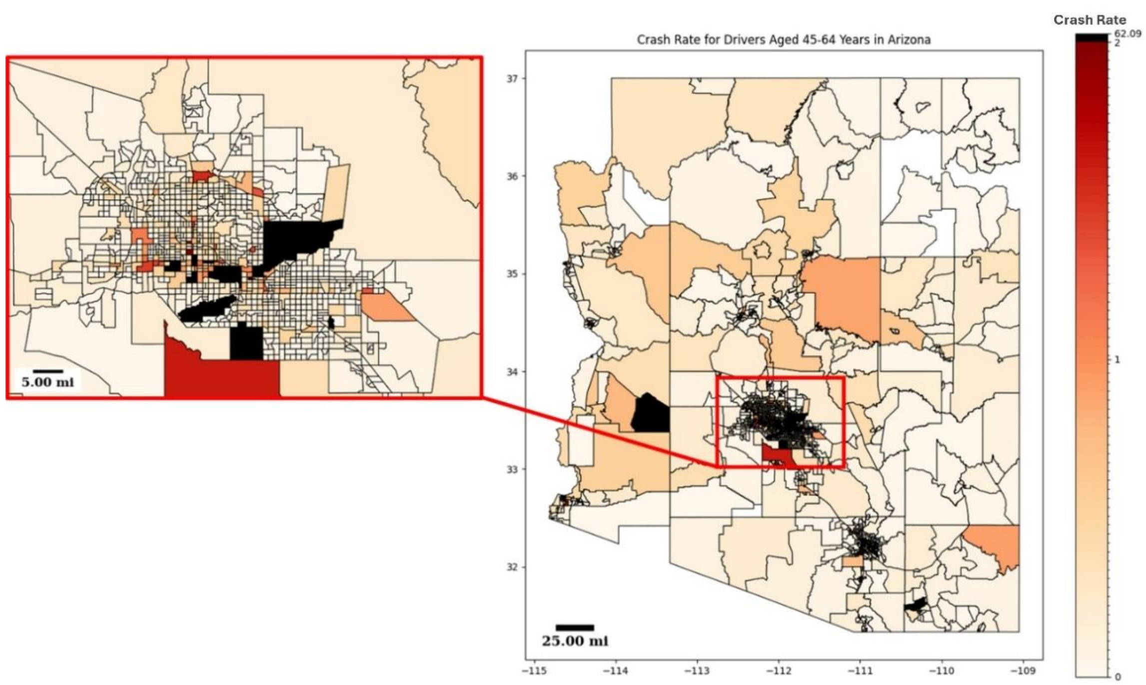


Figure A24: Weighted crash rate for drivers aged 45–64 years in Arizona

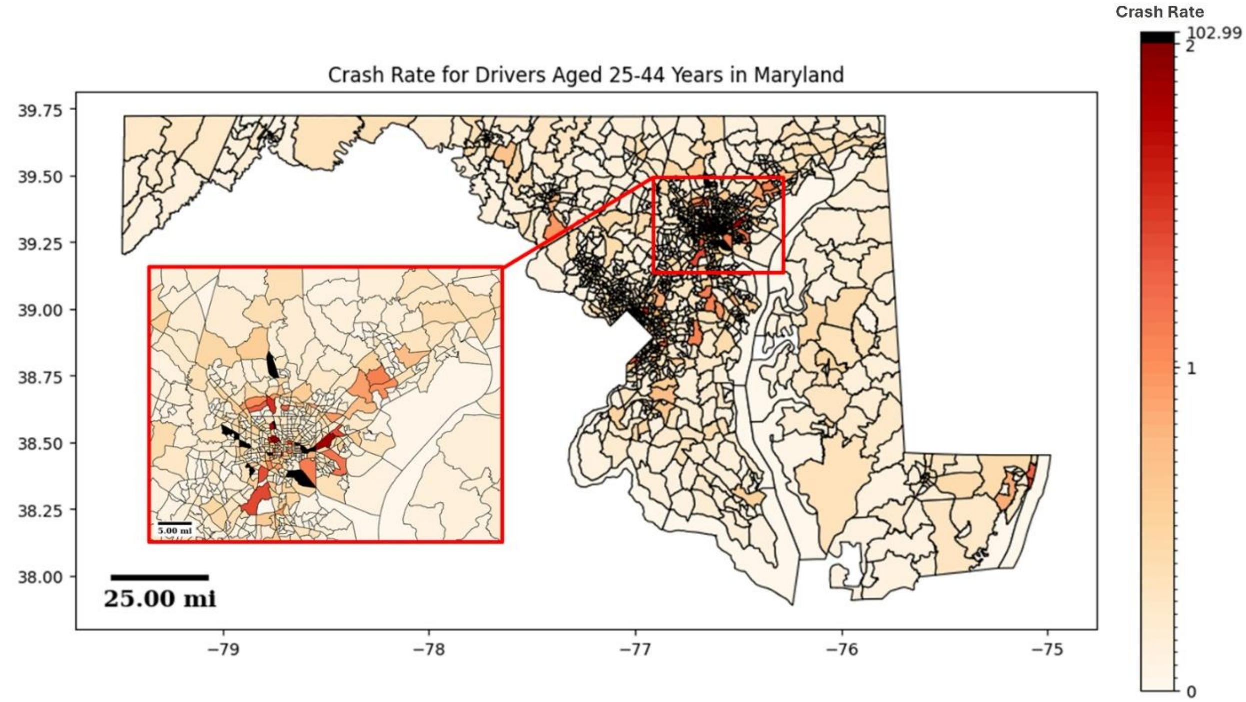


Figure A25: Weighted crash rate for drivers aged 25–44 years in Maryland

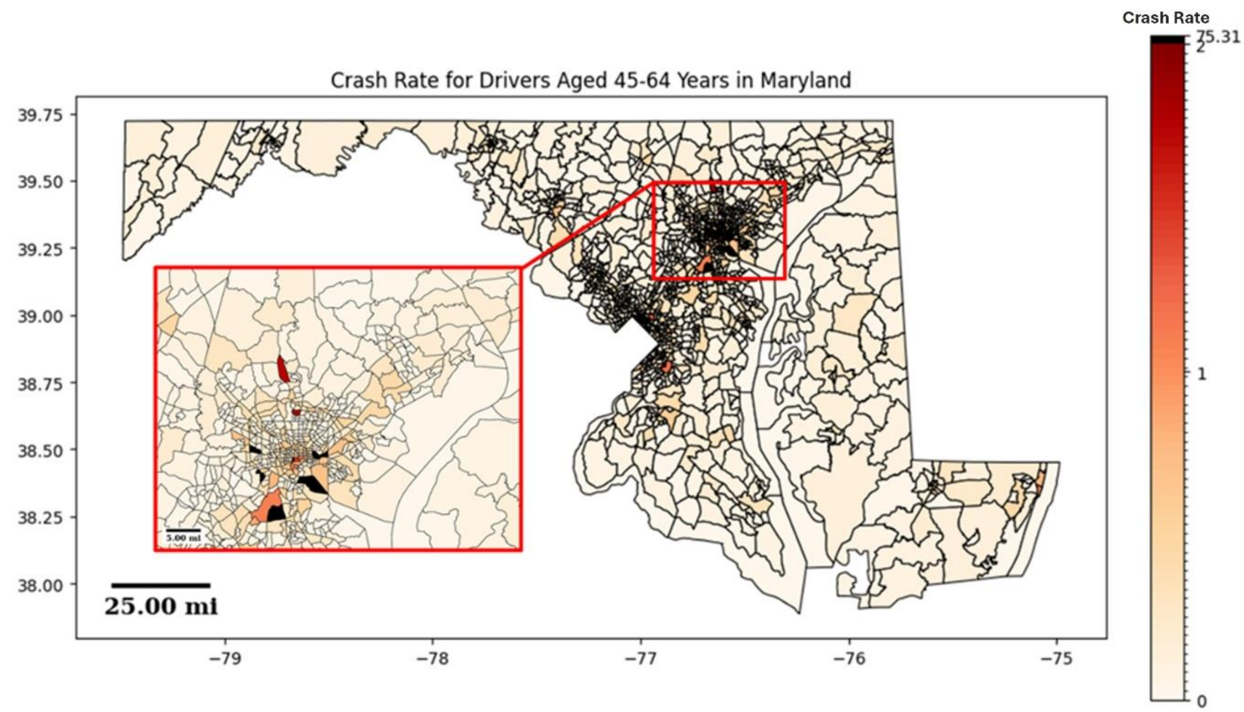


Figure A26: Weighted crash rate for drivers aged 45–64 years in Maryland

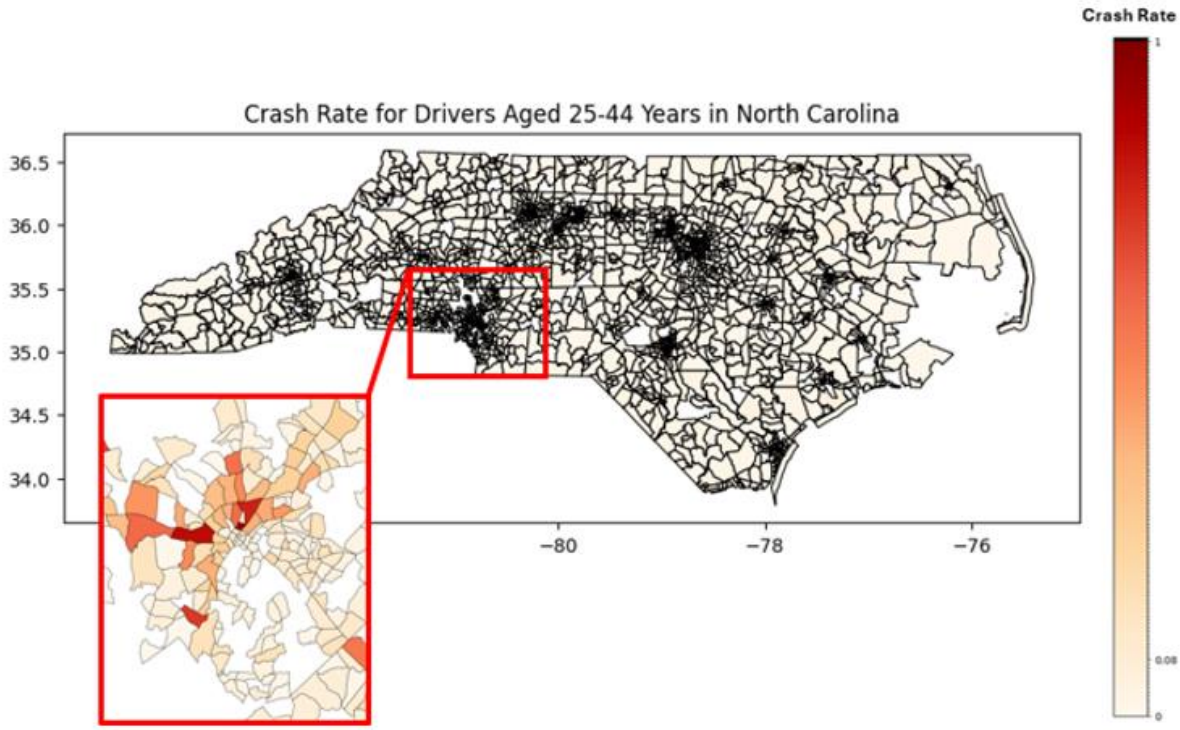


Figure A27: Weighted crash rate for drivers aged 25–44 years in North Carolina (fatal and serious injuries only)

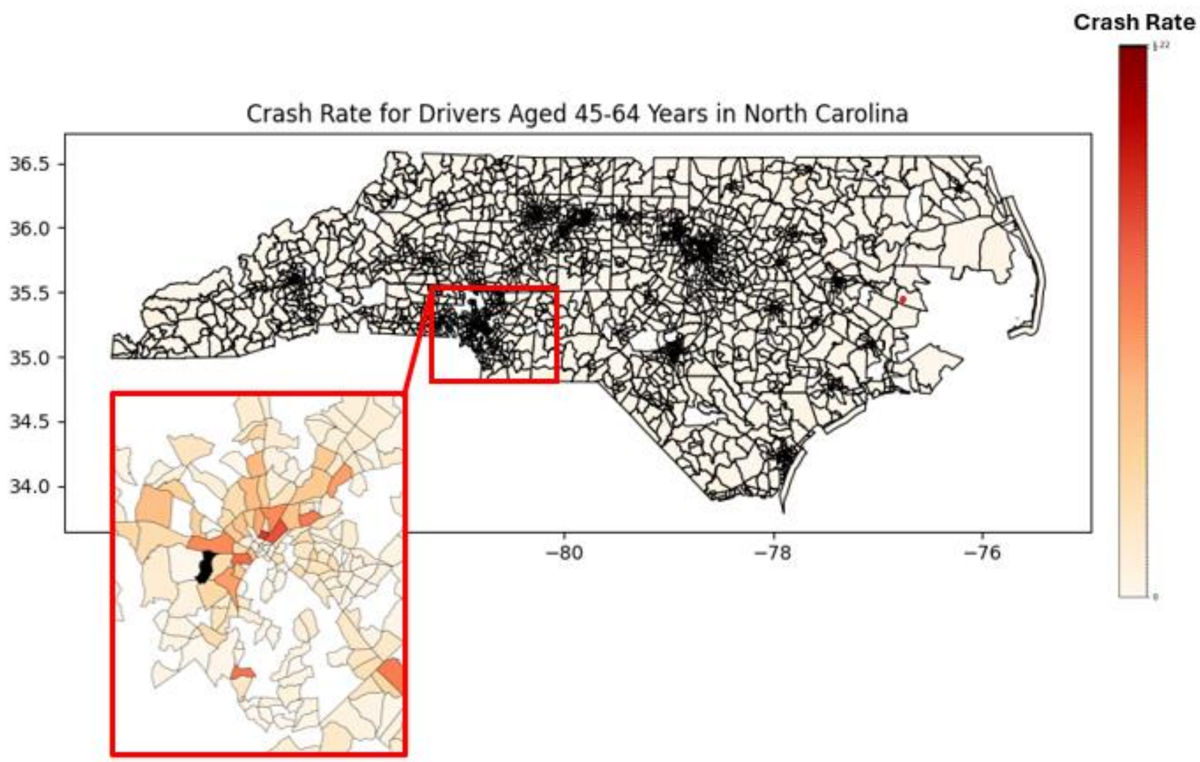


Figure A28: Weighted crash rate for drivers aged 45–64 years in North Carolina (fatal and serious injuries only)

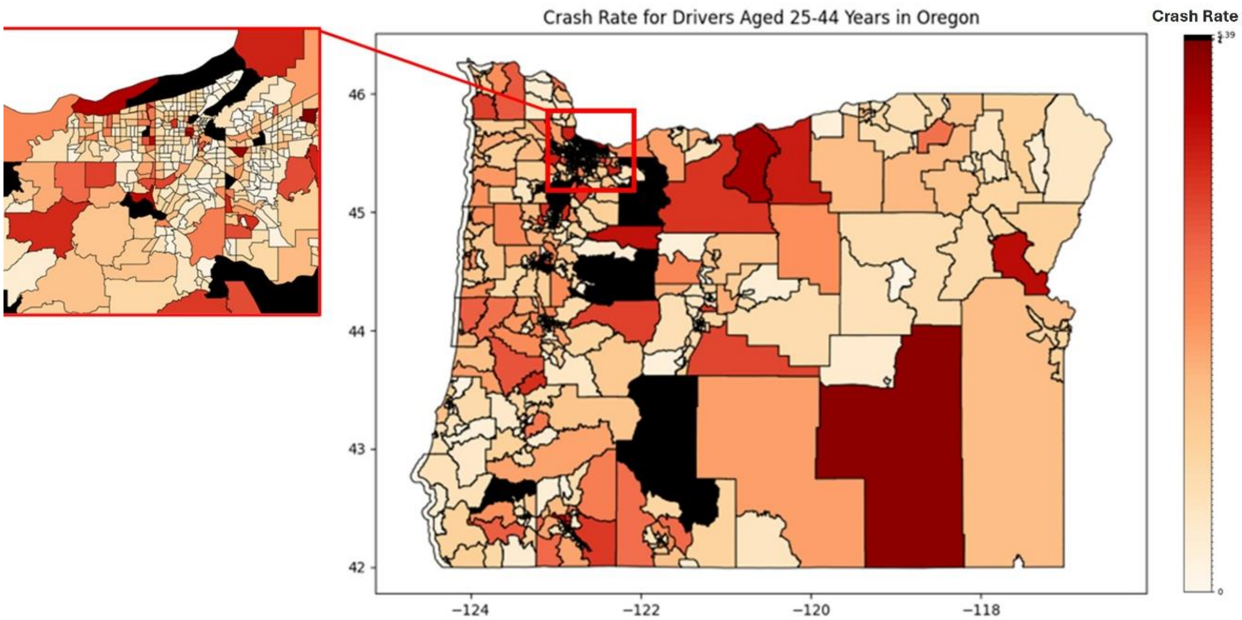


Figure A29: Weighted crash rate for drivers aged 25–44 years in Oregon

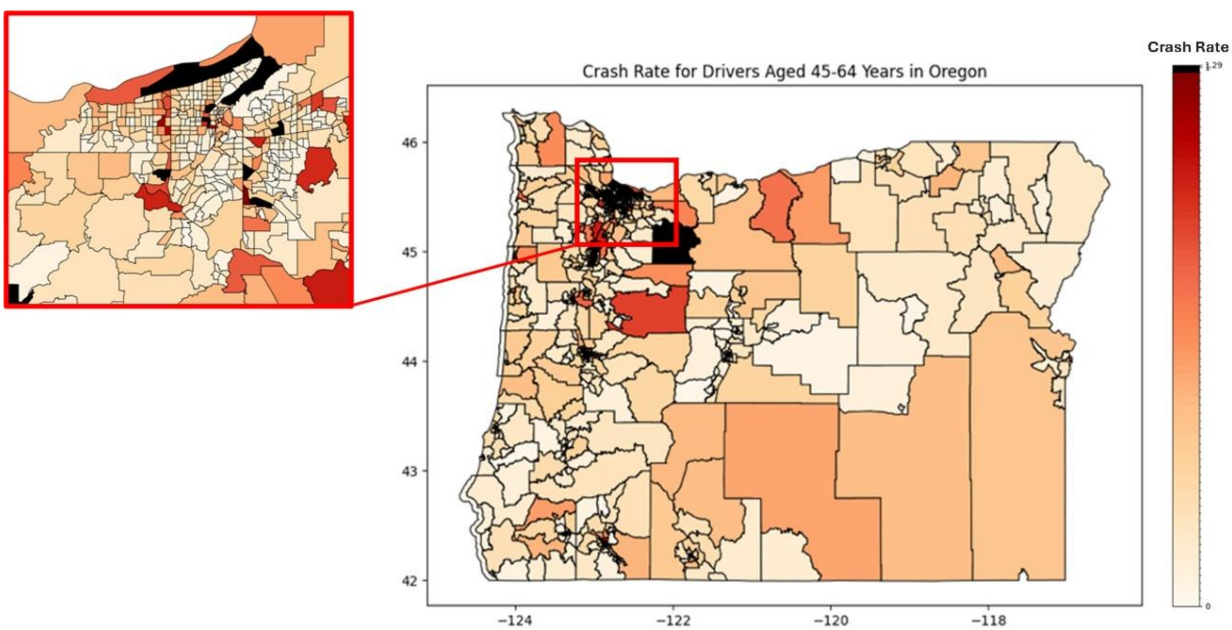


Figure A30: Weighted crash rate for drivers aged 45–64 years in Oregon

Appendix K: Statistical Tests

Table A1: Chi-square test results analyzing serious injury differences across sex and age groups amongst pedestrians

State	Group	Severity Rate per 100,000 Pop.	p-value
Arizona	Male	12.2	<0.001
	Female	5.7	
	15–24	4.9	<0.001
	25–44	6.4	
	45–64	5.6	
	65+	3.3	
Maryland	Male	14.6	<0.001
	Female	7	
	15–24	5.3	<0.001
	25–44	6.5	
	45–64	5.1	
	65+	3.6	
National^	Male	3.5	<0.001
	Female	1.4	
	15–24	0.7	<0.001
	25–44	1.3	
	45–64	1.4	
	65+	1.2	
Oregon	Male	6.53	<0.001
	Female	3.37	
	15–24	4.52	<0.001
	25–44	5.39	
	45–64	5.14	
	65+	4.49	

^*National estimates include fatalities only.*

Table A2: Chi-square test results analyzing serious injury differences across sex and age groups amongst bicyclists

State	Group	Severity Rate per 100,000 Pop.	p-value
Arizona	Male	4.3	<0.001
	Female	1.1	
	15–24	1.3	<0.001
	25–44	1.5	
	45–64	1.7	
	65+	1.3	
Maryland	Male	2.5	<0.001
	Female	0.4	
	15–24	0.8	0.1632
	25–44	0.7	
	45–64	0.9	
	65+	0.4	
National^	Male	0.6	<0.001
	Female	0.1	
	15–24	0.1	<0.001
	25–44	0.1	
	45–64	0.2	
	65+	0.2	
Oregon	Male	2.3	<0.001
	Female	0.6	
	15–24	1.28	<0.001
	25–44	1.51	
	45–64	1.79	
	65+	0.97	

^National estimates include fatalities only.

Table A3: Chi-square test results analyzing serious injury differences across sex and age groups amongst drivers

State	Group	Severity Rate per 100,000 Pop.	p-value
Arizona	Male	124.9	<0.001
	Female	60.0	
	15–24	65.8	<0.001
	25–44	64.7	
	45–64	50.8	
	65+	31.1	
Maryland	Male	63.7	<0.001
	Female	25.6	
	15–24	27.0	<0.001
	25–44	29.3	
	45–64	18.6	
	65+	11.4	
National^	Male	14.5	<0.001
	Female	4.0	
	15–24	4.8	<0.001
	25–44	5.2	
	45–64	4.2	
	65+	4.0	
Oregon	Male	59.1	<0.001
	Female	31.7	
	15–24	57.7	<0.001
	25–44	59.3	
	45–64	54.2	
	65+	44.6	
North Carolina	Male	72.7	<0.001
	Female	29.4	
	15–24	71.2	<0.001
	25–44	77.6	
	45–64	54.2	
	65+	38.8	

^*Estimates include fatalities only.*

The chi-square tests examine whether observed severe injury rates differ significantly from expected rates, assuming injuries would occur proportionally across demographic groups. All injury rates are reported per 100,000 population. Results consistently demonstrated highly significant gender differences across all road user types and geographic locations ($p<0.001$), with males showing higher severe injury rates than females, most notably among bicyclists where the national gender gap reached 6-fold (0.6 vs 0.1). Age-related patterns showed more variability, with most comparisons reaching statistical significance ($p<0.001$) except for Maryland bicyclists, where age groups showed no significant differences in severe injury rates ($p=0.163$), suggesting that local factors may influence risk distributions differently across geographic regions. Drivers consistently exhibited the highest severe injury rates compared to pedestrians and bicyclists, with younger driver age groups demonstrating elevated risk that generally decreased with age. North Carolina crash data did not include pedestrian and bicyclist crashes that did not result in a fatality and as such were not included in this analysis.

Appendix L: Supplementary DEA Model Results

Further exploration was conducted through a sensitivity analysis to determine additional variables that could influence crash rates and injury severity at the national and state level. Along with the sociodemographic variables which indicate the demographic composition of an area, the ADI from the Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics data, as defined in the Smart Location Database (SLD), and the Centers for Disease Control and Prevention and Agency for Toxic Substances and Disease Registry's Social Vulnerability Index (SVI) were added to assess their impact on safety risks in the state and national DEA models.

The following two variables were added:

1. Activity Diversity Index (D2b_E5Mix from SLD): This variable measures employment diversity using five categories: retail, office, industrial, service, and entertainment. It calculates how evenly employment is spread across these types using an entropy formula, normalized by the number of employment types present. Higher values indicate greater employment diversity.
2. Social Vulnerability Index (RPL_THEMES in SVI): This variable is the overall summary ranking that reflects the combined social vulnerability of an area. It is calculated by summing the percentile ranks of the four themes, which are socioeconomic status, household characteristics, racial and ethnic minority status, and housing type and transportation, and then ranking these totals across all census tracts. The final percentile ranges from zero to one, with higher values indicating greater social vulnerability.

The models including these variables are presented in Tables A4 through A8 below:

Table A4: National, with activity diversity index and social vulnerability index

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	298.93*	626.59	822.43	302.70*	606.57	788.66
Unemployment Rate	91.24*	160.41	181.08	81.93*	140.75	162.52
% White	−89.18*	−178.27	−157.66	−92.31*	−184.16	−160.11
% Black	−67.62*	−135.46	−119.46	−66.36*	−132.63	−113.85
% Native American	−126.90*	−253.00	−221.36	−127.22*	−253.24	−217.45
% Asian	16.34*	26.92	31.98	16.70*	27.24	32.82
% Pacific Islander	−60.42*	−119.90	−103.21	−77.81*	−154.21	−133.75
% Other Race	29.86*	49.93	58.61	32.56*	53.07	63.88
% Two or More Race	−14.40*	−30.84	−26.06	−19.75*	−40.83	−33.58
% Hispanic	1.40*	1.58	5.03	5.35*	8.33	12.95
% High School Graduate or less	−146.98*	−291.67	−258.85	−152.29*	−302.11	−264.16
% Graduate Degree	−16.08*	−32.67	−26.93	−25.24*	−50.64	−41.51
% Below Poverty	−126.65*	−251.43	−221.51	−128.37*	−254.67	−220.31
ADI	30.95*	52.79	61.45	39.14*	66.00	77.62
SVI	81.11*	141.85	160.98	80.88*	138.95	160.39

The DEA models examined the relationship between community characteristics and traffic fatalities using road miles (Mile Model) and population (Population Model) as the input for national level fatality data. Both models revealed consistent patterns: lower unemployment rates, greater percentages of individuals with low educational attainment, and higher poverty levels were associated with increased fatality risks. Areas with higher proportions of White, Black, Native American, and Pacific Islander populations generally experienced lower safety outcomes, as indicated by significantly negative coefficients. Conversely, the presence of Asian and individuals categorized as Other Race was linked to safer outcomes, while the effects of Hispanic ethnicity were small but positive. The ADI and SVI both showed positive associations with fatality counts.

Table A5: Arizona, with activity diversity index and social vulnerability index

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	−209.10*	−4925.73	−3171.08	−126.14*	−3923.12	−2490.74
Road miles				−1053.25*	−2019.66	−167.80
Population	961.68*	1689.04	3202.84			
Unemployment Rate	1455.19*	3107.39	5338.78	289.56*	2729.02	4285.79
%65+	−3059.54*	−5635.50	−3520.71	−2600.19*	−4828.72	−3367.19
% White	−55125.82*	−145145.40	−124153.33	−66015.93*	−179665.00	−156169.80
% Black	−20092.47*	−56465.27	−46813.16	−25692.00*	−73610.32	−62741.81
% Native American	−32386.35*	−102451.57	−81854.55	−46207.00*	−143261.00	−120630.00
% Asian	−39599.44*	−114466.43	−92621.58	−52586.00*	−153757.00	−128785.00
% Pacific Islander	−5452.08*	−16017.18	−12925.61	−7340.82*	−21659.67	−18149.45
% Other Race	−40175.70*	−116709.77	−95841.28	−53088*	−155661	−132261
% Two or More Race	−24890.08*	−71081.67	−58542.78	−32414.38*	−93831.23	−79696.28
% Hispanic	−4685.37*	−8831.85	−6447.10	−4061.23*	−7570.17	−5797.61
% Some College	33014.43*	83549.67	104330.08	46925.98*	122702.79	145385.47
% Bachelor's degree	25818.55*	65372.53	81954.39	37002.02*	96680.37	114933.01
% Graduate Degree	14133.84*	36909.65	47704.23	21611.03*	57387.40	69451.56
% High School Graduate or less	32034.77*	78035.99	96460.92	44199.13*	111603.66	132440.82
ADI	−21.77	−65.66	32.28	−18.50	−76.12	40.78
SVI	−3180.22*	−6229.60	−4963.18	−2626.25*	−4981.43	−3374.06

The DEA results for Arizona, using weighted crash counts as the output and road miles or population as the input, highlight strong sociodemographic influences on traffic safety. In the Mile Model, population size significantly increased fatality counts, while in the Population Model, road miles had a similarly strong negative association, indicating both exposure types play distinct roles in fatality distribution. Across both models, higher unemployment rates were associated with lower injury risks. Older populations (65+), along with greater percentages of White, Black, Native American, Asian, Pacific Islander, Other Race, Two or More Race, and Hispanic residents, were consistently linked to lower safety outcomes. In contrast, communities with higher proportions of individuals with some college, bachelor's, or graduate degrees experienced significantly better outcomes. The ADI was not significantly associated with crashes in either model, while the SVI showed a strong and negative relationship.

Table A6: Maryland, with activity diversity index and social vulnerability index

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	−262.24*	−4621.90	−3193.17	−1577.71*	−3144.35	−2880.23
Road miles				40.34*	72.55	79.65
Population	−2843.68*	−5212.70	−720.33			
Unemployment Rate	−2156.33*	−4246.71	−2068.01	−42.66*	−84.37	−76.11
%65+	−4120.64*	−7837.75	−4854.84	−105.25*	−207.62	−190.40
% White	8416.13*	17275.29	22695.43	−55.15*	−135.08	−89.24
% Black	9746.13*	19893.62	25709.45	−53.69*	−132.02	−86.48
% Native American	708.35*	664.08	2547.12	4.78*	5.52	11.75
% Asian	9248.37*	15985.18	19398.28	−29.78*	−74.59	−47.28
% Pacific Islander	4572.60*	8049.06	9531.28	29.34*	48.83	58.13
% Other Race	12008.00*	22775.38	25550.43	−48.48*	−120.26	−76.59
% Two or More Race	3453.84*	5683.15	8465.06	−21.88*	−50.83	−36.58
% Hispanic	−766.22*	−2320.31	−293.02	−38.61*	−76.86	−68.07
% Some College	−18720.34*	−36970.35	−32085.72	−23.95*	−62.88	−15.92
% Bachelor's degree	−5154.47*	−12429.71	−9625.94	30.57*	49.60	74.76
% Graduate Degree	−7036.56*	−16807.14	−13608.74	26.17*	38.31	71.74
% High School Graduate or less	−19799.15*	−38614.48	−32519.00	13.83*	11.23	54.03
ADI	−2058.88*	−3830.83	−2637.29	14.00*	24.88	27.64
SVI	−4360.23*	−8432.08	−4310.17	35.06*	63.24	69.13

The DEA analysis for Maryland reveals contrasting patterns depending on whether population or road miles were used as the input. In the Mile Model, higher population size significantly decreased fatality counts, while in the Population Model, increased road miles were associated with more fatalities. Across both models, unemployment rate and percentage of population aged 65+ were consistently linked to higher crashes. Racial and ethnic patterns diverged sharply by model: the Mile Model associated higher percentages of White, Black, Asian, Pacific Islander, Other Race, and Two or More Race populations with decreased crash risk, whereas the Population Model linked most of these same variables to less safe outcomes. ADI and SVI were negatively associated with fatalities in the Mile Model but showed positive associations in the Population Model, suggesting these community factors may interact differently with road infrastructure versus resident exposure.

Table A7: Oregon, with activity diversity index and social vulnerability index

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	39.97	−1520.91	−403.34	−132.04*	−608.26	−433.53
Road miles				0.49*	20.90	28.09
Population	−1129.92*	−1418.24	−738.74			
Unemployment Rate	−114.97	−166.84	106.92	−20.92*	−47.02	−40.56
%65+	−769.61*	−1062.10	−728.46	−103.31*	−177.30	−158.47
% White	−51048.12*	−116822.54	−106119.94	−57.67*	−126.73	−73.44
% Black	−12234.18*	−29656.13	−27163.24	29.12*	59.87	78.01
% Native American	−45539.08*	−105342.02	−94934.80	−106.02*	−174.18	−120.54
% Asian	−26665.13*	−61469.44	−55705.56	−54.68*	−142.61	−114.35
% Pacific Islander	−9079.13*	−21589.15	−19696.74	38.63*	70.11	84.92
% Other Race	−18406.35*	−42480.39	−38437.62	−12.21*	−24.50	−4.36
% Two or More Race	−17038.89*	−39375.07	−35809.20	−29.71*	−70.81	−52.49
% Hispanic	−238.36*	−371.91	−180.79	−41.70*	−63.11	−54.67
% Some College	29011.54*	61766.04	67969.85	11.00*	−38.48	−5.04
% Bachelor's degree	42321.29*	90300.88	99304.03	−45.00	−44.51	4.06
% Graduate Degree	25456.16*	54833.57	60254.57	13.17	−15.42	14.51
% High School Graduate or less	37638.52*	78836.87	86962.90	53.02*	122.13	161.96
ADI	−313.67	−49.62	138.40	−7.91*	−27.14	−23.54
SVI	206.84*	215.13	399.38	11.82*	3.23	6.63

When including the ADI and SVI in the analysis it was found that neither index has an impact on crash rates within Oregon. Other variables in both the Mile Model and Population Model were found to confirm the results from the original two DEA models with road miles having a higher impact on crash rates than total population.

Table A8: North Carolina, with activity diversity index and social vulnerability index

	Mile Model			Population Model		
Variable	**Coefficient**	**2.50%**	**97.50%**	**Coefficient**	**2.50%**	**97.50%**
(Intercept)	−956.46*	−10458.59	−5733.31	−828.48*	−2188.68	−1830.78
Road miles				29.94*	28.91	35.08
Population	−12459.71*	−18116.77	−13531.58			
Unemployment Rate	−22164.06*	−34897.30	−31628.38	−34.3*	−46.09	−39.86
%65+	−29468.34*	−47735.63	−42716.55	−29.72*	−48.80	−41.32
% White	−95357.3*	−157773.64	−136634.35	−54.96*	−128.33	−40.15
% Black	−15047.68*	−22080.02	−18305.52	−53.5*	−130.28	−43.68
% Native American	−17297.33*	−29055.37	−26385.23	−39.38*	−113.66	−30.68
% Asian	−18899.04*	−32859.2	−30720.7	−76.16*	−134.97	−77.77
% Pacific Islander	−3118.74*	−6001.42	−4752.02	−35.17*	−28.65	−19.21
% Other Race	−15867.8*	−27014.8	−23620.82	−40.18*	−68.47	−23.02
% Two or More Race	38902.37*	56797.71	63187.74	−1.21	−26.96	2.75
% Hispanic	12668.29*	18265.82	21888.63	−2.68*	−15.45	−12.63
% Some College	−6164.49*	−8282.59	−2498.61	35.35*	40.05	127.8
% Bachelor's degree	735.48	−2255.25	3647.32	19.70*	6.35	93.47
% Graduate Degree	1304.71	−431.87	3904.84	15.28*	7.37	94.10
% High School Graduate or less	−12424.22*	−13492.85	−7898.94	38.48*	32.58	120.37
ADI	−18191.21*	−28167.31	−24333.05	−3.63*	−1.76	−1.04
SVI	3005.59*	13164.59	16351.73	12.2*	20.51	24.09

Both the ADI and SVI were found to have an impact on the Mile Model while none was found for the Population Model. The diversity of activity that a community experiences is found to lead to higher crash risks, whereas social vulnerability was found to lead to lower crash risks. Notably, other variables found to be influential on higher crash risks in the original DEA models were also found here.