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The Central Role of Perceived Safety in Connecting Crash Risk Factors and Walking Behavior

Kyu Ri Kim
Portland State University

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by

Kyu Ri Kim

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Dissertation Committee:
Jennifer Dill, Chair
Christopher M. Monsere
Sirisha Kothuri
Liming Wang

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Abstract

Despite advanced policies, plans, and facilities, many pedestrians are still injured and killed in traffic crashes in the United States. To improve pedestrian safety and the walking environment, the relationship between surrounding crash risk factors and perceived safety that influence people's behavior needs to be studied. This study aims to examine pedestrian crash risk factors, the relationship between crash risk factors and perceived safety, measured as threatened experiences and safety attitudes, and the relationship between safety attitudes and walking behavior.

The analysis used data from three primary sources: (1) an original survey of 551 residents in 10 neighborhoods in Oregon conducted in 2023; (2) pedestrian crash data that occurred in Oregon for 2018 – 2022; and (3) pedestrian count data collected at 65 sites in 2022. 729 pedestrian crashes occurred in the census block groups surrounding the 65 sites over five-year periods. These were complemented with built environment data.

The dissertation first tested whether crash risk factors predict actual pedestrian crashes in the study areas. One of the results shows that the pedestrian volume measured as pedestrian count data has better predictive power to explain the pedestrian crashes, cumulated for a shorter period of time than the pedestrian volume measured as population density. Though the count data was collected only for two days, it was more accurate than the population density. This result supports the need to collect pedestrian volume data in various places to develop road safety plans and policies. In addition to pedestrian volume, crash risk factors in macro-level areas, including mixed-use land areas, commercial land areas, and public transit stops, are significant in predicting pedestrian

crashes. However, in this study, the number of intersections, speed limit, and vehicle speed were not statistically significant in predicting crash cases.

The structural equation model (SEM) results for the second research question show that the threatened experiences influenced by the surrounding environment significantly affect safety attitudes. Pedestrians feel more threatened in areas with higher intersection density and mixed-use land areas after controlling other risk factors, including speed and pedestrian and traffic volumes. However, intersection density is not significantly related to the cumulated pedestrian crashes. This may be because vehicle speeds decrease as the density of intersections increases. This implies that when pedestrians encounter intersections more frequently, they perceive that they have had more threatened experiences, even though the environment is not significantly riskier. Pedestrian crashes did not affect pedestrians' threatened experiences and safety attitudes in the SEMs. This can be interpreted as pedestrians' attitudes being mainly determined by their perceived experiences in a given environment rather than an actual crash risk.

In modeling results for the third research question, positive safety attitudes and nearby sidewalks increase walking frequency. On the other hand, larger commercial areas, faster vehicle speeds, and more vehicles in their households significantly reduce walking frequency. One likely reason for the negative relationships with having commercial areas nearby is that most survey respondents were walking primarily for exercise, to walk their pets, or for entertainment rather than to visit specific destinations such as work, school, or restaurants.

This study has several limitations despite meaningful findings. One limitation relates to the unit of analysis. For this analysis, crash risk factors, such as intersection types, road classification, weather conditions, or street lights, were aggregated around each respondent's home. In addition, pedestrian count data was available only for one or two major intersections within that area. Such aggregation does not account for details of the risk of each crash event or in micro-level places. The other limitation relates to cross-sectional analysis. If panel data can be collected and time-series analysis is possible, it would likely investigate how people's attitudes toward safety and behaviors change due to surrounding crash risk factors and threatened experiences.

Dedication

I dedicate my dissertation to my family and friends, especially my admiring parents, loving younger brother, and his wife.

I am grateful to my friend Mariah, who gave me her sympathy and helped me adjust to life in the United States, which has an entirely different culture and lifestyle from my home country, Korea.

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1 Introduction

1.1 Background

Improving transportation safety is one of the essential goals in transportation planning. Despite various and continuous efforts, in the U.S., more than 42,900 people were killed in road crashes in 2021 alone, and among vulnerable road users, more than 7,500 pedestrians were killed in 2022 (National Highway Traffic Safety Administration, n.d.). Furthermore, over the last decade (2012-2021), the percentage of pedestrian fatality has increased from about 14% to 17% (National Highway Traffic Safety Administration, n.d.). The number of pedestrian fatalities in 2018 increased compared to 2008, while the total crash fatalities decreased between 2008 and 2018 (National Highway Traffic Safety Administration, n.d.). Even though travel distance and frequency decreased significantly in 2020-2021 during the pandemic caused by COVID-19, fatal traffic crashes increased compared to 2019 before the pandemic (33,487 in 2019, 35,935 in 2020, and 39,508 in 2021, respectively). The number of pedestrian fatalities also increased (6,565 in 2020 and 7,388 in 2021, respectively) (National Highway Traffic Safety Administration, n.d.). Given these numbers and trends, the first goal of the USDOT strategic plan for the fiscal year 2018-2022 is safety (U.S. Department of Transportation, 2018).

In the U.S., pedestrian safety issues in the urban environment are especially noticeable due to the increased exposure and proximity to vehicles than in rural areas. Land use diversity and better accessibility increase the demand for walking in urban areas, which causes denser pedestrian activities (volume), which increases the probability of pedestrian exposure to traffic flow (Monsere et al., 2017). According to the Pedestrians

Traffic Safety Fact Sheets from 2015 to 2019 (National Highway Traffic Safety Administration, 2017, 2018, 2019, 2020, 2021), from 2015 to 2017, pedestrian fatalities in urban areas were more than three times the number of pedestrian deaths in rural areas. In 2018 and 2019, pedestrian fatalities in urban areas were more than four times the number of deaths in rural areas.

1.2 Motivation & Research Purpose

Pedestrian safety has emerged as one of the primary challenges facing transportation professionals. Despite many efforts, pedestrian crashes have increased, even during the pandemic. To protect road users, including drivers and pedestrians, from the risk of crashes, many existing researchers have defined crash risk factors, tested their influence, and predicted the likelihood of crashes. In addition to identifying factors that influence crash frequency, models have been developed to predict the severity of injuries resulting from crashes. In most of these studies, external environmental characteristics were investigated, including traffic volume, spatial characteristics such as road and land use types, and conditions of facilities in addition to roads (Al-Mahameed et al., 2019; Almasi et al., 2021; Chen & Zhou, 2016; Cho et al., 2009; Clifton et al., 2009; Gill et al., 2022; Lee & Abdel-Aty, 2005; Mahmoud et al., 2021; Sanders et al., 2017; Schneider et al., 2004, 2021). Some studies also investigated demographic characteristics of road users related to crash risk (Anderson et al., 2022; Campbell et al., 2004; Campos-Outcalt et al., 2002; Carter et al., 2017; Chang, 2008; Loukaitou-Sideris et al., 2007; Moyano Díaz, 2002; Zegeer & Bushell, 2012). Despite these research results and policy efforts such as

Vision Zero, road users, especially pedestrians, still need to be protected from the risk of crashes.

Traffic crashes are probabilistically rare events from an individual’s perspective (Carter et al., 2017). Nonetheless, a crash can physically and psychologically primarily affect those involved once an incident occurs. In this study, my question begins with how objectively quantifiable real risks can affect an individual's perceptions and behaviors. In other words, how well are road users, especially pedestrians, who represent vulnerable road users, aware of these risks? Also, could this perceived risk be related to their daily travel? Perceptions and behaviors in this study are not the risk cognition in a specific situation or the immediate reaction. People use different modes of transportation in their daily lives and are exposed to various risk factors. However, not all of these risks are perceived as dangerous, and individuals may have different standards for safety. Instead of focusing on immediate risk awareness and reaction, my research aims to explore travelers’ experiences in their everyday surroundings, how they interpret these experiences, and how their attitudes and experiences can impact their daily activities.

Recent research also emphasizes understanding travelers’ risk perception, which may affect their travel behavior and be able to explain factors contributing to crashes (Cho et al., 2009; Rankavat & Tiwari, 2016; Schneider et al., 2004). However, unanswered questions remain regarding human factors in crash risk. The perceptions and attitudes of travelers influence their behavior and can increase the likelihood of crashes or near-crashes involving pedestrians and vehicles.

The other reason to raise these questions is the decrease in Americans' daily physical activities. Walking is a representative physical activity that can be done routinely and continuously at all ages. However, according to the U.S. Census Bureau's American Community Survey (ACS) statistics released by the Centers for Disease Control and Prevention (CDC), the national proportion of adults commuting to work by walking or biking decreased from 3.4% in 2012 to 2.9% in 2022 (Centers for Disease Control and Prevention, n.d.). The 2020 survey shows that only 25% of Americans over-met the physical activity guidelines for aerobic and muscle-strengthening activities (Elgaddal et al., 2022). In addition, according to the results of the National Youth Risk Behavior Surveillance System (YRBSS) survey, adolescents' physical activity, which was measured as the national percent of students in grades 9-12 who achieve 1 hour or more of moderate and vigorous-intensity physical activity daily, also decreased from 28.7% in 2011 to 23.2% in 2019 (Centers for Disease Control and Prevention, n.d.).

There may be many reasons why people choose walking as a physical activity or one of the modes of transportation. Perceived safety may also impact the amount or frequency of walking since experiences, attitudes, and perceptions may influence a person's behavioral intentions. Therefore, this research aims to understand how the typical crash risk factors affect actual pedestrian crashes and pedestrians' perceived safety. Also, I strive to understand the relationship between pedestrians' perceptions of safety and walking behavior.

2 Literature Review

This second chapter defines 'pedestrian safety' and how it differs from 'pedestrians' perceived safety.' Definitions of two main concepts are followed by what crash risk factors are studied in the previous research related to pedestrian safety and perceived safety. This chapter also reviews studies about the relationship between pedestrians' perceived safety and walking behavior. Lastly, analysis methods predicting pedestrian crashes and estimating the relationship between crash risk factors, perceived safety, and walking behavior are reviewed.

2.1 Definition of Pedestrian Safety & Perceived Safety

Transportation safety can be defined as the absence of crashes between road users (Carter et al., 2017). So, this study defines pedestrian safety as the absence of crashes between pedestrians and other transportation mode users. Perceived safety can be defined as the human feelings resulting from evaluating a situation where the existing risk is less than the permitted risk. Permitted risk is a risk perception criterion defined as controllable and not potentially harmful (Proske, 2019). Viewed in this light, pedestrians can feel safe after determining or predicting (self-rating) that the perceived existing crash risk is less dangerous than their criteria on whether the risk is controllable or not (permitted risk).

Definitions of pedestrian safety and perceived safety are different because the probability that crash risk factors cause a crash in a certain situation and the perceived risk of pedestrians who confront it may be different. For example, people may over-evaluate a risk when they first perceive it. However, when similar risks are repeated, they may under-evaluate the danger (Proske, 2019). This changeable perceived risk need not be the same as the objective risk, since objective risk prediction models can be built based on detailed data. The objective risk is measured by a certain probability with a margin of error, while the perceived risk is subjective and is often affected by misconception or misunderstanding (Raue & Schneider, 2019).

In the safety literature, observed pedestrian crash risk is defined as the observed pedestrian-involved crashes divided by pedestrian exposure estimates (Turner et al., 2018), while the pedestrians' perceived safety has been defined and measured in more diverse ways depending on research questions and purposes than observed crash risk (Basu et al., 2022; Cho et al., 2009; Mehta, 2008; Rankavat & Tiwari, 2016, 2020; Schneider et al., 2004; Yoh et al., 2022).

Several researchers measure perceived safety with pedestrians' safety attitudes, which refers to how safe one feels in particular situations, scenarios, or previous experiences. In measuring perceived safety, safety attitudes are sometimes measured separately from threatening situations or threatened experiences. Cho et al. (2009) used survey items to measure perceived safety related to surrounding environments and their experiences. Rankavat & Tiwari (2020) also used a survey to measure perceived risk and study the relationship between perceived risk and preference for crossing behavior. Basu et al. (2022) measured perceived safety as attitudes regarding ten different walking environment scenarios. On the other hand, Mehta (2008) and Yoh et al. (2022) have studied perceived safety through the relationship between walking experience and attitudes, emphasizing the importance of experiences as reasons for safety attitudes. In common, researchers considered travelers' surrounding built environments, threatened experiences, and safety attitudes for measuring pedestrians' perceived safety.

Pedestrian's perceived safety is essential for analyzing safety issues since the pedestrian's perceived information affects their behavior in dangerous situations despite not always being consistent (Basu et al., 2022; Cho et al., 2009; Holland & Hill, 2007; Jacobsen et al., 2009; Mehta, 2008; Rankavat & Tiwari, 2016, 2020; Schneider et al., 2004; Yoh et al., 2022). Therefore, the following sections will review which crash factors and pedestrians' perceived safety are explained in research and how their relationships have been studied.

2.2 Crash Risk Factors & Perceived Safety

2.2.1 Pedestrian Exposure

Pedestrian volume is one of the strongest predictors of pedestrian crashes (Griswold et al., 2019) along with other road risk factors. Pedestrian exposure can be defined as their activity rate encountering potentially harmful vehicular traffic, and it can be measured by their volume in a certain unit of time and area (Raford & Ragland, 2004). Several recent studies have identified pedestrian exposure to traffic flow as a critical factor in pedestrian crashes and found relationships between 'pedestrian exposure and crash frequency' or 'pedestrian exposure and their perceived safety (Al-Mahameed et al., 2019; Almasi et al., 2021; Cho et al., 2009; Gill et al., 2022; Lee & Abdel-Aty, 2005; Mahmoud et al., 2021; Sanders et al., 2017; Schneider et al., 2004, 2021). Higher numbers of pedestrians are related to more frequent crash events (Al-Mahameed et al., 2019; Mahmoud et al., 2021), and longer segments, more intersections, and denser activities at intersections are significantly related to higher levels of police-reported crashes (Lee & Abdel-Aty, 2005; Schneider et al., 2004, 2021). On the other hand, pedestrian exposure does not only increase the probability of crash events but also affects the interaction between pedestrians and motorists, including indistinct communication and intentions, when the number of pedestrians increases (Elvik & Bjørnskau, 2017). Therefore, pedestrian exposure to traffic flow should be considered in relation to pedestrian crash risk and perceived safety.

Measuring pedestrian exposure is challenging because of the lack of direct pedestrian count data or estimated volume data. Additionally, since the number of pedestrians is usually smaller than the number of vehicles, slight variations may cause a more significant impact on statistical models. Inaccuracy of pedestrian volume estimations may cause a more substantial effect on crash model accuracy than that of vehicles. Thus, researchers have measured pedestrian exposure in a variety of ways using census population data and GIS data as follows: the rate of employees walking to work (Al-Mahameed et al., 2019); population or employment density (Almasi et al., 2021; Almasi & Behnood, 2022; Cho et al., 2009; Lee & Abdel-Aty, 2005; Raford & Ragland, 2004; Sanders et al., 2017); and facilities for pedestrians, including intersection or crosswalk density, pedestrian route network, and public transit (Al-Mahameed et al., 2019; Almasi et al., 2021; Almasi & Behnood, 2022; Cho et al., 2009; Raford & Ragland, 2004). Recently, scholars have used actual pedestrian count data to measure pedestrian exposure (Gill et al., 2022; Griswold et al., 2019; Mahmoud et al., 2021; Schneider et al., 2021). Gill et al. (2022) and Schneider et al. (2021) used manually counted video data and

Mahmoud et al. (2021) used Automated Traffic Signal Performance Measures (ATSPM) data for pedestrian volume and pedestrian movement data using automatic video recognition techniques. Although these measuring methods tried to measure pedestrian volume as accurately as possible, these have both pros and cons. Using only pedestrian count data may represent their activity at a particular time and area, while using only walk commute estimates from census data represents only one trip purpose and pedestrians who regularly walk (Schneider et al., 2021).

2.2.2 Demographic and Socioeconomic Factors

Demographic and socioeconomic factors are necessary to be considered in studies on pedestrian crash frequency, perceived safety and the relationship between them. First, age is an important demographic variable in pedestrian crash analysis. Adults younger than 65 have the most considerable crash frequency, injury, and fatality rates since they make up the largest portion of pedestrians (Campbell et al., 2004; Chang, 2008). However, several researchers target the older or children’s pedestrian populations because those groups are considered more vulnerable than the other age groups (Anderson et al., 2022; Carter et al., 2017; Zegeer & Bushell, 2012). Older pedestrians, especially, may struggle to meet situational demands because of slower walking speeds and reactions (Levi et al., 2013). Researchers have elucidated the relationship between age and pedestrian crash risk based on not only activity level, which is related to pedestrian exposure, but also their attitudes, behavioral intention, and perceived safety (Abdullah et al., 2019; Barton & Schwebel, 2007; Campbell et al., 2004; Olvera et al., 2012; Oxley et al., 2005). Research on children’s safety shows they are more likely to be involved in crashes at intersections and crosswalks (Campbell et al., 2004). Children may experience a different cognitive process than adults since they are more likely impacted by parental control and repeated learning related to their safety (Barton & Schwebel, 2007; Olvera et al., 2012; Oxley et al., 2005). On the other hand, research on older pedestrians' walking behavior shows that they tend to stick to their previously chosen routes (conservative travel choices), which can lead to more crashes despite their efforts to be more careful compared to other age groups, especially at crossings (Abdullah et al., 2019; Campbell et al., 2004; Oxley et al., 2005).

Gender is also often studied as a demographic factor affecting pedestrian crash risk. Data from several studies show that the rate of male fatality and severe injury from crashes are higher compared to females. Researchers found that boys are less careful when they walk on the sidewalk compared to girls (Wang et al., 2018). This is not only because of their age; in general, male pedestrian's behavior shows that they tend to take more risk while walking in several studies (Campbell et al., 2004; Clifton & Livi, 2005; Onieva-García et al., 2016; Useche et al., 2021; Zegeer & Bushell, 2012) because of lesser perceived risk compared to female pedestrians (Rankavat & Tiwari, 2019). In addition, younger males had more positive attitudes toward violations, errors, and lapses, and their attitude affected their intention to violate traffic regulations more frequently (Moyano Díaz, 2002).

Race and ethnicity are also important demographic factors in pedestrian safety (Monsere et al., 2017). Campos-Outcalt (2002) and Loukaitou-Sideris (2007) reported that African American, Latino, Hispanic, and American Indians were more likely to be involved in pedestrian-vehicle crashes. Recently, African American and American Indian pedestrians are more likely to be killed in crashes (Smart Growth America & National Complete Streets Coalition, 2019). According to the Governors Highway Safety Association's (GHSA) recent report, the proportion of Black, Indigenous, and People of Color (BIPOC) pedestrian fatalities from 2015-2019 was larger than expected for minority populations (Governors Highway Safety Association, 2021). This could be due to economic disparities such as less access to public transportation, private vehicles, and immediate medical care (Campos-Outcalt et al., 2002).

Socioeconomic factors like income are also important considerations in pedestrian safety. Low social status measured by low wage, poverty level, zero vehicle household, and low education level is positively related to more often pedestrian crash frequency (Al-Mahameed et al., 2019). Moreover, low income directly affects pedestrians' behavior and travel choices (Al-Mahameed et al., 2019; Noland et al., 2013; Zegeer & Bushell, 2012). It also indirectly affects pedestrian safety regarding spatial inequality (Kravetz & Noland, 2012; Sallis et al., 2011; Siddiqui et al., 2014; Thornton et al., 2016). Noland et al. (2013) studied the relationship between income and safety, and there were more casualties from pedestrian-vehicle crashes in areas with low-income households. This means that the income factor can be related to household vehicle ownership or individual mode choice, which links to spatial inequality regarding transportation safety. The following research suggests an indirect impact due to a discriminatory built environment. While higher-income neighborhoods have lower population density on street segments and more walkable streets (King & Clarke, 2015), low-income neighborhoods may lack safe amenities and facilities in the pedestrian streetscape (Sallis et al., 2011; Siddiqui et al., 2014; Thornton et al., 2016). Therefore, the disparity in neighborhood income levels relates to the disparities in the built environment and pedestrian safety. In conclusion, although socioeconomic factors and income levels are considered individual-level factors, they can be macro-level issues when the factors that make individual choices are spatially aggregated.

2.2.3 Land Use

According to the 2015-2019 Pedestrians Traffic Safety Fact Sheet of the National Highway Traffic Safety Administration (NHTSA), more U.S. pedestrian-vehicle crashes and fatalities occur in urban rather than rural areas (National Highway Traffic Safety Administration, 2017, 2018, 2019, 2020, 2021). This is because a higher population, employment density, and denser street connectivity in urban areas relate to the higher pedestrian exposure to traffic flow. This results in increased crash frequency and fatalities (Al-Mahameed et al., 2019; Almasi et al., 2021; Cho et al., 2009; Gill et al., 2022; Lee & Abdel-Aty, 2005; Mahmoud et al., 2021; Sanders et al., 2017; Schneider et al., 2004, 2021).

Since pedestrian volume and density of their activity (pedestrian exposure) are highly related to land use characteristics, researchers have studied the relationship between land-use type and pedestrian-vehicle crashes (Campbell et al., 2004; Dissanayake et al., 2009; Kadali & Vedagiri, 2015; Loukaitou-Sideris et al., 2007; Pulugurtha & Sambhara, 2011; Wier et al., 2009). Results about the relationship between 'land use and pedestrian crash rates' and 'land use and perceived safety' vary by researchers. This may be because details of land use classifications and characteristics defined by researchers and regional context vary (e.g., countries, states, and cities).

Some land use types, such as commercial land, high-density residential, and mixed-use land areas, are highly related to pedestrian crash frequency since these induce pedestrian travel demand and other mode users'. Commercial land areas, especially those related to alcohol establishments, are positively associated with a higher number of pedestrian crashes compared to different types of land use (Campbell et al., 2004; Long & Ferenchak, 2021; Loukaitou-Sideris et al., 2007; Wier et al., 2009). However, Dissanayake et al. (2009) show that high-density residential land areas are negatively associated with child pedestrian casualties, while retail, low-density residential, and educational land areas are positively associated with child pedestrian casualties. Pulugurtha & Sambhara (2011) find that single-family, urban residential commercial (areas with residential, retail, office, recreational, and cultural uses), and neighborhood service areas (mixed-use areas focusing on neighborhood retail and service activities) lower pedestrian crashes.

Research results on pedestrians' perceived safety by land use type differ by studies. In the Cho et al. (2009) study, low-density and non-mixed land areas (less compactness) increase general perceived crash risk, which means denser places make people feel safer despite more crashes than living in low-density areas. This can be called "perception mismatch," when people feel safer when more crash events occur (Schneider et al., 2004). Cho et al. (2009) study shows that pedestrians are more influenced by how dense the neighborhood is than by the condition of the pedestrian path itself. In other words, perceived safety is more affected by the relationships between the built environment and pedestrians, or groups of facilities and pedestrians, than the characteristics of a pedestrian facility alone. However, Kadali & Vedagiri (2015) found that mixed-use, residential, and commercial lands with higher traffic volume made pedestrians feel more unsafe while they were crossing the road.

These inconsistencies may come from differences in how land use types are categorized and how researchers measure pedestrian perceived safety. Therefore, land use type should be well designed in the analysis model as an essential variable to explain pedestrian exposure, crash risk, and perceived safety.

2.2.4 Facilities for Pedestrians

Like the land use factor, facilities for pedestrians, such as marked or unmarked crosswalks, crosswalk density, medians, sidewalk width and density or connectivity, and transit stops are related to pedestrian crash risk and perceived safety since they are linked with pedestrian exposure (Chen & Zhou, 2016; Cho et al., 2009; Clifton et al., 2009; Mfinanga, 2014; Mukherjee & Mitra, 2019; Rankavat & Tiwari, 2016; Schneider et al., 2004; Zegeer & Bushell, 2012). Regarding this, intersections are one of the most critical locations for pedestrian safety (Diogenes & Lindau, 2010; Gitelman et al., 2017; Loukaitou-Sideris et al., 2007; Sandt & Zegeer, 2006; Zegeer et al., 2005). At marked crosswalks, pedestrians may feel safer to walk than unmarked crosswalks at intersections. However, pedestrian crash rates can be controversial depending on motor vehicle traffic and traffic calming measures at intersections (Zegeer et al., 2005). Diogenes & Lindau (2010) found that the pedestrian crash rate decreases as the sidewalk width and the number of crossing stages (such as parts of a crosswalk separated by refuge islands) increase. Structural improvements at crosswalks, such as curb extensions and bulb-outs, can increase visibility for both pedestrians and drivers while reducing the driving speed and shortening the crossing distance (Sandt & Zegeer, 2006). In addition, public transit stops or stations can be important factors regarding pedestrian safety since transit stops induce people to gather at public transit stations, such as bus stops in the middle of sidewalks (Diogenes & Lindau, 2010; Monsere et al., 2017; Pulugurtha & Sambhara, 2011). Therefore, they need safer design guidelines with more visibility, lower speed limits, and education programs for children (Zegeer & Bushell, 2012).

Other types of pedestrian facilities, such as traffic signals, street lights, speed humps, or speed limits, are also related to pedestrian safety by protecting pedestrian activity from automobiles and making pedestrians feel safer (Kadali & Vedagiri, 2015; Mfinanga, 2014; Schneider et al., 2004). Several countermeasures for controlling vehicle speeds, such as speed humps, and signals, are preferred options for pedestrians at intersections (Mfinanga, 2014). These facilities protect pedestrian activities from high-speed vehicles or separate traffic spaces from each other in space and time.

On the other hand, in the Delhi, India case study, Rankavat & Tiwari (2016) show that actual high crash locations are not the same as pedestrian-perceived high-risk crash spots. In their research, the number of road lanes, vehicle speed, street lights, the width of the sidewalk, and marked crosswalks are related to pedestrians' risk perception (Rankavat & Tiwari, 2016).

2.2.5 Speed

Speed is also an important risk factor related to pedestrian crashes. Vehicle speed significantly impacts the probability of crashes and the severity of injuries from crash events (Aarts & van Schagen, 2006; Elvik, 2013; Hussain et al., 2019; Mahmoud et al., 2021, 2023; Monsere et al., 2017). Especially, higher speed is significantly related to the higher probability of fatality from crashes (Clifton et al., 2009; Davis, 2001; Elvik, 2013; Haleem et al., 2015; Hussain et al., 2019; Monsere et al., 2017; Nilsson, 2004; Nishimoto et al., 2019; Rosén et al., 2011; Rosén & Sander, 2009). Rosén & Sander (2009) showed that there are apparent differences in pedestrian fatality rates from crashes between different speed intervals. In their findings, pedestrian fatality risk at 50 km/h (about 31 mph) is more than twice the probability of the risk at 40 km/h (about 24 mph) and more than five times higher than the probability of the risk at 30 km/h (about 19 mph). Hussain et al. (2019) recommended 30-40 km/h (about 19-24 mph) in areas with high pedestrian traffic to reduce the probability of pedestrian fatality.

Vehicle speed affected by surrounding road conditions and facilities also may relate to pedestrians' and drivers' perceptions regarding safety. Aceves-González et al. (2020) showed whether a road's speed limit is posted and how fast surrounding vehicles are traveling can affect pedestrians' attitudes toward safety, in addition to lack of signages. On the other hand, Kwon et al. (2022) showed the results based on virtual reality (VR) experiments showed that visual exposure to information related to vehicle speed did affect perceived safety.

There are studies on the relationships between speed and pedestrian crash frequency or injury severity, especially fatalities, or the relationships between speed and perceived safety. These previous studies measured the speed as the average or max of the posted speed limit (Haleem et al., 2015; Nilsson, 2004; Nishimoto et al., 2019) or using vehicle speeds at crash impact (Davis, 2001; Elvik, 2013; Kwon et al., 2022; Rosén & Sander, 2009). Although not all drivers drive below the speed limit, a significant correlation exists between the average vehicle speeds and the posted speed limit (Elvik et al., 2004). However, the model results may vary depending on the measurement method, spatial unit of this speed, and analysis method. Previous studies used posted speed limits at the spatial level of intersections or short road segments or used speeds at the moments of crashes as an explanatory variable. This is because the probability of crashes between vehicles and pedestrians and the degree of injury vary depending on subtle speed changes. Fundamentally, as vehicle speed can strongly explain pedestrian safety issues, aggregated speed can also sufficiently explain the impact (Elvik et al., 2019). Nevertheless, the aggregated speed limit calculated spatially or temporally may act as a limitation within the crash prediction model rather than using the actual speed when the event occurred. In addition, a person's perception of speed can be subjective rather than objective since the surrounding environment influences it (Kwon et al., 2022; Papić et al., 2020; Shi et al., 2020; Sudkamp & Souto, 2023). Thus, explanations of measuring the speed variable are necessary when it is used to explain crashes or perceived safety in the model.

2.2.6 Weather & Lighting

Weather affects pedestrian safety in two ways: pedestrian volume through behavior changes and crash injury severity. Aultman-Hall et al. (2009) point out the relationship between temperatures, wind speed, humidity, and precipitation affect the degree of pedestrian activity. In their study, humidity varies by season and affects pedestrian activities, while only extreme temperatures affect pedestrian behavior (Aultman-Hall et al., 2009). Although this study did not address pedestrian safety directly, the weather can be thought of as affecting pedestrian behavior and volume, which may affect pedestrian exposure to traffic flow. On the other hand, some studies directly explain the relationship between weather and pedestrian crashes. For example, rainy days affect injury severity (Zhai et al., 2019), although most pedestrians involved in crashes occur when the weather is clear (Fitzpatrick et al., 2014).

Additionally, insufficient lighting can be a serious risk factor since it is related to road users' visibility (Monsere et al., 2017). Zegeer & Bushell (2012) show that about 65% of pedestrian fatalities occur under low light conditions or at night. More crashes occur during the fall and winter, especially for older pedestrians (Campbell et al., 2004). Campbell et al. (2004) also emphasize that fatal pedestrian crashes occurred at night while non-fatal pedestrian crashes occurred during the day.

Because of these reasons, lighting at night is essential for pedestrians' safety by making pedestrians more visible to motorists (Zegeer & Bushell, 2012). In addition, brightness is also important in terms of perceived safety (Haans & de Kort, 2012; Holland & Rabbitt, 1992). Based on Appleton's (1975) prospect-refuge theory, street lights are important pedestrian facilities. Under low-light conditions, they provide forward visibility and visual context, which makes fast escape possible if pedestrians encounter danger (Haans & de Kort, 2012).

2.3 Perceived Safety & Walking Behavior

Previous research discussed how perceived safety and experiences regarding walking influence people's attitudes and mode choice (Alton et al., 2007; Foster et al., 2004; Kweon et al., 2021; Lyu & Forsyth, 2021; Mehdizadeh et al., 2017). Kweon et al. (2021) investigated attitudes and behavioral intentions regarding whether people want to walk in specific built environments by showing and letting them compare several virtual scenarios of the pedestrian-built environments. They found that safer (virtual) built environments from the parent's perspective affect them to allow their children to walk to school. Alton et al. (2007) explain the relationship between a child's walking level and the local environment. Walking frequency increases when people feel that the surrounding walking environment, which is affected by traffic, is safe. However, concerns about strangers have a negative effect on walking frequency, and the lack of nearby leisure facilities such as parks also reduces walking frequency. Lyu & Forsyth (2021) found that people walk more when they perceive the environment as safe and experience or expect discomfort due to traffic jams. Specifically, people walk more, especially when they are safe from the risk of crashes at intersections and when accessibility increases due to the convenience of public transportation.

The relationship between perceived safety and walking behavior may differ depending on gender. Foster et al. (2004) examined whether perceived safety, which is influenced by time of day (day or night), surrounding land use, and level of traffic, influenced walking frequency for men and women. For men, there was a difference in walking frequency depending on whether a park was nearby, but perceived safety was not significant in predicting walking frequency. In the case of women, whether there were stores within walking distance and whether the walking environment was safe during daytime significantly influenced walking frequency. Their study suggests that surroundings can significantly impact walking while influencing perceived safety and that this influence may vary by gender.

2.4 Analysis Methods

2.4.1 Predicting Pedestrian Crash

The Poisson and negative binomial regression models are the two most popular methods for predicting pedestrian crashes (count data). Poisson regression model is more popular and is more widely applied to estimate transportation count data, including crash events (Washington et al., 2003). However, pedestrian crash events rarely occur. Excessive zero cases in the dataset can happen depending on spatial and time units used for analysis. Even in macro-level crash analysis, if there are too many zero-valued cases, statistical models based on a zero-inflated probability distribution can be an option to allow excessive zero-valued observations (Cai et al., 2016; Chen et al., 2022; Lord et al., 2005; Pew et al., 2020). Several discussions have concerned the legitimacy of considering zero-inflated models in crash analysis. To handle too many zero cases in data distribution, Cai et al. (2016) argue that it is necessary to estimate crash models based on assumptions about places where they are inherently safe and where they are not.

Washington et al. (2003) and Lord et al. (2005) assert that an underlying justification should be needed for the splitting process in models (two distinct states) since this process assumes that there are completely safe places; in reality, this cannot be the case. Several studies agree with this assertion (Lord et al., 2007; Mitra & Washington, 2012). However, Pew et al. (2020) assert that zero-inflated models do not assume there are inherently safe or unsafe places. Zero-inflated models, e.g., zero-inflated Poisson (ZIP) or zero-inflated negative binomial (ZINB), can also be considered as an option in model selection from the perspective of selecting the model that best explains the given data, especially in micro-level conflict analysis. This method will be helpful if the models can better predict zero-value cases when analyzing crashes at the intersection or short road segment levels (Dong et al., 2014; Pew et al., 2020). However, whether they will also be helpful in macro-level conflict analysis needs to be confirmed through the underlying distribution of the data. In addition, for the final model selection among these different types of models, Akaike’s information criterion (AIC) and Bayesian information criterion (BIC) can be considered to evaluate how well models predict or explain the data (Chakrabarti & Ghosh, 2011; Shmueli, 2010).

2.4.2 Perceived Safety Between Crash Risk & Walking

Considering perceived safety has often been measured as latent variables with multiple survey items in previous research (Cho et al., 2009; Dinh et al., 2020; Gill et al., 2022; Rankavat & Tiwari, 2020), structural equation modeling (SEM) is useful to investigate relationships between crash risk factors and walking behavior mediated by perceived safety. This is because SEM allows the testing of various statistical models, including regression, path, and confirmatory factor analysis (Kline, 2012, 2016; Schumacker, 2016). In the SEM, confirmatory factor analysis can be employed to investigate how consistently survey items measure perception. Furthermore, SEM allows the testing of path models that extend multiple regression models and specify direct, indirect, and correlated effects among variables (Schumacker, 2016). Pedestrians' perceived safety can connect the relationship between crash risk factors and pedestrians' walking behavior as a mediator. Structural equation models, including the path model, will be helpful in understanding these relationships. Several recent pedestrian safety studies also use structural equation modeling. Many of them use path analysis with mediators in models (Cho et al., 2009; Dinh et al., 2020; Gill et al., 2022; Rankavat & Tiwari, 2020).

Although SEM has many advantages as an analysis method, it requires many samples to test complex relationships (Kline, 2012, 2016; Schumacker, 2016). There is no completely agreed-upon minimum number of samples needed to estimate SEM. However, depending on the estimator type in SEM and the characteristics of factors (items) measuring latent variables, the required minimum sample size can be 250 or more (Hu & Bentler, 1999). In particular, the structure regarding the relationship between pedestrians' perceived safety and risk factors can become complex, and it may require more samples. In several previous studies on pedestrians' perceived safety or behavior, 1,000 or more samples were used to estimate models (Rankavat & Tiwari, 2020; Useche et al., 2021).

3 Research Questions

3.1 Research Gap

Motivated by the aforementioned research, this study aims to enhance understanding of the following three knowledge gaps.

First, more accurate measuring of pedestrian exposure, including pedestrian counts, is needed to investigate the observed crash risk more accurately, which refers to observed crashes divided by exposure estimates (Turner et al., 2018). Estimating more accurate pedestrian exposure with real pedestrian counts has been challenging because of insufficient data sources and difficult measurements. Several previous studies estimated pedestrian exposure to traffic flow calculated with indirect measurements of pedestrian activity such as population density, the rate of employees walking to walk, and pedestrian facility density (Al-Mahameed et al., 2019; Almasi et al., 2021; Almasi & Behnood, 2022; Cho et al., 2009; Lee & Abdel-Aty, 2005; Sanders et al., 2017). Despite the difficulty of estimating pedestrian volume, some other studies used the actual pedestrian count to measure pedestrian exposure using video and signal performance data (Gill et al., 2022; Mahmoud et al., 2021; Schneider et al., 2021). However, these pedestrian counts can be sensitively affected by time, season, weather, and so forth (Schneider et al., 2021). Since it is very difficult to obtain pedestrian counts, particularly at all times and seasons and at many locations in the network, it is often necessary to estimate pedestrian volume and exposure through other types of data that previous researchers have used, such as densities of population and employees walking to work.

Second, research on how external crash risk factors, including built environment factors, pedestrian exposure, actual crash events, and internal individual characteristics, affect pedestrians' perceived safety is necessary for proactive transportation planning to improve pedestrian safety. Several studies found the relationship between actual pedestrian crash risk factors and pedestrians' perceived safety. Their findings show that external crash risk factors can affect pedestrians' perceived safety (Abdullah et al., 2019; Aceves-González et al., 2020; Barton et al., 2016; Campbell et al., 2004; Cho et al., 2009; Gill et al., 2022; Kadali & Vedagiri, 2015; Kwon et al., 2022; Mfinanga, 2014; Moyano Díaz, 2002; Olvera et al., 2012; Oxley et al., 2005; Papić et al., 2020; Rankavat & Tiwari, 2019; Schneider et al., 2004; Shi et al., 2020; Sudkamp & Souto, 2023; Wang et al., 2018). However, their findings on environmental factors and pedestrian exposure have been limitedly explained because of the small area or short length of the spatial unit of analysis. Moreover, these findings can be different by region. Individuals' demographic and socioeconomic characteristics can also be studied further regarding the relationship between crash risk and perceived safety.

By understanding perceived safety, we can identify which built environmental factors directly or indirectly relate to pedestrian's perceptions. However, perceived safety can be a broad concept that measures the perception process of the surrounding environment related to pedestrian safety. So, separating the concept of perceived safety with threatened experiences and pedestrians' safety attitudes may be helpful in measuring and explaining in detail how pedestrians' perceived safety is affected by the surrounding environment or situations. This is because previous experiences can predict following attitudes (Fazio et al., 1978), and experiences can affect attitudes toward a walking environment (Johansson et al., 2016).

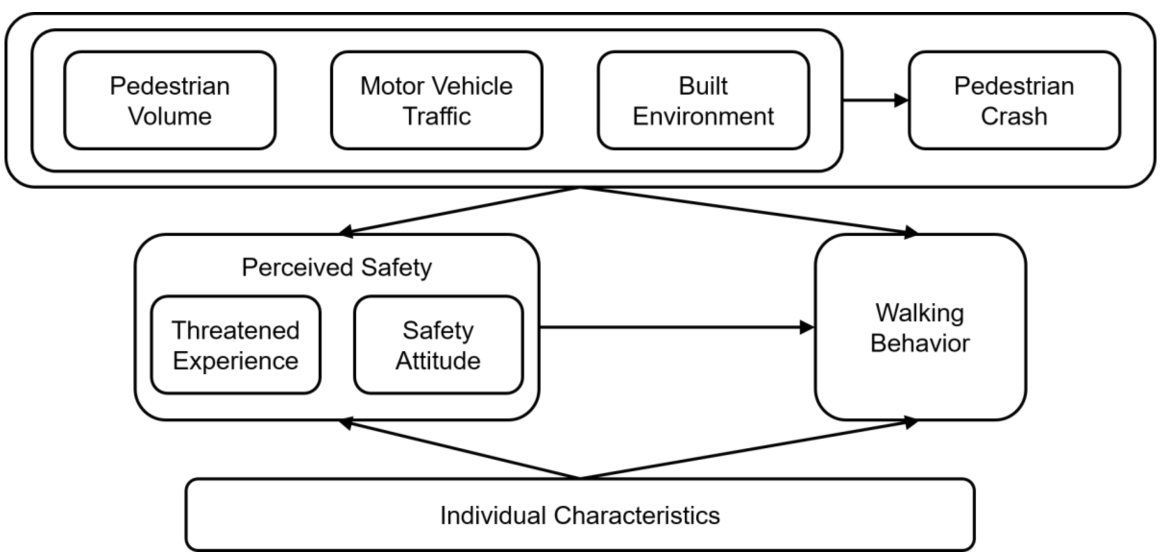
In addition, understanding pedestrians' perceived safety can help to design more effective countermeasures to make pedestrians act more safely where more pedestrian-involved crashes have occurred in a proactive approach. To design proactive countermeasures effectively, it is necessary to cover a more diverse spatial context beyond specific intersections, road segments, or places with particular purposes, such as a campus (Rankavat & Tiwari, 2016; Schneider et al., 2004). Therefore, interrelationships among those factors, including built environmental factors, pedestrian exposure, pedestrians' perceived safety, and actual crashes, are needed.

Lastly, research on whether pedestrians' perceived safety affects walking behavior is necessary to investigate what makes people hesitate to walk in their neighborhoods to encourage people to walk more and choose active transportation modes. Previous studies found some relationships between perceived safety and walking frequency (Alton et al., 2007; Foster et al., 2004; Kweon et al., 2021; Lyu & Forsyth, 2021; Mehdizadeh et al., 2017). However, there is a tendency for researchers to focus more on individual characteristics, including gender and age, or specific relationships (e.g., the perceived safety of parents about their children's walking). In addition to these individual characteristics, further study should be conducted to determine how external crash risk factors and built environmental factors affect pedestrians' perceived safety and walking behavior for efficient planning and design to improve pedestrian safety.

3.2 Overview of Research Questions

Based on the above three research gaps, three research questions separately ask about the relationship between pedestrian exposure, crash risk factors, individual characteristics, perceived safety, and walking behavior. The following conceptual framework schematizes the assumptions and logical structures (Figure 3-1), followed by brief research questions. Figure 3-1 shows that crash risk factors, including pedestrian volume, motor vehicle traffic, and related built environmental factors, may predict pedestrian crash cases. In addition, it shows that crash risk factors may affect both pedestrians' perceived safety and walking behavior, as individual characteristics do. For measuring perceived safety, perceived threatened experiences and safety attitudes are used. More detailed follow-up questions of three research questions will be explained in each research question and finding chapters.

Figure 3-1 Conceptual Framework



1. Can pedestrian count and crash risk factors identified in previous studies explain actual pedestrian crashes in the research sites?
2. Do pedestrian and motor vehicle traffic, the built environment, crashes, and individual characteristics affect pedestrians' perceived safety, measured as threatened experiences and safety attitudes?
3. How do pedestrian crash risk factors and individual characteristics affect the walking frequency mediated by safety attitudes?

The following chapter will explain the data collection methods, descriptive analysis of each data set, analysis methods, and units of analysis. Three research questions and result chapters will follow the methods chapter.

4 Methods

4.1 Overview Methods

4.1.1 Overview of Data Collection

Table 4-1 shows each research question's spatial unit of analysis and data collection methods. To answer the first question, I tested crash risk factors and whether they predict pedestrian crash frequency in my research target area. I used the census block group as a spatial analysis unit in the first question. Using crash factors tested in the first question, I investigated whether crash factors and pedestrian crash frequency affect pedestrians' perceived safety and walking frequency to answer the second and third research questions. I used half-mile straight-line buffer areas from survey respondents for the following research questions.

Table 4-1 Overview of Data Collection by Research Question

Research Question	Spatial Unit of Analysis	Data Collection
Crash Factors	Census Block Group	Secondary data: pedestrian volume, motor vehicle traffic, and built environment factors
Perceived Safety	0.5-mile straight-line buffer areas from the residential address of survey respondents	Survey: perceived safety (threatened experiences, safety attitudes), individual characteristics, walking purpose, and behavior Secondary data: pedestrian volume, motor vehicle traffic, and built environment factors
Walking Behavior		

I selected 346 census block groups near 65 signalized intersections with available pedestrian count data for the first research question about crash factors. Selected census block groups are within a half-mile straight-line buffer from each signalized intersection. However, I excluded block groups if more than half of the total area was not land (e.g., river). This is because it is difficult to say the pedestrian count collected at the intersection represents the pedestrian volume of those block groups.

For the following two research questions, I selected research sites containing signalized intersections with available pedestrian count data before I collected all datasets in two ways: conducting surveys and collecting secondary data. Note that the final location of intersections where pedestrian count could be obtained was 65. However, before starting the survey, the number of intersections where I could obtain pedestrian count data was 47. After excluding four sites with a low rate of residential area (census tract), the number of candidate study sites for the survey near intersections was 43. I scored census tracts based on pedestrian crash risk factors, including densities of crashes of all types over the past five years (2016-2020), pedestrian crashes, pedestrian fatalities, public transit stops, intersections, population density, spatially aggregated (average) annual average daily traffic (AADT), and the ratio of commercial land and mixed-use land area. I grouped census tracts into five based on the order of the score of each tract from the safest to most dangerous. I selected two of each group, a total of ten research sites spread over nine cities (two sites in Portland): Albany, Hillsboro, Lake Oswego, McMinnville, NW Portland, SE Portland, Tigard, Wilsonville, Wood Village, and Woodburn.

I purchased randomly selected 250 mailing addresses within a half-mile of each intersection where I could obtain the pedestrian count data. I sent survey invitations to a total of 2,500 mailing addresses. I alternated twice between sending postcards and paper questionnaires and received 551 completed responses from 514 households online and by mail. Frequency, purpose, and timing of walking, types of walking paths, perceived safety, experiences being threatened, and individual characteristics were collected.

Pedestrian volume is another essential data in this study to estimate the effect of pedestrian exposure on traffic flow in crash analysis. The pedestrian volume is measured in two ways: actual pedestrian count and population density (proxy). A project collected a pedestrian count: "Active transportation counts from existing on-street signal and detection infrastructure" PI: Sirisha Kothuri, Portland State University, and Patrick Singleton, Utah State University in 2022 (Kothuri et al., 2024). I used Census Block Group 2020 data (U.S. Census Bureau, 2020) and population change by city from the US Census for measuring population density and scaling population density of 2018, 2019, 2021, and 2022 (US Census Bureau, 2020, 2023).

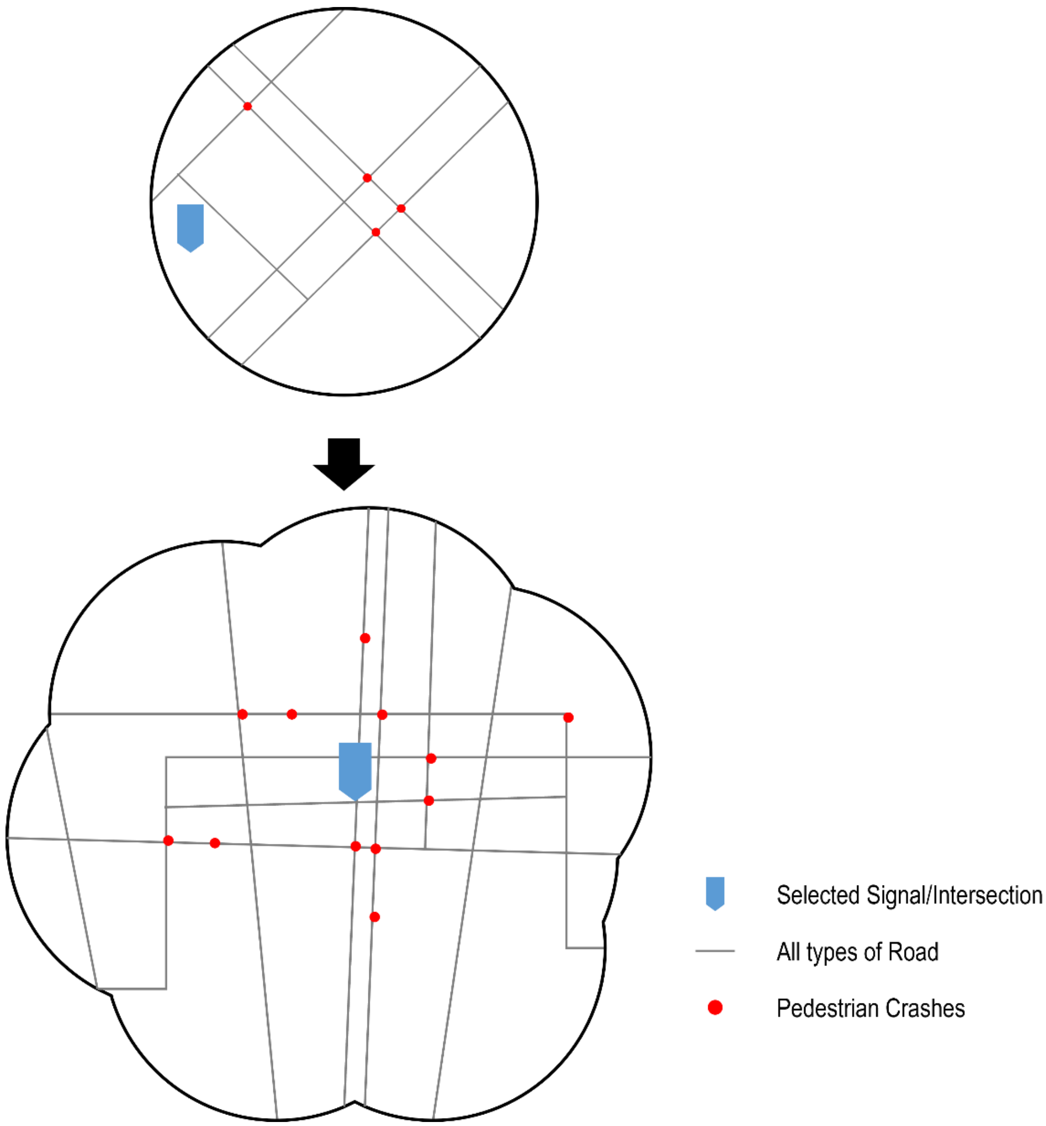
Another data to estimate pedestrian exposure to motor vehicle traffic was measured with the average annual average daily traffic (AADT) within a half-mile straight-line buffer from each survey respondent's residence address from 2018 to 2022, except for the volume collected on the highway (freeway). I collected the annual average daily traffic (AADT) data from 2018 to 2022 from the Traffic Count Database System (TCDS: Oregon Traffic Monitoring System) from the open data source of the Oregon Department of Transportation (ODOT).

ODOT's Crash Data system provided data on pedestrian crashes. Using ArcGIS Pro, I marked the locations of pedestrian crashes between 2018 and 2022 on a map and counted pedestrian crashes within a half-mile straight-line buffer from each survey respondent’s residence address.

As pedestrian crashes were measured by a half-mile straight-line buffer (circle) from each survey respondent’s address, other built environment factors were also measured by a half-mile straight-line buffer from each survey respondent’s address: sidewalk, intersection, public transit stops, commercial area, mixed-use area, and park. So, all measurement values equal the densities of each built environment factor in 0.785 square miles. I collected these factors from ODOT, Metro’s Regional Land Information System (RLIS), and open data sources from the city of McMinnville and Albany. Figure 4-1 shows how I spatially analyzed all variables by survey respondents. Note that Figure 4-1 is not a real research site but an example image for the reader’s understanding.

The top circle shows the analyzed area of each survey respondent’s address, and the light-blue pin stands for the nearest signal location where I could obtain the pedestrian count data. Lastly, small red dots stand for pedestrian crashes. The bottom bold black bubble-shape or flower-shape boundary line shows the overlapped areas from each survey respondent’s address around the light-blue pin in the middle of the boundary standing for the selected intersection (Figure 4-1). So, research sites included ten bubble-shape or flower-shape boundaries from the selected signalized intersections.

Figure 4-1 Example Map for Spatial Unit for Analysis (0.5-mile straight-line buffer)



4.1.2 Overview of Analysis Methods

As shown in Table 4-1, I used two types of spatial units for two different analysis methods to answer three research questions. For the first research question, I estimated generalized linear models (GLM) to find how well pedestrian count explains pedestrian crashes with other crash risk factors than a proxy of pedestrian volume does. My final model types are negative binomial regression models based on the distribution of the dependent variable (cumulated pedestrian crash cases) and model fit.

I used structural equation modeling that allows path analysis and factor analysis to investigate relationships between pedestrian exposure factors, actual crash risk, perceived safety, and walking behavior for the second and third research questions. This analysis method affected the goal of the sample size, based on both statistical meaning and the previous research. After testing which crash risk factors can predict the actual pedestrian crashes in my selected research sites in the first research question chapter, I used those crash risk factors in the second and third research question chapters. Each path model by research question can have a different combination of explanatory variables depending on the purpose of the research question. More detailed analysis methods and limitations of the methods will be explained in the chapters for each research question. The following paragraphs provide a detailed explanation of site selection for the survey.

4.2 Site Selection

4.2.1 Purpose

I planned to distribute the survey based on mailing addresses to investigate how the built environment can influence perceived safety in residential neighborhoods and the actual risks of pedestrian crashes.

Structural equation modeling (SEM) necessitates substantial sample sizes. While there is no absolute minimum sample size for this modeling, the previous review about the median sample size for SEM is about 200 (Shah & Goldstein, 2006); however, Kline

(2016) argues that 200 may be too small to estimate complex models. Recent studies utilizing SEM to study pedestrian crash risk and their perceived risk have used a larger dataset with nearly 1,000 cases (Dinh et al., 2020; Rankavat & Tiwari, 2020; Useche et al., 2021). The reasons for the sample size of these studies were not explicitly stated; it appears that a relatively large sample size was necessary because they estimated models that included latent variables and multiple complex paths. Considering that survey respondents may not answer all questions, the data from the survey can have missing data. For this reason, the robust adjustments with full information maximum likelihood estimator can deal with the missing data in SEM, and it works well with sample sizes of about 400 or more (Savalei & Bentler, 2005). Therefore, I set a goal for a sample size of 500 or more for this study. To collect responses from 500 people, survey invitations were sent four times, alternating between two times of postcards and two times of paper questionnaires with cover letters to 2,500 households.

The selection of 2,500 households to receive survey invitations and paper questionnaire packets was based on two meticulous criteria. I used census tract 2020 as the spatial unit for site selection. This choice was made because the unit should be small enough to be separated by signal intersections but large enough to be ordered by the number of crashes, intersections, and public transit stops, in addition to the number of populations and households by spatial unit. It is important to note that I used census tract 2020 solely for the site selection, and the model's spatial unit of analysis is within a half-mile straight-line buffer from the respondent's address.

1. I selected areas where I could obtain pedestrian count data and where enough households lived near the site to send sufficient survey invitations.

2. For the possibility of pedestrian crashes, I selected areas with diverse built environments related to pedestrian safety.

4.2.2 Three Steps to Select

Figure 4-2 shows the flowchart of the site selection process for the survey and other data collection. There were largely three steps before finalizing ten sites for data collection.

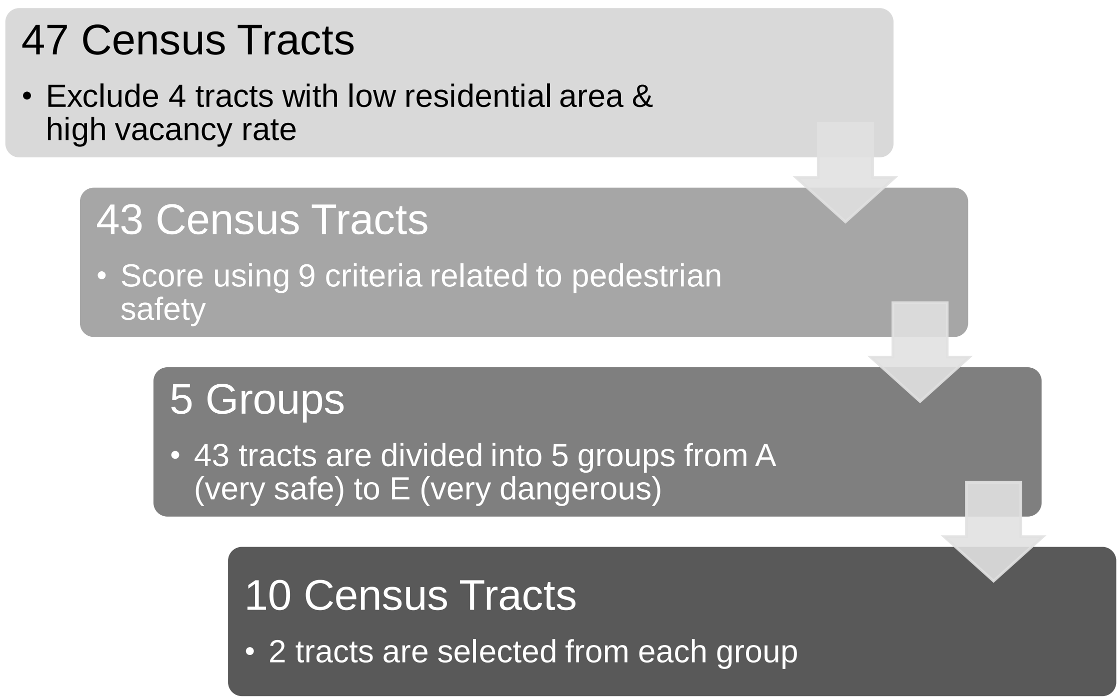
Firstly, I selected census tracts that have pedestrian count data. The number of pedestrians is one of the critical variables affecting actual crash risk in my models, and I needed responses from residents near signalized intersections with pedestrian count data. Before conducting the survey, a list of 47 signalized intersections with available pedestrian count data was available. Note that the final number of signal locations for pedestrian count data is 65. I excluded 4 census tracts from the 47 available tracts that had too low a residential land area ratio or a high household vacancy rate, which could have lowered the response rate.

Next, I selected ten census tracts with residents living in diverse environments among 43 tracts. I did not choose simply the 2,500 households around 43 signalized intersections. This is because the response rate in some areas (especially Portland) could be much higher than in others. When multiple respondents live in very similar physical environments, it is difficult to observe changes in perceived safety and behavior due to the external built environment factors. Therefore, to survey people living in various settings, I divided 43 areas into five groups ranging from low to high risk of pedestrian crashes or high traffic flow exposure. I used the nine criteria described below to score, rank, and divide 43 tracts into five groups. The score for each indicator ranges from 1 to 10. Each census tract scores higher as the number or degree of relevant indicators increases (e.g., less than the ten percentile goes to 1; more than the 90 percentile goes to 10). The nine indicators that I used to score are as follows.

- Density of the crashes of all types over the past five years (2016-2020) (n/mi^2)
- Density of pedestrian crashes over the past five years (2016-2020) (n/mi^2)
- Density of crashes involving pedestrian fatalities over the past five years (2016-2020) (n/mi^2)
- Population density (persons/mi^2)
- Average motor vehicle traffic using spatially aggregated annual average daily traffic
- Density of public transport stops (n/mi^2)
- Commercial land area ratio (%)
- Mixed-use land area ratio (%)
- Intersection density (n/mi^2)

Lastly, I selected ten census tracts from the five groups regarding pedestrian crash safety and exposure frequency. I chose two from each group for a total of 10 intersection regions: (A) very safe, (B) somewhat safe, (C) neither safe nor dangerous, (D) somewhat dangerous, and (E) very dangerous. I then selected two intermediate rankings in each group. When only one region is selected from each group, one tract with a small number of survey responses could not represent that group. To prevent this, two tracts were chosen from each group.

Figure 4-2 Site Selection Process



I purchased 2,500 street addresses and resident names from DataAxle. Since I selected ten tracts and needed 2,500 street addresses, I asked for 250 street addresses within a half-mile straight buffer of each signalized intersection. However, less than 250 addresses were available for purchase from DataAxle for some selected locations. In this case, I selected the following ranked tract. For example, 250 addresses were requested for the 4th and 5th ranked tract among the eight tracts in Group A, respectively. If DataAxle can provide less than 250 residential addresses in the 5th ranked tract, I requested addresses around one of the 3rd or 6th signalized intersections with 250 or more addresses that could be provided.

4.2.3 Final Selection

Table 4-2 and Table 4-3 summarize the characteristics of ten selected research sites by group (safest group A – most dangerous group E). Figure 4-3 shows ten selected intersections where I could obtain the pedestrian count data. Table 4-2 does not include the number of crashes involving pedestrian fatalities since most neighborhoods do not have the case. The ten cities (neighborhoods) selected are near Interstate 5 (I-5) in northeastern Oregon, listed alphabetically: Albany, Hillsboro, Lake Oswego, McMinnville, NW Portland, SE Portland, Tigard, Wilsonville, Wood Village, Woodburn. Ten maps of specific research sites, including dissolved half-mile buffers of survey respondents by the city, are in Appendix B Ten Maps of Selected Research Sites.

Table 4-2 Crashes & Pedestrian Exposure of Ten Selected Research Sites

Group	City Name	All Types of Crash	Pedestrian Crash	Population Density (person/mi^2)	Motor Vehicle Traffic
A	Tigard	39	1	4,522	18,808
	Wilsonville	556	2	794	19,290
B	Woodburn	483	7	629	14,740
	McMinnville	223	1	3,713	21,468
C	Lake Oswego	49	3	6,126	12,548
	SE Portland	279	1	5,631	40,975
D	Albany	476	9	4,239	15,644
	NW Portland	248	4	5,335	27,636
E	Hillsboro	810	27	1,694	19,053
	Wood Village	342	14	6,185	16,537

Table 4-3 Built Environment Characteristics of Ten Selected Research Sites

Group	City Name	Density (n/mi^2)		Commercial area (%)	Mixed-use area (%)
		Transit stops	Intersection		
A	Tigard	5.62	90	3.90	< 0.01
	Wilsonville	6.22	26	4.87	< 0.01
B	Woodburn	1.92	15	3.62	0.11
	McMinnville	6.58	151	2.50	0.10
C	Lake Oswego	2.13	167	0.38	9.06
	SE Portland	31.62	229	0.00	7.78
D	Albany	12.59	233	17.22	5.07
	NW Portland	42.96	278	< 0.01	28.09
E	Hillsboro	11.56	75	6.92	11.60
	Wood Village	18.05	165	5.55	26.98

Figure 4-3 Selected Ten Research Sites

4.3 Survey

4.3.1 Overview of Survey

A survey for this research was conducted from April to August 2023 to measure individual perceived safety, walking behavior, and personal or household characteristics that may affect daily walking. The survey had 25 questions, which was expected to take about 10 minutes to complete. Responses from over 500 adults (aged over 18) who are Oregon residents were received. This research and data collection methods, including the survey instrument and protocol, were approved by Portland State University's Institutional Review Board (IRB) in November 2022, and the amendment was approved in March 2023 (Human Research Protection Program Number: 227889-18).

4.3.2 Survey Development

To measure walking safety experience and walking behavior, I referred to the second national survey of bicyclist and pedestrian attitudes and behavior conducted in 2012 and the draft of the third national survey by the National Highway Traffic Safety Administration (NHTSA) (National Highway Traffic Safety Administration, 2022; Schroeder & Wilbur, 2013a, 2013b, 2013c). Next, I referred to the Family Activity Study (FAS) survey instrument using measurement items developed by Mokhtarian and Handy to measure safety attitudes related to walking and individual characteristics (Cao et al., 2006; Dill et al., 2014). The following criteria show the features of the participant's age group and spatial boundary for my questionnaire.

- My research question pertains to the general perception of safety and its influence on walking behavior rather than focusing on specific age groups. I have designated the survey participants as adults over 18, as their mode of transportation may be less restricted compared to younger children.

- The survey aims to assess the perceived safety of walking and related behaviors and correlate these with factors contributing to the risk of crashes in the vicinity of the respondent's residence, although it did not directly ask about the crash experiences. The survey questions pertain to walking behavior, perceived safety, and instances of feeling unsafe. The scope of walking activities in the survey encompasses walking, jogging, or running within the respondent's neighborhood.

The survey questions were structured with easier concepts at the beginning to encourage survey participation, understanding, and completion (Dillman et al., 2014). Items about walking behavior in Part 1 are for answering the third research question, while ones about perceived safety, attitude, and experience in Parts 2 and 3 are for answering both second and third research questions (Table 4-4). The following paragraphs explain the details of each part of the survey, and the paper version of the whole survey is in Appendix A Paper Questionnaire.

Table 4-4 Summary of Survey Development

Part	Item	Answer Format	Reference
Part 1: Walking Behavior	Number of walking days a week	Enter/write the number	National Survey of Bicyclist and Pedestrian Attitudes and Behavior
	Walking frequency by time in a day	Check one of three options to indicate how often	
	Number of weekly walking days by season: weekdays & weekends	Check one of the numbers	
	Walking purpose	Check one of the categorized options	
	Walking frequency by path type	Check one of four options to indicate how often	
	Reason why not choose “usually” for walking on the sidewalk*	Allow checking multiple categorized options	
Part 2: Safety Attitudes	Attitude related to (possible) unsafe situations for walking	Check one of four options to indicate how much agree or N/A	Family Activity Study
	Child(ren) in household	Check “Yes” or “No”	
	Attitude related to (possible) unsafe situation for walking with child(ren) **	Check one of four options to indicate how much agree or N/A	
Part 3: Threatened Experiences	Threatened experiences regarding other road user’s behaviors	Check one of three categorized frequency options	National Survey of Bicyclist and Pedestrian Attitudes and Behavior
	Threatened experiences regarding facilities		
	Other threatened experiences	Write your answer (it can be a short essay type)	
Part 4: Individual & Household Characteristics	Age	Enter/write the year	National Survey of Bicyclist and Pedestrian Attitudes and Behavior Community Planning Survey
	Gender	Check one of the categorized options	
	Race/Ethnicity		
	Income		
	Frequency of use by mode of transportation		
	Disability (Y/N/NA)		
	Type of disability***	Allow checking multiple categorized options	
	Type of mobility aids***		
	Residence period in the current neighborhood	Enter/write the number	
	Household members (adults and children)		
	Number of vehicles		

* Respondents were asked this question only if they answered that they do not walk usually on the sidewalk.

** Respondents were asked this question only if they answered that they have a child (or children).

*** Respondents were asked this question only if they answered that they have a disability (or disabilities).

4.3.3 Recruit Survey Participant

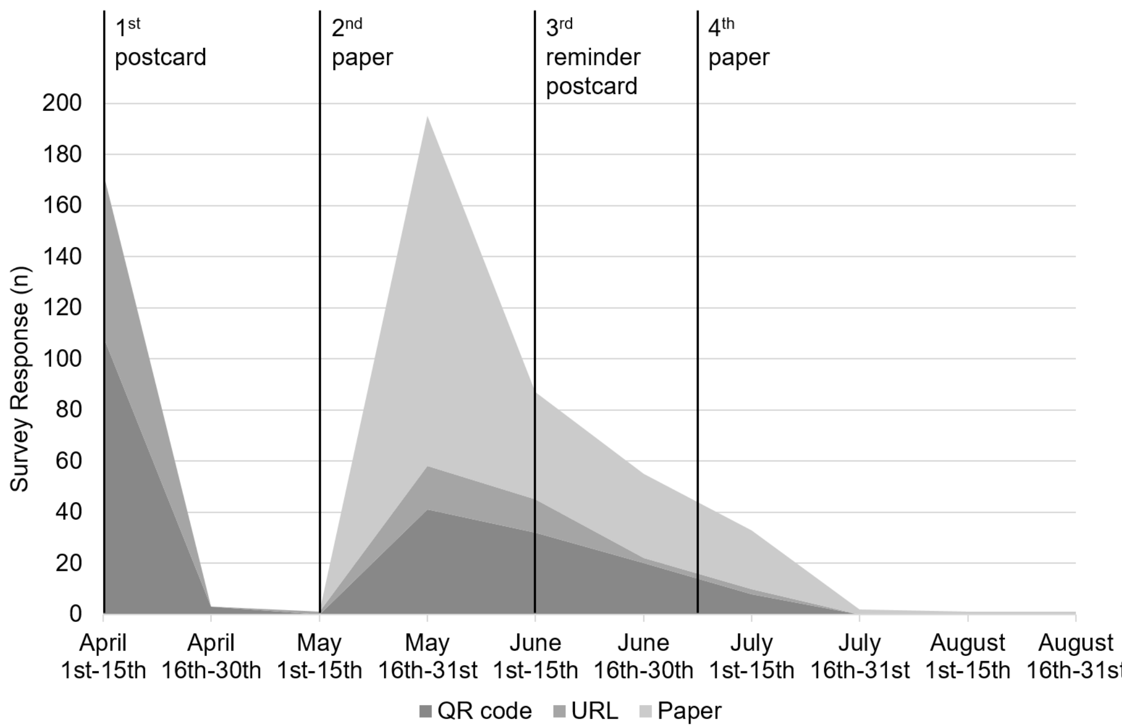
The survey data sample size aimed to have more than 500 adults residing in the ten selected regions. I decided on areas around ten signalized intersections according to the site selection method. I obtained a random sample of 250 residential addresses from each location, or 2,500 total, from a marketing company, DataAxle.

Invitations to recruit survey participants were distributed in four steps from April to July 2023. I sent 2,500 postcards with a Uniform Resource Locator (URL) and a QR code to link to the online survey. Each postcard had a unique code with two digits of letters from the city name and five digits of numbers to allow adults receiving postcards to respond to the online survey. After about a month, in May 2023, I sent a paper version of the survey, including an invitation cover letter, business reply envelope, and reward form, to 2,181 households other than those that had already responded or were returned due to an address error or change of residence. Three weeks after the first paper survey packets, I sent reminder postcards to 2,084 households that had not responded in the first week of June 2023. Lastly, in the last week of June 2023, I sent the second paper survey packet to 1,871 addresses that had not responded. I received 551 completed replies from 514 residential addresses based on survey codes by August 31st, 2023. The deadline for responding to the survey on the last cover letter was July 15th. However, some paper responses arrived late due to shipping delays. For this reason, I received the responses online or posted by August 31st. All survey participants who finished the survey and wanted to receive compensation for the survey were sent a five U.S. dollar Starbucks gift card, and one randomly selected participant won a hundred U.S. dollar Amazon gift card.

4.3.4 Response Rate

Figure 4-4 shows my survey response timeline and the number of responses by distribution method. Note that Figure 4-4 and Table 4-5 include online and paper responses, but only completed cases were recorded (arrived) by August 31st. Respondents who answered online accessed the survey via the QR code more than the URL.

Figure 4-4 Timeline of Survey Response



After the first postcard inviting the survey was distributed, most first-round participants responded within two weeks. After that, I waited for responses for another two weeks, but there were not many responses. When I distributed the paper survey to households that did not respond (enclosing a cover letter with a QR code and URL to enable access to the online survey), I received responses for about two months. Survey recruitment through postcards with online access codes can receive responses relatively immediately (two weeks). However, relying solely on this recruitment method may result in missing responses from people who have difficulty accessing online surveys or do not prefer them, which can lead to bias in the data. Before conducting the survey, it was expected that most people would have access to online surveys because of the increase in personal smartphone use. However, nearly half (43%) of all respondents returned paper survey responses (paper survey responses: 239, total responses: 551).

Table 4-5 shows that the overall survey response rate is approximately 26%, excluding returned mailing addresses. SE Portland, Tigard, NW Portland, and Lake Oswego have more than a 30% response rate. On the other hand, response rates for Wood Village, Hillsboro, and Woodburn were relatively low, ranging from 13% to 15%.

Table 4-5 Response Rate by City (signalized intersection)

Signal (City)	Sent (number of househoulds)	Return (number of households)	Response (number of responses*)	Rate (%)
Albany	250	26	60	27
Hillsboro	250	21	29	13
Lake Oswego	250	52	67	34
McMinnville	250	54	54	28
NW Portland	250	26	76	34
SE Portland	250	64	69	37
Tigard	250	5	86	35
Wilsonville	250	88	45	28
Wood Village	250	18	30	13
Woodburn	250	23	35	15
Total	2,500	377	551	26

* Numbers excluding incomplete responses, missing or incorrectly coded responses, completely identical responses from one household (matching age, gender, and all other responses), or submitting multiple responses even though the number of people in the household is only one.

4.4 Descriptive Analysis of Survey Data

4.4.1 Individual & Household Characteristics

I measured individual characteristics, including age, gender, race/ethnicity, income, frequency of use by mode of transportation, disability, residence period in the current neighborhood, household members (adults and children), and the number of vehicles. I choose characteristics that can affect walking behavior, mode choice, perceived safety, and crash risk (Cho et al., 2009; Monsere et al., 2017; Moyano Díaz, 2002; Rankavat & Tiwari, 2016; Schneider et al., 2004; Schroeder & Wilbur, 2013c). For the answer format of the disability questions, I used options for the item from the Community Planning Survey developed by Dr. Corbin and Dr. Dill.

Table 4-6 summarizes survey respondents' individual and household characteristics. Of the 551 survey participants, over 50% were female, and about 40% were male. I received survey responses from ages 19 to 91. The age of the respondents was not biased towards a specific age group. Except for those in their 80s or older, more than 60 responses were received from all age groups. More survey responses were received from females in all age groups. Note that age was measured as a continuous variable (unit: year). Among 551 respondents, 74 people responded that they have certain types of disability, and 44 among them have a mobility disability.

Regarding race and ethnicity, more than 75% of respondents were 'White/Caucasian,' and more than 10% of people did not answer or answered that they prefer to identify themselves or prefer not to say. 5% of respondents were 'Hispanic/Latino/a/x' and another 5% were 'Asian/Asian American.' About 3% of people were 'Black/African American/African,' 'American Indian, Native American, Alaska Native,' 'Native Hawaiian/Pacific Islander,' 'Slavic/Eastern European,' 'South Asian/Indian,' or 'Middle Eastern/North African.'

According to the Census's Quick Facts of Oregon, the median household income in Oregon between 2018 and 2022 is about $76,000 (U.S. Census Bureau, 2023). More than 50% of respondents said their household income was over $75,000. About 40% of the total answered that their household income is $100,000 or more. About 95% of respondents owned one or more vehicles per household.

In this survey sample, the period respondents have lived in their neighborhood ranges from 2 months to 75 years; on average, respondents have lived in their current neighborhood for more than 11 years (median: 6.5 years). More than 90% of respondents had lived in their current residence for over one year.

Table 4-6 Individual & Household Characteristics

Category	Characteristics	Percent (%)
Gender	Female	57
	Male	39
	Non-binary or third gender	2
	Prefer Not to self-identify	<1
	Prefer not to say	2
Age	19-29	13
	30-39	18
	40-49	15
	50-59	12
	60-69	16
	70-79	17
	80+	7
	Did not respond	1
Income	Less than $15,000	3
	$15,000 to less than $24,999	4
	$25,000 to less than $34,999	6
	$35,000 to less than $49,999	9
	$50,000 to less than $74,999	17
	$75,000 to less than $99,999	16
	$100,000 to less than $149,999	21
	$150,000 or over	17
	Did not respond	7
Disability	Yes	13
	No	84
	Prefer not to say	2
	Did not respond	1
Kids	Yes	24
	No	76
	Did not respond	0
Number of Motorized Vehicles	None	5
	1	34
	2	45
	3+	16
	Did not respond	<1
Total (n)		551

4.4.2 Walking Behavior

I measured the participant's walking behavior by asking the number of walking days and walking time of the day during the previous seven days. I categorized the walking time of day into five groups: morning before sunrise, morning after sunrise but before noon, afternoon, evening before sunset, and evening after sunset. The time of the day was not divided by the exact time because sunrise and sunset times are different depending on the survey respondents (survey distributed and response period: April – August). For the walking time of day, the participant can check their walking frequency between 'never or rarely,' 'sometimes,' or 'often' by category. These questions measured respondents' recent walking frequency and how often they walk during the day or night. The number of days of walking during weekdays and the number of days of weekends during the four seasons (spring, summer, fall, and winter) were also asked. Seasons were divided into four: spring (March-May), summer (June-August), fall (September-November), and winter (December-February). The walking days by season were used to calculate the average annual walking number.

Since only a few Americans walk to commute to work or school, I asked about their reason for walking, as shown in Table 4-4. The answer format and options are referred from the NHTSA's decadal survey: National Survey of Bicyclist and Pedestrian Attitudes and Behavior (National Highway Traffic Safety Administration, 2022; Schroeder & Wilbur, 2013a, 2013b, 2013c).

Lastly, the type of path or road of walking is asked to measure how often people walk on sidewalks. If they did not usually use sidewalks, participants can check why did not in the following question. The answer options were also referred to the NHTSA's decadal survey (National Highway Traffic Safety Administration, 2022; Schroeder & Wilbur, 2013a, 2013b, 2013c).

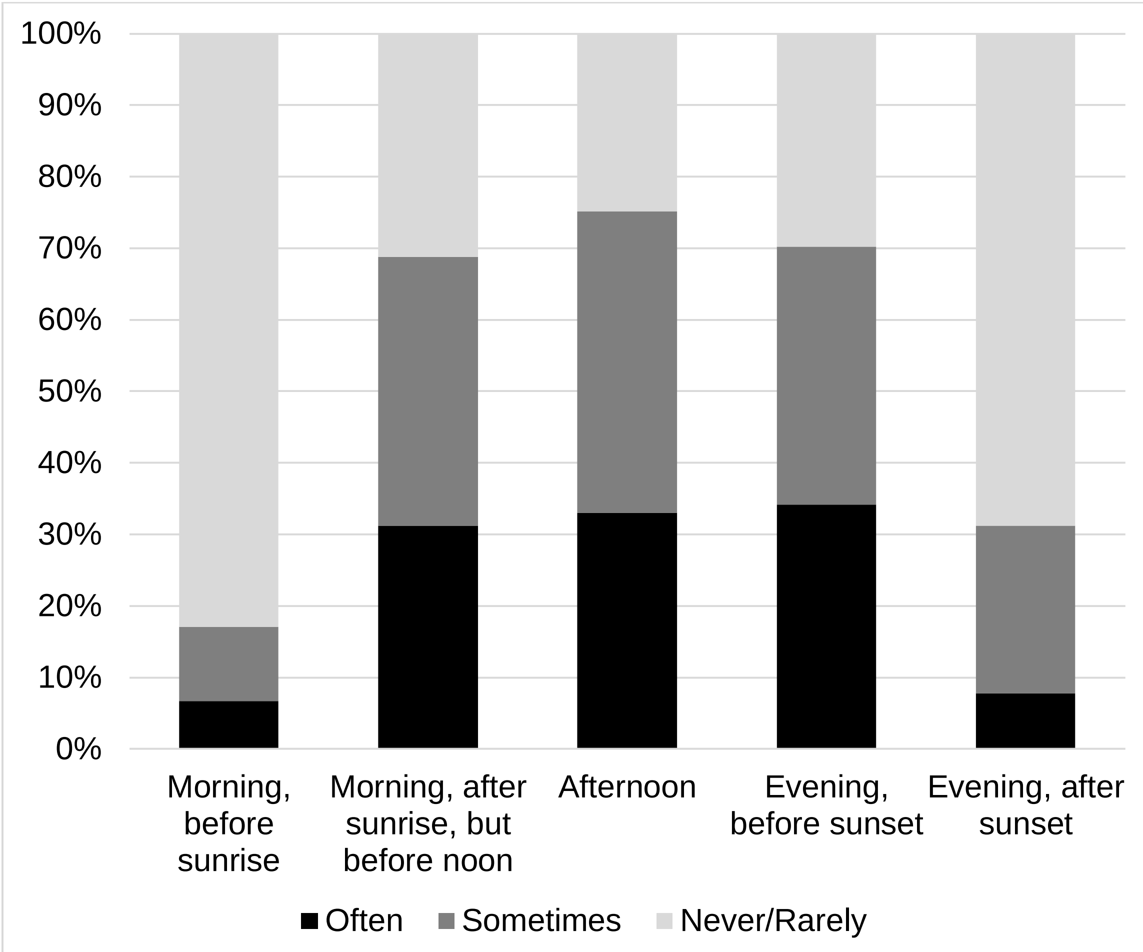
Table 4-7 shows survey respondents' number of days of walking a week. The annual average is 4.3 (median: 4.5). More than half of respondents walk at least four days a week annually, and they walk more days during the summer season (June–August) while walking less during the winter season (December—February).

Table 4-7 Days of Walking a Week: last week, four seasons, and annually

Statistics	**Last 7 days**	**Spring**	**Summer**	**Fall**	**Winter**	**Annually**
Average	4.28	4.58	5.06	4.45	3.24	4.33
Standard deviation	2.36	2.11	2.14	2.16	2.38	2.00
Minimum	0	0	0	0	0	0
25th percentile	3	3	4	3	1	3
Median	5	5	6	5	3	4.5
75th percentile	7	6	7	6	5	6
Maximum	7	7	7	7	7	7

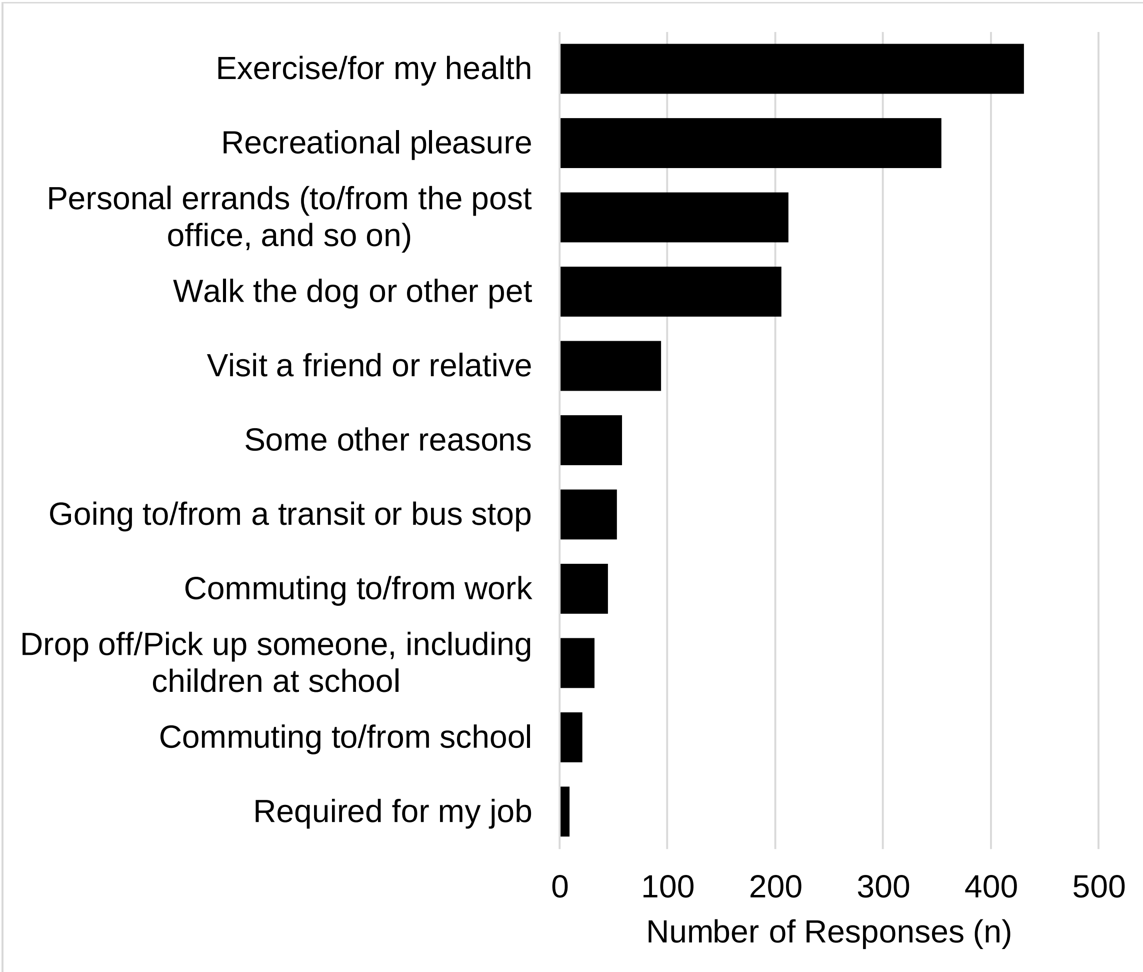
Figure 4-5 shows that respondents mainly walk after sunrise before sunset. In particular, fewer people answered that they walk in the morning before sunrise. Although more people walk in the evening after sunset than before sunrise, it is still less than half the number of people who say they walked in the afternoon.

Figure 4-5 Walking Time



The question asking the purpose of walking allowed multiple answers. Figure 4-6 shows that people who walk to commute to work or school in this survey were only about 10%, and after including people who walk to use public transportation, they were about 15% of the total. Most people walk for recreational pleasure or exercise for their health, followed by walking their pets rather than to a specific destination.

Figure 4-6 Purpose of Walking (multiple responses possible)



As the following two figures show (Figure 4-7, Figure 4-8), it is evident that a majority of people prefer walking on the sidewalk. However, some individuals opt to walk elsewhere due to the absence of a sidewalk or unsafe walking conditions. Furthermore, those who view the sidewalk as hazardous cited reasons such as unleashed dogs, homeless individuals camping on the sidewalk, people using drugs, and the presence of sharp debris and trash.

Figure 4-7 Walking Path Selection by Type

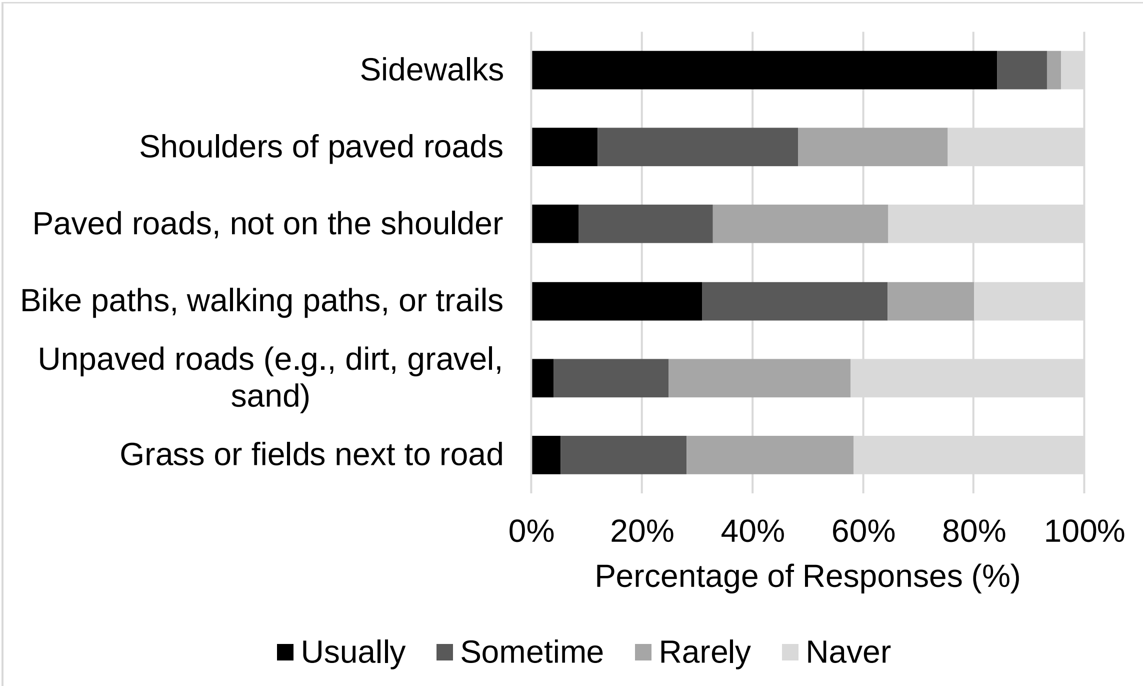
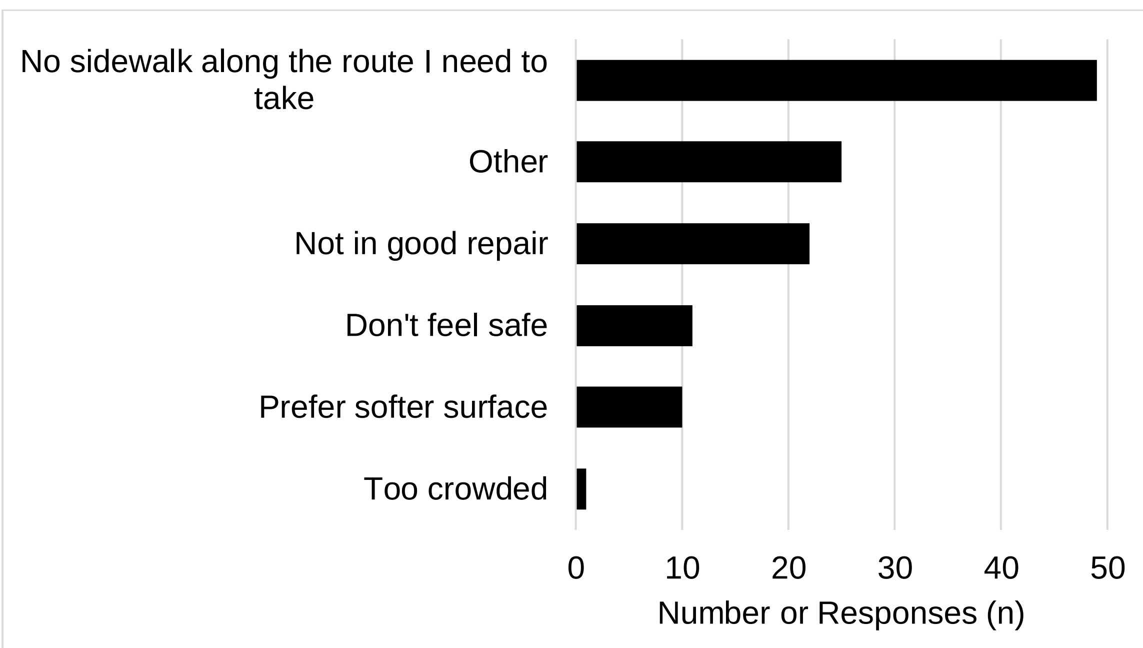


Figure 4-8 Reason Why People Do Not Usually Use the Sidewalk (multiple responses possible)

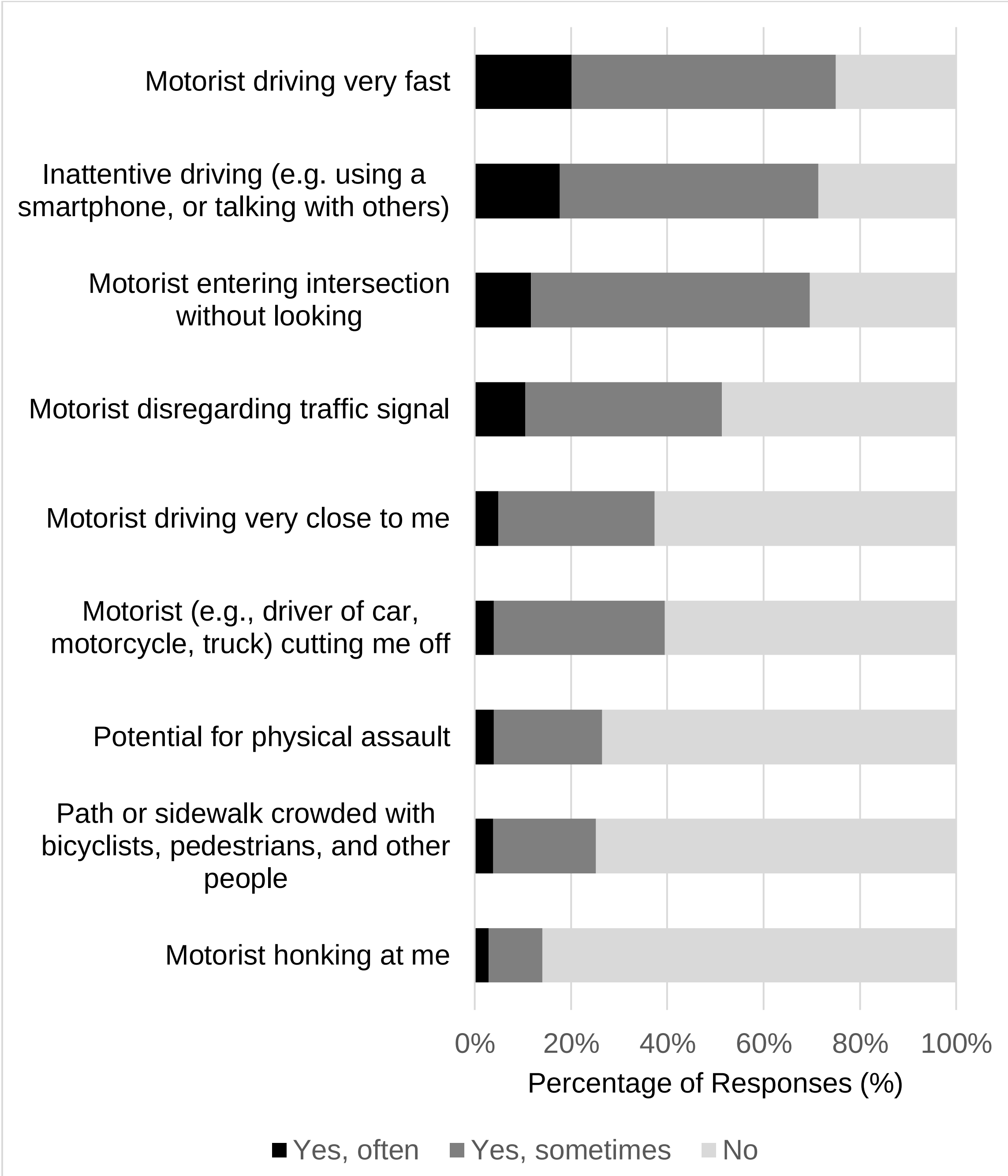


4.4.3 Perceived Safety: Threatened Experiences

The perceived safety was measured in two different ways: threatened experiences and safety attitudes. Note that questions about safety attitudes were asked first in the survey, and then questions about threatened experiences were asked (Table 4-4). However, this descriptive analysis results section explains the threatened experiences first since threatened experiences came before the safety attitudes in the path model for the second research question in Chapter 6. Threatened experiences were measured into two categories: nine different threatening behaviors of other road users, especially motorists, and six different threatening situations because of the qualities or status of facilities. I used the items related to possible threatened experiences developed for NHTSA's decadal survey (National Highway Traffic Safety Administration, 2022; Schroeder & Wilbur, 2013a, 2013b, 2013c).

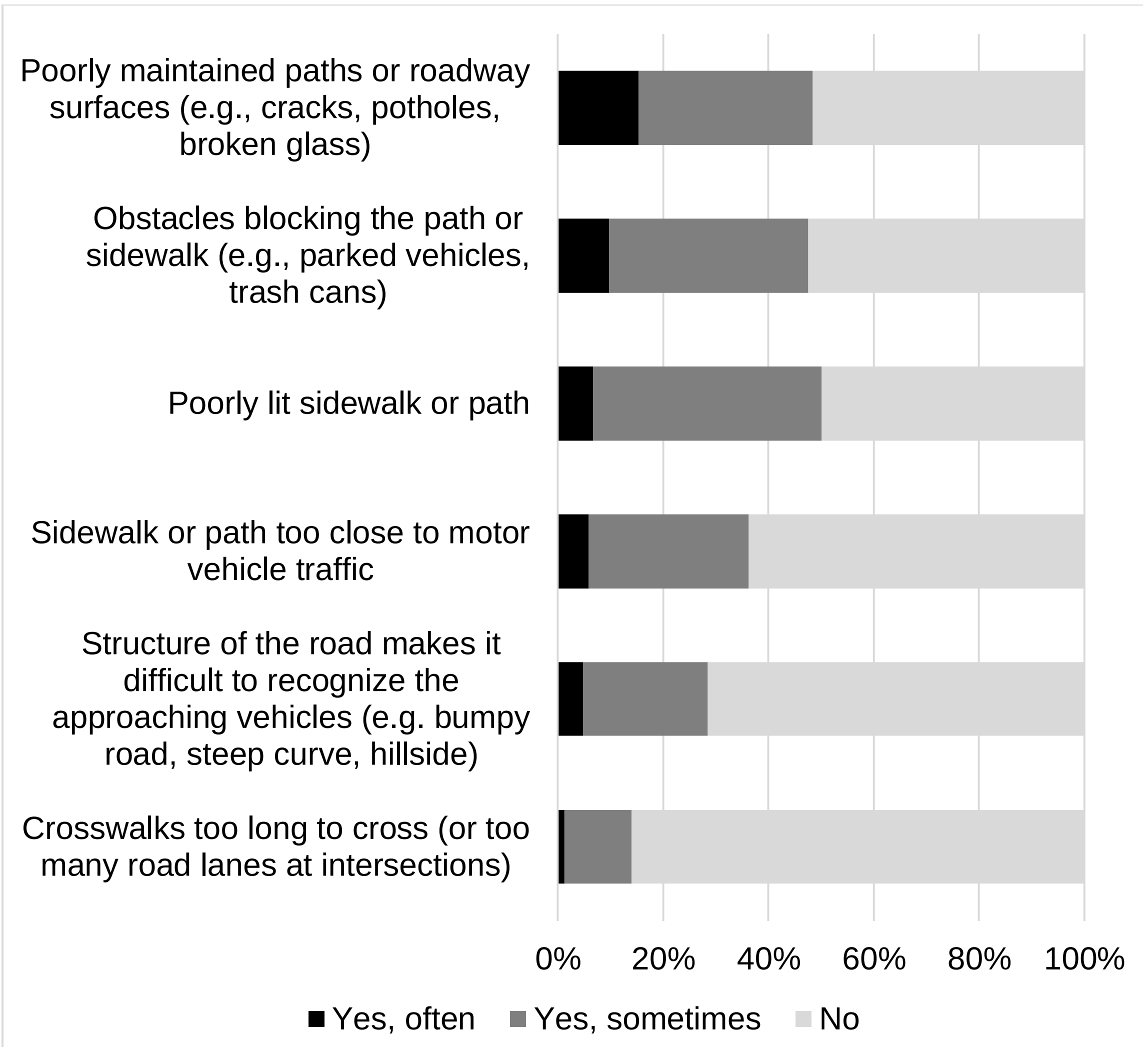
I measured threatened experiences on a three-point ordered scale: no (0), yes, sometimes (1), and yes, often (2). Figure 4-9 shows that about 75% of my survey respondents had experienced being threatened by motorists' fast driving in their neighobhoords. About 70% of them also experienced being threatened by motorists' inattentive driving and entering intersections without looking. However, not many of respondents had experienced being threatened by motorists' honking, crowded sidewalks, or potential physical assaults.

Figure 4-9 Threatened Experiences (other road users' behaviors)



On the other hand, Figure 4-10 shows that no item makes more than 50% of the respondents experience being threatened by facilities. Relatively more respondents experienced being threatened by poorly maintained paths, obstacles on the path, or poorly lit sidewalks or paths. Interestingly, motorists' inattentive behaviors at intersections threatened people in the above Figure 4-9; however, not many respondents thought crosswalks were too long to cross in the Figure 4-10.

Figure 4-10 Threatened Experiences (facilities)



4.4.4 Perceived Safety: Safety Attitudes

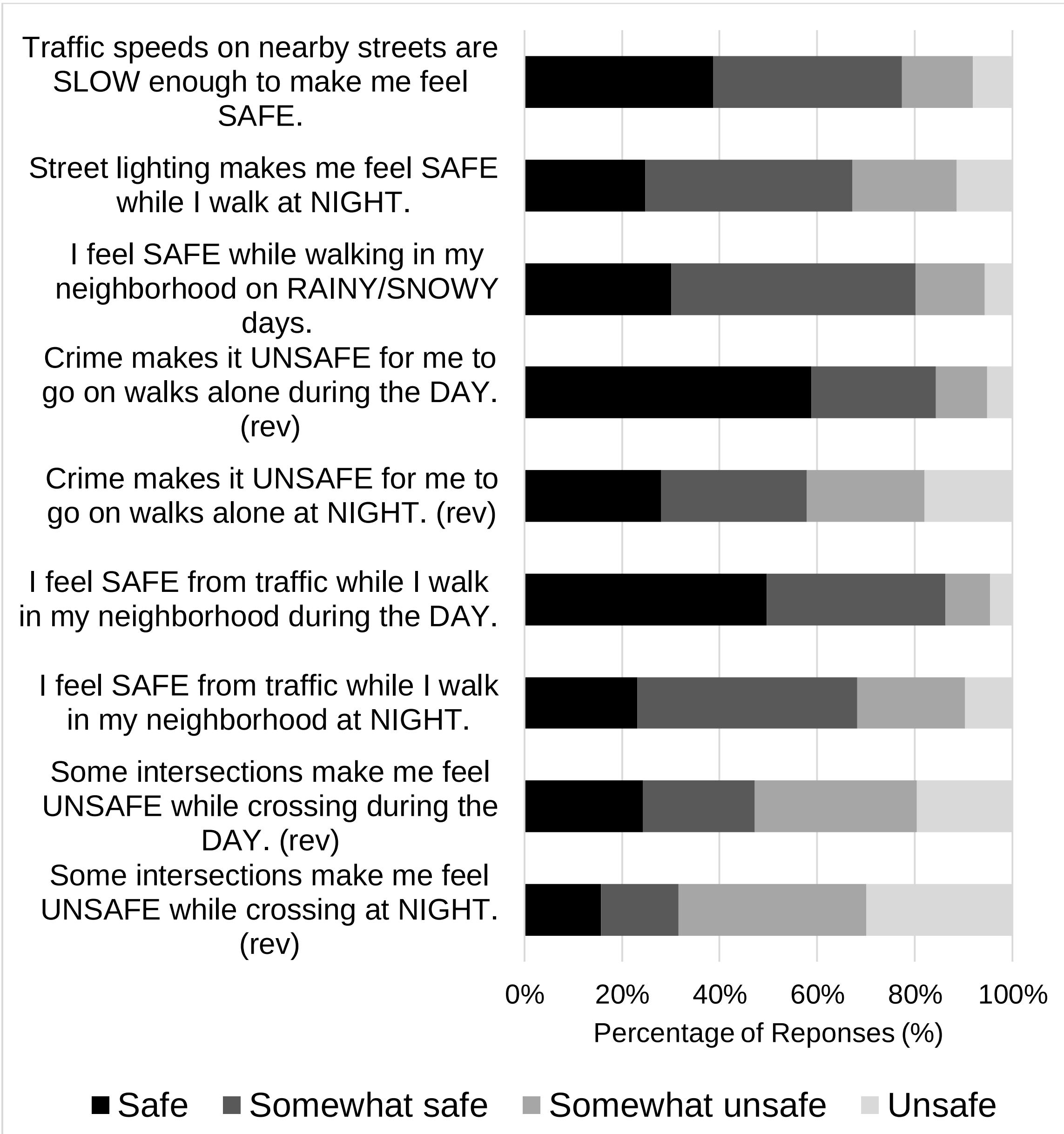
To measure safety attitudes, I asked nine questions about how people feel safe or unsafe related to traffic speeds, street lighting, walking on rainy or snowy days, and crime during the day and at night were asked on a four-point ordered scale from 'strongly disagree' to 'strongly agree.' I referred to the Family Activity Study (FAS) survey instrument using measurements developed by Mokhtarian and Handy (Cao et al., 2006; Dill et al., 2014).

To investigate whether participants who have a child or children in their household are more conservative concerning pedestrian safety, I asked if participants have a child (or children) under the age of 18 in their household. In this case, they can answer follow-up questions about safety attitudes when walking in the neighborhood with their child (or children) on a four-point ordered scale from 'strongly disagree' to 'strongly agree.'

To prevent survey participants from checking the same answer to all questions, a survey question was created using negative and positive sentences. Regarding the positive sentence items, the more they agreed, the safer they felt, and they were coded a higher score. In the case of the negative sentence item, the more they disagreed, the safer they felt, and they reversed-coded this item. Therefore, the higher score in both cases means that respondents felt safer.

Figure 4-11 shows how people perceived the nine different situations related to safety while walking in their neighborhood. They felt safer regarding traffic, crime during the day, and vehicle speed. However, they responded that they felt unsafe regarding street lighting, crime, and traffic at night. In particular, people answered that they felt relatively less safe at intersections during the day and at night than in other situations.

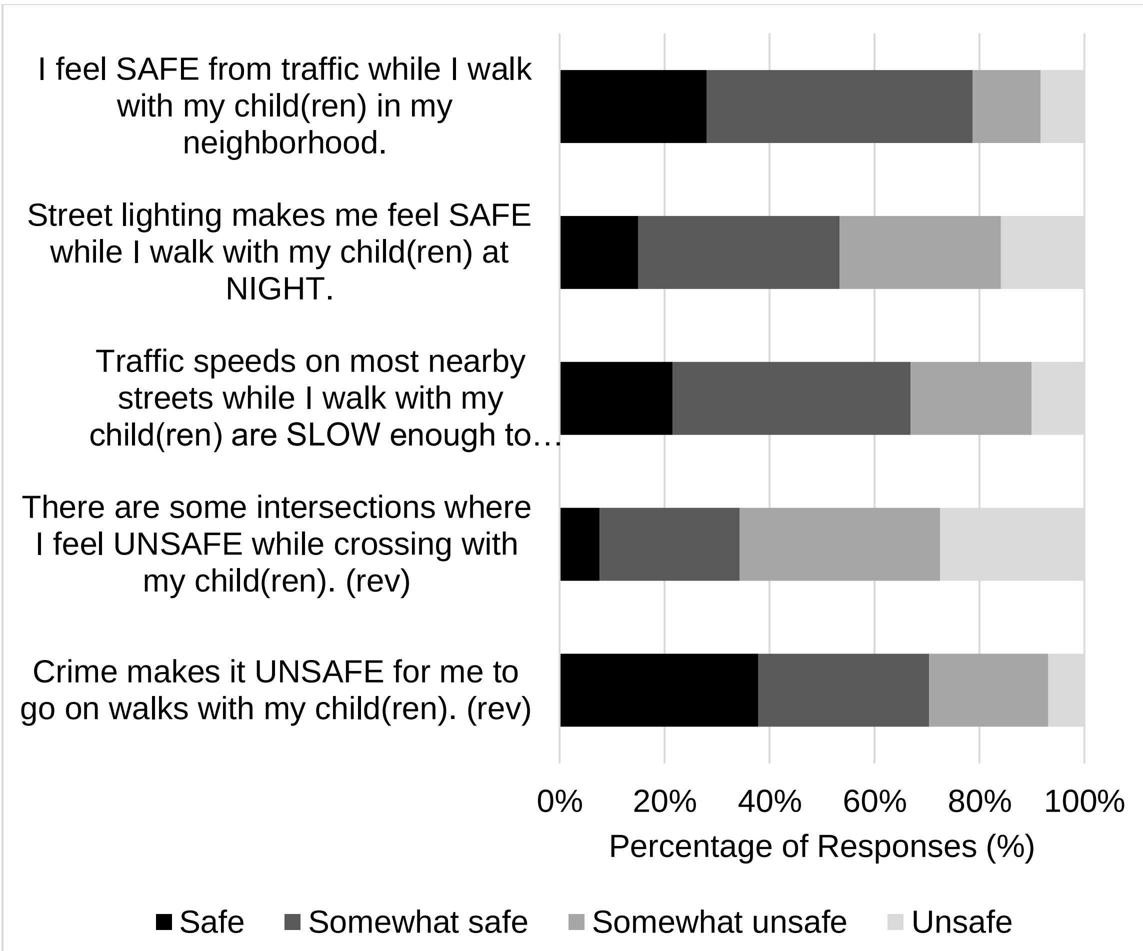
Figure 4-11 Safety Attitudes



Item with “(rev)” was reversely coded, and the right part of this chart shows the same direction regarding safety attitudes.

In Figure 4-12, regarding walking with their children, the street lighting at night and walking at intersections made them feel less safe than other possible safety issues about traffic or crime.

Figure 4-12 Safety Attitudes: Walking with Kids



Item with "(rev)" was reversely coded, and the right part of this chart shows the same direction regarding perceived safety.

4.5 Secondary Data[1]

4.5.1 Pedestrian Volume

4.5.1.1 Pedestrian Counts

Pedestrian volume is measured in two ways. The first is using pedestrian count data, which was collected from a project called "Active transportation counts from existing on street signal and detection infrastructure," funded by Oregon Department of Transportation (ODOT), PI: Sirisha Kothuri, Portland State University and Patrick Singleton, Utah State University in 2022 (Kothuri et al., 2024). Pedestrians are counted in multiple directions, including north-south and east-west, and for different hours (but mostly 48 hours) by intersections. I scaled the pedestrian counts to 24 hours by intersections. These signalized intersections are located on various road classification types, including interstate, principal arterial, minor arterial, or major collector, but mostly on principal arterial or major collector roads.

Each survey respondent's address was linked with the count data of the nearest intersection within a half-mile straight-line buffer. I assumed that the number of pedestrians counted at an intersection could represent the pedestrian volume of about a half-mile buffer area from a specific street address. Note that two Portland areas in ten selected census tracts (Figure 4-3) had multiple signalized intersections collecting the

[1] Basic statistics of each variable of secondary data are by half-mile straight buffer. Basic statistics by census block group for the first research question are explained in Chapter 5.

pedestrian counts within a half-mile. In this case, I used the average of the count data from the available signalized intersections.

The pedestrian count data collected in 2022 was scaled to the count of the previous four years, 2018–2021, using the city's annual population change in Oregon released by the U.S. Census. Using this scaled pedestrian number, I also estimated cumulated pedestrian crashes in several different periods including 2022: 2018-2022 (average of pedestrians in the last five years) and 2020-2022 (average of pedestrians in the previous three years).

4.5.1.2 Proxy: Population Density

Based on the census block group 2020 data, the average population density (number of people per square mile) of block groups included within a half-mile straight buffer from the address of 514 households was used as a proxy to measure pedestrian volume (U.S. Census Bureau, 2020). I also scaled the population density based on the annual population change from 2018 to 2022 by city in Oregon released by the Census (US Census Bureau, 2020, 2023).

Based on these two pedestrian volume measurements, I could estimate the latest one-year, three-year, and five-year cumulated pedestrian crashes. Table 4-8 shows the distribution of both pedestrian count and population density in three different periods: average in the previous five years (2018 – 2022), during the COVID-19 pandemic (2020 – 2022), and recent year (2022). Note that the scaled pedestrian count including the pandemic period can be different from the real pedestrian number since the pandemic affected pedestrian activities.

Table 4-8 Pedestrian Volume: Count & Proxy (0.5-mile straight-line buffer)

n=514

Statistics	Pedestrian Count (24-hr)			Population Density (person/mi^2)		
	2018-2022 5-year	2020-2022 3-year	2022 1-year	2018-2022 5-year	2020-2022 3-year	2022 1-year
Average	226.90	226.92	225.81	6,425	6,439	6,404
Std. deviation	223.12	221.43	218.13	4,923	4,877	4,791
Minimum	13	13	13	1,007	1,036	1,034
25th percentile	124	126	130	3,936	3,955	4,006
Median	155	154	152	4,818	4,835	4,839
75th percentile	313	311	312	7,372	7,341	7,246
Maximum	816	811	800	26,679	26,532	26,168
Skewness	1.63	1.62	1.60	2.32	2.32	2.32
Kurtosis	1.67	1.66	1.62	5.04	5.07	5.08

4.5.2 Motor Vehicle Traffic

To measure the motor vehicle traffic, I used annual average daily traffic (AADT) data from 2018 to 2022 provided by the Traffic Count Database System (TCDS: Oregon Traffic Monitoring System) of the Oregon Department of Transportation (ODOT).

I tested eight different motor vehicle traffic types by measurement type. Table 4-9 shows how the motor vehicle traffic were measured in eight different ways. First, for aggregating motor vehicle traffic by spatial unit, the measurements can be divided into two ways based on the difference in details of traffic counting places/points based on the data source. One is including the AADTs only on highway and the other includes other road types, including interstate, highway/freeway, arterial, collector, and local roads. The

TCDS does not provide AADTs for all roads and all years; however, the motor vehicle traffic is collected on the various road types (classification), including local, minor collector, major collector, principal arterial (other), principal arterial (freeway & expressway), and interstate. Thus, including AADTs provided by TCDS can capture more detailed differences in motor vehicle traffic by spatial unit of analysis than AADTs counted only on the highways.

Table 4-9 Eight Methods of Motor Vehicle Traffic Measurements

Detail of Counting Points	**Interstate**	**Calculation for Aggregation**
Highway Segment Traffic Data provided by ODOT	Not Include	Average (1)
		Maximum (2)
	Include	Average (3)
		Maximum (4)
All Other Counting Points provided by TCDS of ODOT	Not Include	Average (5)
		Maximum (6)
	Include	Average (7)
		Maximum (8)

Second, another criterion for dividing motor vehicle traffic measurement is whether the motor vehicle traffic on the interstates was included. It is difficult to assume that pedestrians easily access or routinely use interstate highways, which have more traffic and faster vehicle speeds than other roads. So, it can be assumed that the traffic measured on interstate highways may not be the traffic volume that affects pedestrian crashes. However, pedestrian-involved crashes have occurred on interstate highways such as I-84 and I-5. This is why testing two values of the motor vehicle traffic, including AADTs on the interstate or without AADTs on the interstate, is necessary.

Lastly, to aggregate motor vehicle traffic by spatial unit, I tried average and maximum values. The average motor vehicle traffic may be able to represent the traffic volume of a particular area. However, if the motor vehicle traffic on a specific road in the area is much larger than on other roads, the highest motor vehicle traffic may better predict the likelihood of a crash. Additionally, because the number of spots that count traffic volume is different by region, it is difficult to say that the average always best represents the aggregated motor vehicle traffic by spatial unit. Thus, I respectively tried the average and maximum of motor vehicle traffic for estimating models.

Figure 4-13 shows an example of how motor vehicle traffic is aggregated by a half-mile straight-line buffer. Multiple motor vehicle traffic collecting points can be located in the spatial unit. If no collecting points are within the boundary, motor vehicle traffic was calculated by spatially joining the nearest collecting point. Table 4-10 summarizes how the number of motor vehicle traffic collecting points is different by the spatial unit.

Figure 4-13 Example of Measuring Motor Vehicle Traffic in Buffer Around Respondent's Mailing Address

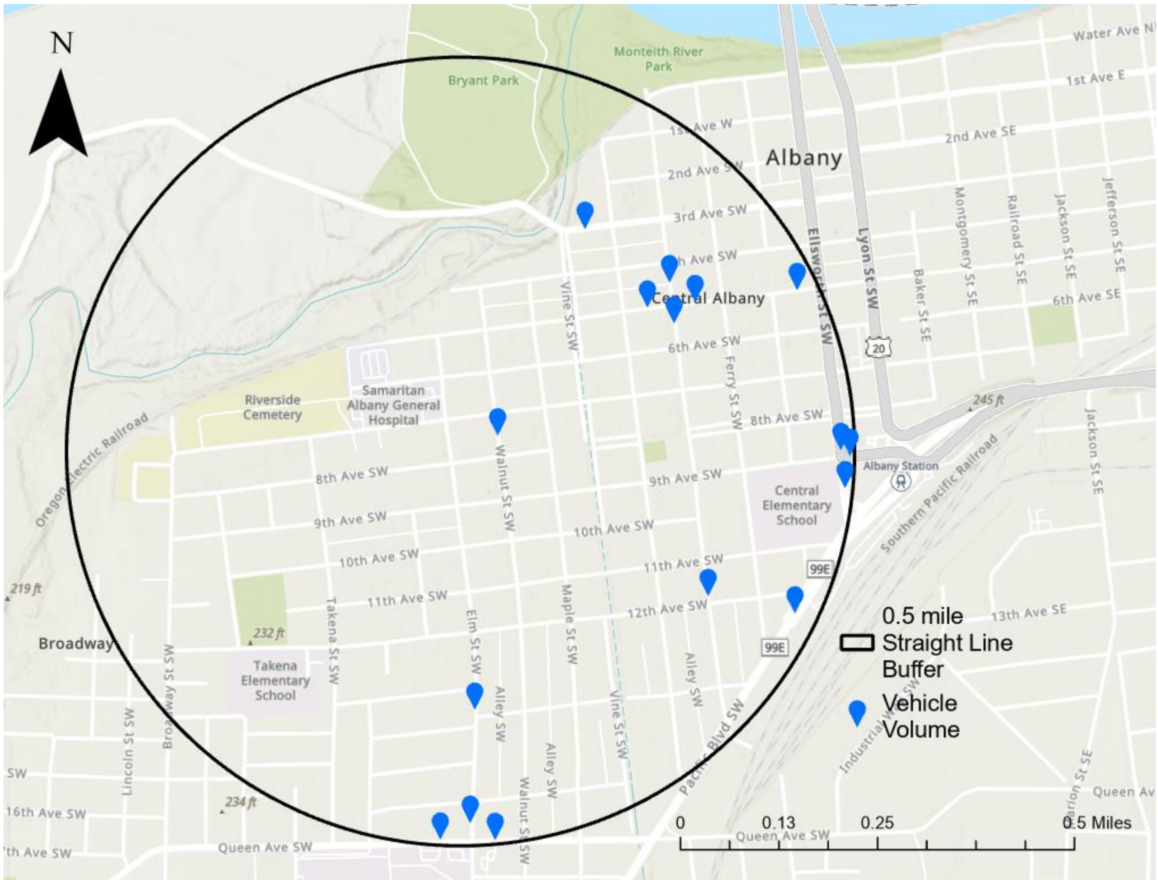


Table 4-10 Number of Motor Vehicle Traffic Collecting Points

Statistics	Census Block Groups (n= 346)	Half-mile Straight-line Buffer (n=514)
Average	4.8	14.8
Std. deviation	7.4	12.8
Minimum	1	1
25th percentile	1	5
Median	3	13
75th percentile	7	22
Maximum	52	64

After testing and comparing eight different types of motor vehicle traffic, the model with the eighth motor vehicle traffic[2] in Table 4-9 was the best predictor in estimating pedestrian crashes for the first research question. This eighth motor vehicle traffic was also used for the second and third research questions. Table 4-11 shows the basic statistics of aggregated motor vehicle traffic of three different periods: the last five years (2018–2022), three years of the pandemic (2020–2022), and the latest year (2022). Comparing three different periods, it can be seen that motor vehicle traffic has decreased in the last five years. This can be interpreted as a reflection of the reduced motor vehicle traffic during the pandemic compared to the traffic volume in 2018 and 2019.

Table 4-11 Motor Vehicle Traffic: All(TCDS)/Interstate/Max (0.5-mile straight-line buffer)

n=514

Statistics	**2018-2022 5-year**	**2020-2022 3-year**	**2022 1-year**
Average	39,165	38,116	37,902
Std. deviation	36,897	35,258	34,970
Minimum	173	170	178
25^{th} percentile	18,627	18,195	18,920
Median	24,803	24861	24,970
75^{th} percentile	38,325	37,670	39,348
Maximum	157,800	153,870	154,838
Skewness	2.11	2.15	2.23
Kurtosis	3.48	3.80	4.20

[2] Motor vehicle traffic was measured at all counting points provided by the Traffic Count Database System of the Oregon Department of Transportation; included interstate traffic volume; and was aggregated as maximum by spatial unit of analysis.

4.5.3 Pedestrian Crash

Crash data from 2018 to 2020 was collected through a shapefile (a vector data file format for geospatial analysis) provided by ODOT. In August 2023, I could create shapefiles of crashes that occurred in 2021 and 2022 based on text-type data provided by ODOT's Crash Data system. The crash data was extracted by county: seven counties containing ten study sites (Benton, Clackamas, Linn, Marion, Multnomah, Washington, and Yamhill).

Crashes are rare events, so they are generally analyzed in more extended periods: one year or more (Carter et al. 2017). Table 4-12 shows the descriptive statistics of cumulated pedestrian crashes by different periods: a recent five-year period (2018-2022), three-year (2020-2022), and one year (2022). Cumulated pedestrian crashes are normally distributed within a half-mile radius buffer from each address according to the cutoffs for skewness and kurtosis suggested by West et al. (1995).

Table 4-12 Pedestrian Crashes (0.5-mile straight-line buffer)

n=514

Statistics	**2018-2022 5-year**	**2020-2022 3-year**	**2022 1-year**
Average	7.41	3.78	0.83
Std. deviation	6.36	3.23	0.96
Minimum	0	0	0
25th percentile	2	1	0
Median	6	3	1
75th percentile	11	5	1
Maximum	32	18	6
Skewness	1.09	1.36	1.32
Kurtosis	0.90	2.33	2.85

4.5.4 Sidewalk

Data were collected from various sources by location (neighborhood) to measure the length of the sidewalk. However, a consistent strategy was used to collect the data. Note that in this study, the variable "sidewalk" only refers to the portion of the walkway installed adjacent to the road and not the ones installed separately (e.g., multi-use path).

- Seven cities in Clackamas, Multnomah, and Washington counties: sidewalk data for seven cities provided by Metro's Regional Land Information System (RLIS) was used. The sidewalk data provided by RLIS distinguishes whether there are sidewalks on both sides of the road (full), one side or incomplete (partial), or there are no sidewalks on both sides of the road (missing). I also coded the sidewalk data of the following three cities in this way: McMinnville, Albany, and Woodburn as follows.
- McMinnville and Albany: I used road network and sidewalk data provided by the city governments of these two cities. Since Oregon State's road network shapefile did not include the detailed road network in the city of McMinnville, I used the data provided by the city government.
- Woodburn: I used road network data from the Oregon Transportation Network and checked whether sidewalks existed in each road section or on both sides of the road in Google Street View. In the case of Woodburn, the most recent data on roads in the target area was taken in July 2023, and changes in the condition of sidewalks were confirmed through previous data.

The sidewalk length was aggregated by spatial unit, census block group, and half-mile straight-line buffer area, using three different weights (full = 2, partial = 1, missing = 0). Table 4-13 displays the descriptive statistics of the sidewalk and road length. Two different methods were used to calculate the length of the sidewalk. The first method considers the length of the sidewalk regardless of whether it is on both sides or only on one side. The second method calculates the length of the path differently depending on whether there are sidewalks on both sides, only one side, or no sidewalks at all. For instance, if there are 10 miles of road in a half-mile radius buffer, out of which three miles have no sidewalks, two miles have sidewalks on one side only, and five miles have sidewalks on both sides, then the number of miles calculated using the first method would be seven miles, whereas the second method would yield 12 miles.

Table 4-13 Length of Road & Sidewalk (0.5-mile straight-line buffer)

n=514, unit: mi

Statistics (mile)	**Road**	**Sidewalk (missing or not)**	**Sidewalk (full/partial/missing)**
Average	16.57	12.76	22.59
Std. deviation	5.34	5.27	10.33
Minimum	3.34	2.43	3.80
25^{th} percentile	13.55	8.96	13.38
Median	16.90	14.02	24.81
75^{th} percentile	19.52	16.24	29.23
Maximum	30.45	25.07	49.06
Skewness	-0.35	-0.26	-0.09
Kurtosis	0.50	-0.79	-0.84

4.5.5 Intersection and Public Transit Stops

An intersection is a point where two or more roads cross and pedestrians can encounter motorized vehicles. To create an intersection data set as a shapefile, I created intersection points on lines using ArcGIS Pro and the road network data from the ODOT and the city of McMinnville's[3] open data source.

The number of public transit stops in this study was measured as the number of stop locations of all kinds of regularly scheduled public transit services in Oregon as derived from General Transit Feed Specification (GTFS) data, and the GIS data created date is 2020 January 8. Most of the transit service data has been updated after the spring of 2023, when my survey was conducted, although data update dates vary for each region[4]. Based on this update, there has been no confirmed change in the number of stops within a half mile of the survey respondent's address. Table 4-14 shows the descriptive statistics and distribution of the intersection and public transit stops.

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[3] The road network shapefile of McMinnville data was in polygon, I created line data from polygons in ArcGIS Pro.

[4] Newly updated General Transit Feed Specification (GTFS) data in Oregon: https://www.oregon-gtfs.com/

Table 4-14 Intersection & Public Transit Stop (0.5-mile straight-line buffer)

n=514

Statistics	Intersection	Public Transit Stop
Average	127	17
Std. deviation	53	13
Minimum	16	0
25th percentile	87	8
Median	135	13
75th percentile	163	25
Maximum	271	55
Skewness	-0.08	0.92
Kurtosis	-0.23	0.03

4.5.6 Land Use: Commercial & Mixed-Use and Park

Pedestrians can encounter motorized vehicle flows in commercial land, mixed-use land, and park areas since these areas have multiple destinations for exercise, fun, and walking their pets. In estimating models, I excluded residential to avoid high multicollinearity among land use variables.

I used Oregon's Department of Land Conservation and Development (DLCD) to calculate areas by zone, which provides the statewide land use zoning (2017)[5] shapefile data. Table 4-15 shows commercial land, mixed-use land, and park areas are normally distributed.

[5] Data source: ftp://ftp.gis.oregon.gov/adminbound/Oregon_Zoning_2017.zip

Table 4-15 Land use (0.5-mile straight-line buffer)

n=514, unit: mi^2 (%)

Statistics	Park	Mixed-use land area	Commercial land area
Average	0.04 (5%)	0.10 (13%)	0.05 (7%)
Std. deviation	0.05	0.14	0.06
Minimum	0.00	0.00	0.00
25^{th} percentile	0.01 (1%)	0.00 (0%)	0.00 (0%)
Median	0.03 (3%)	0.03 (4%)	0.03 (4%)
75^{th} percentile	0.05 (7%)	0.15 (19%)	0.10 (13%)
Maximum	0.26 (33%)	0.61 (78%)	0.26 (33%)
Skewness	1.85	1.78	1.08
Kurtosis	3.00	2.98	0.39

4.5.7 Posted Speed Limit & Actual Speed

Speed limits or ranges of speed scenarios were used in crash studies as indirect measurements for actual speed (Aceves-González et al., 2020; Hussain et al., 2019; Kwon et al., 2022; Rosén & Sander, 2009). However, speed variable is needed to be aggregated in crash model for macro-level spatial units such as neighborhoods, cities, or traffic analysis zones. Because of this aggregation, some information on speed may be lost depending on the measurement method. Moreover, it becomes difficult to determine the impact of the higher range of speeds when speed is aggregated into specific spatial units because the frequency of crashes and the probability of serious injury from them can increase at high speeds (Aarts & van Schagen, 2006; Elvik, 2013; Hussain et al., 2019; Mahmoud et al., 2021, 2023; Monsere et al., 2017). Therefore, several different measurement strategies can be tried to determine the model to answer research questions. In this study, speed limits and actual speeds were measured differently by two spatial units: census block group and half-mile straight-line buffer.

First, I collected data for speed limits using Portland Maps - Open Data, Oregon Speed Zones, and Google Street View. The speed limits by the half-mile straight-line buffer unit were aggregated in three ways: 1) weighted by road length, 2) maximum value within the unit boundary, and 3) nearest value from the survey respondent's mailing address. Table 4-16 summarizes the descriptive statistics of weighted, max, and nearest speed limits. Note that there are no nearest speed limit values for the census block groups, and the descriptive statistics of speed limits by census block group are shown in the following chapter.

Table 4-16 Speed Limit (0.5-mile straight-line buffer)

n=514, unit: mph

Statistics	**Speed Limit (weighted)**	**Speed Limit (max)**	**Speed Limit (nearest)**
Average	26.87	44.68	25.57
Std. deviation	4.45	8.70	6.77
Minimum	20	30	20
25th percentile	23	40	20
Median	26	45	20
75th percentile	30	55	30
Maximum	49	65	40
Skewness	0.79	-0.02	0.76
Kurtosis	0.48	-0.85	-0.90

Next, the actual speeds were also tested. I obtained the INRIX probe data, which was generated by the positions of vehicles (roadway sensors) from the Regional Integrated Transportation Information System (RITIS). The 24-hour 50th percentile and 85th percentile speed data from 2018 to 2022 were collected. The 85th percentile of vehicle speed is considered to be unsafe (Oregon Department of Transportation, 2022). According to the Speed Zone Manual of ODOT, this 85th percentile speed has been used to set the posted speed to minimize the probability of crashes. The 50th percentile speed means that 50 percent of motorists drive at this speed or below on road segments, and this speed can be more appropriate for vulnerable road users in urban areas (Oregon Department of Transportation, 2022). The actual speeds by the percentile of speed, 50th and 85th, were aggregated in two ways: 1) weighted by road segment length, and 2) by nearest value from the survey respondent's mailing address.

Figure 4-14 shows an example of how actual speeds are aggregated by a half-mile straight-line buffer. Using the start and end points of the road segments, called TMC segment or TMC code, and the length of each segment, actual speeds by the spatial unit were aggregated. Multiple road segments with actual speed data in the spatial unit are possible within the spatial unit. If there are no start and end points of the segments with actual speed data within the boundary, the actual speed was calculated by spatially joining the nearest collecting point from the spatial unit. Table 4-17 summarizes the number of collecting points (road segments) and total length (mile) by the spatial unit.

Figure 4-14 Example of Measuring Actual Speed within Buffer Around Respondent's Mailing Address

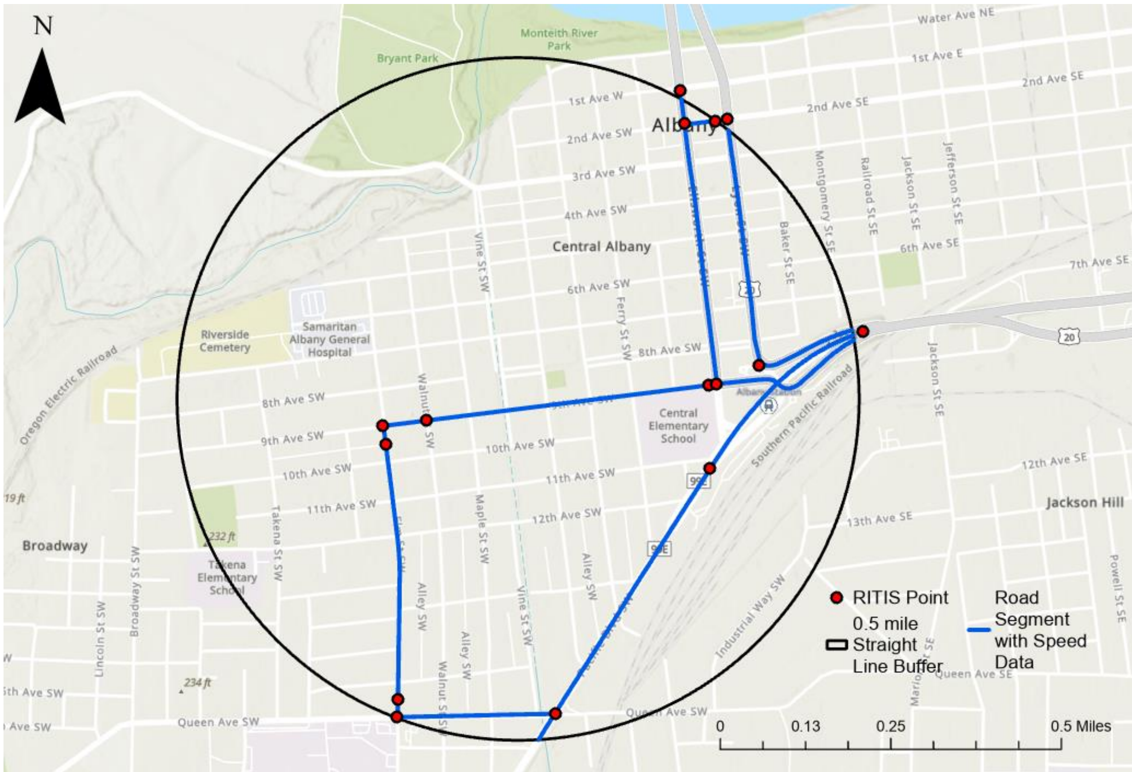


Table 4-17 Number of Actual Speed Collecting Routes

Statistics	**Census Block Groups (n= 346)**		**Half-mile Straight-line Buffer (n=514)**	
	Total segment length (miles)	**Number of segments**	**Total segment length (miles)**	**Number of segments**
Average	4.4	8	5.2	21
Std. deviation	7.0	12	3.2	20
Minimum	0.2	1	0.4	1
25^{th} percentile	0.9	4	3.1	5
Median	2.0	9	4.9	16
75^{th} percentile	4.5	19	7.1	32
Maximum	74.1	87	14.5	85

Table 4-18 summarizes the descriptive statistics of weighted and nearest actual speed in 2022. Note that estimating models predict pedestrian crash frequencies by year periods, five years, three years, and one year. I used the aggregated actual speed of each period, 2018-2022, 2020-2022, and 2022.

Table 4-18 Actual Speed in 2022 (0.5-mile straight-line buffer)

n=514, unit: mph

Statistics	**Actual Speed (weighted)**		**Actual Speed (nearest)**	
	50th	**85th**	**50th**	**85th**
Average	29.2	33.0	27.1	30.6
Std. deviation	5.4	5.5	9.5	9.8
Minimum	18.0	21.0	7.0	9.0
25th percentile	24.9	29.0	22.0	24.0
Median	27.7	32.2	26.0	30.0
75th percentile	32.1	36.1	30.0	34.0
Maximum	46.8	50.6	66.0	69.0
Skewness	0.7	0.6	2.0	1.8
Kurtosis	-0.3	-0.3	5.9	5.0

5 Risk Factors Affecting Pedestrian Crashes

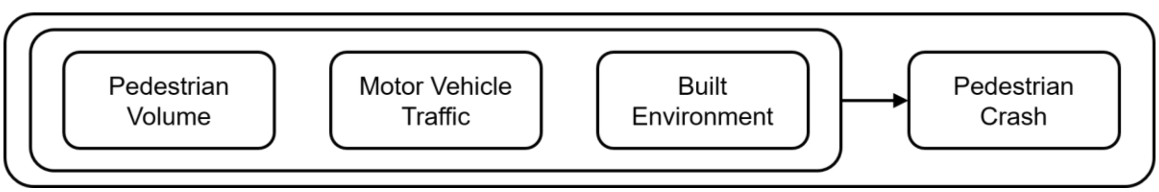
5.1 Research Purpose & Question 1: Crash Risk Factors

5.1.1 Two Research Purposes for Finding Better Crash Risk Factors

This study starts by asking whether crash risk factors and actual crashes affect pedestrians' perceived safety and walking behavior. Before answering this question, it is necessary to define crash risk factors and investigate whether they can explain pedestrian crashes in the research sites of this study. This is because crash risk factors vary by regional characteristics (e.g., state or city) and the size of the analysis spatial unit (e.g., micro-level or macro-level).

The first research question aims to test crash risk factors at the macro level. Figure 5-1 shows the part of the overall conceptual framework that includes the first research question, which, along with this framework, links with the research questions in the following chapters.

Figure 5-1 Research Question 1 Conceptual Framework



For analysis, the characteristics of crash risk factors are needed to be aggregated by spatial unit. Macro-level crash analysis, such as neighborhood, census block group, city, or county level, differs from the micro-level crash analysis, including crash cases at intersection or short road segment level. Micro-level crash studies have focused on spatially more detailed factors: traffic volume at intersections, number of road lanes, individual characteristics of road users involved in crashes, time of day, weather, and light conditions (Al-Mahameed et al., 2019; Haleem et al., 2015; Lee & Abdel-Aty, 2005; Toran Pour et al., 2018; G. Zhai et al., 2022; Zhai et al., 2019). On the other hand, macro-level crash studies consider spatially more aggregated factors: spatially aggregated traffic volume, land use, overall demographic characteristics of residents, and road network (Almasi et al., 2021; Chen & Zhou, 2016; Cho et al., 2009; Ding et al., 2018; Lee et al., 2017, 2019; Schneider et al., 2021; Ukkusuri et al., 2012; Wang et al., 2016). I tested crash risk factors at the macro level, which is defined as a census block group since pedestrians are generally affected by surrounding environments while walking to multiple places, not only a single road network or an intersection.

Another purpose of this first research question is to test whether pedestrian count can explain pedestrian crashes better than population density. As explained in the previous sections, 2.2.1 Pedestrian Exposure and 3.1 Research Gap, collecting pedestrian count data can be challenging, although pedestrian volume is one of the most important predictors of pedestrian crashes (Griswold et al., 2019). Instead of pedestrian count, proxies of pedestrian volume, such as population density, have been used to predict pedestrian crash probability (Al-Mahameed et al., 2019; Almasi et al., 2021; Cho et al., 2009; Lee & Abdel-Aty, 2005; Raford & Ragland, 2004). Recent studies have started to utilize reliable actual pedestrian count data for predicting pedestrian crashes (Gill et al., 2022; Mahmoud et al., 2021; Schneider et al., 2021). Thus, two pedestrian crash model results were compared using actual pedestrian count and population density.

5.1.2 Research Question 1: Crash Risk Factors

My first research question is to test crash risk factors and investigate whether they can explain pedestrian crash cases in the research sites, i.e., the selected census block groups in the state of Oregon. I measured pedestrian volume in two ways: using actual pedestrian counts in 2022 and scaling them by year for estimating pedestrian counts in previous years, 2018-2021, and using population density as a proxy. My detailed research questions for this chapter are as follows.

- Which crash risk factors are statistically significant in explaining pedestrian crashes in the selected census block groups?
- Does pedestrian count data as the measurement of pedestrian volume explain pedestrian crashes better than population density?

5.2 Analysis Methods

The following paragraphs explain spatial and temporal analysis units for this first research question and also explain what data is utilized to measure two volume variables, pedestrian and motor vehicle traffic. Furthermore, better model selection methods are explained regarding the zero cases in the pedestrian crash models.

5.2.1 Analysis Unit

For the first research question, I used reported crash data in 346 census block groups around 65 signalized intersections where the pedestrian count data was collected. Regarding temporal units, the cumulated crash cases for one year or more are mostly predicted in crash analysis. I compared the model results of the crashes for one year (2022), three years (2019-2022), and five years (2018-2022).

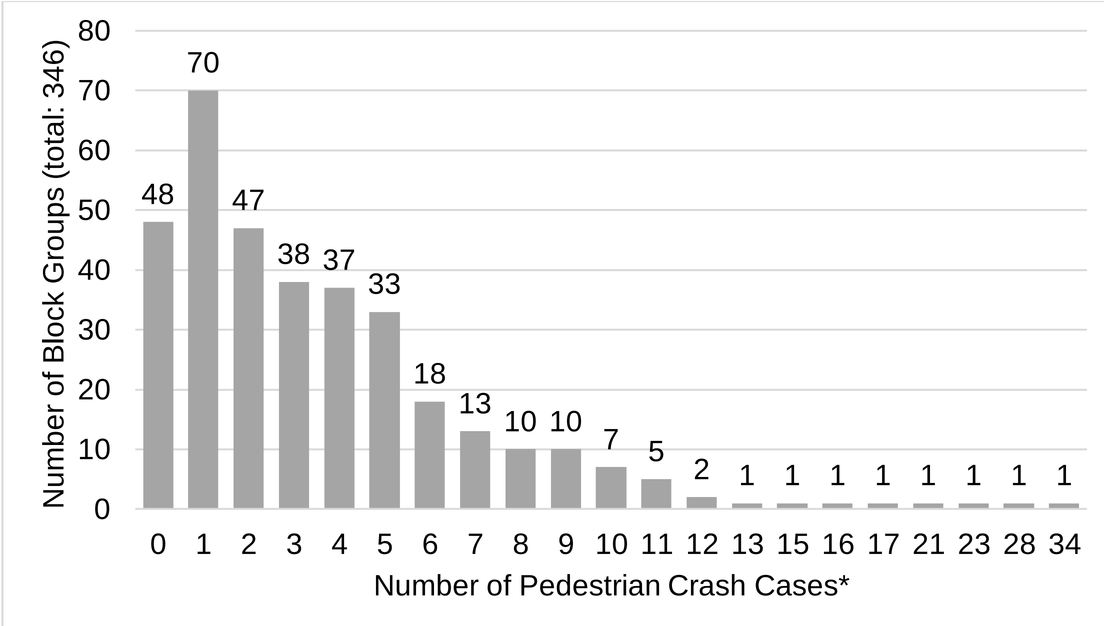
5.2.2 Comparing Volume Data: Pedestrian Volume & Motor Vehicle Traffic

To answer the second research question of this chapter, models using pedestrian count (the number of pedestrian per day) data were compared with models using population density. In addition, since motor vehicle traffic is one of the most significant variables in predicting crashes, the method used to measure motor vehicle traffic can affect the model result and the model fit. Therefore, I found the best model that described the data by comparing eight different vehicle traffic volumes divided by three criteria: type of data included, method of volume aggregation (average or maximum), and road classification criteria (including interstate or excluding interstate). Additionally, macro-level built environmental factors were tested to predict pedestrian crash frequency in three periods, five-year, three-year, and one-year, by census block group. For selecting better models, models were compared based on the Akaike information criterion (AIC), the Bayesian Information Criterion (BIC), and pseudo-R-squared values (Cameron & Trivedi, 1998; Cameron & Windmeijer, 1996).

5.2.3 Zero-valued Cases & Model Selection

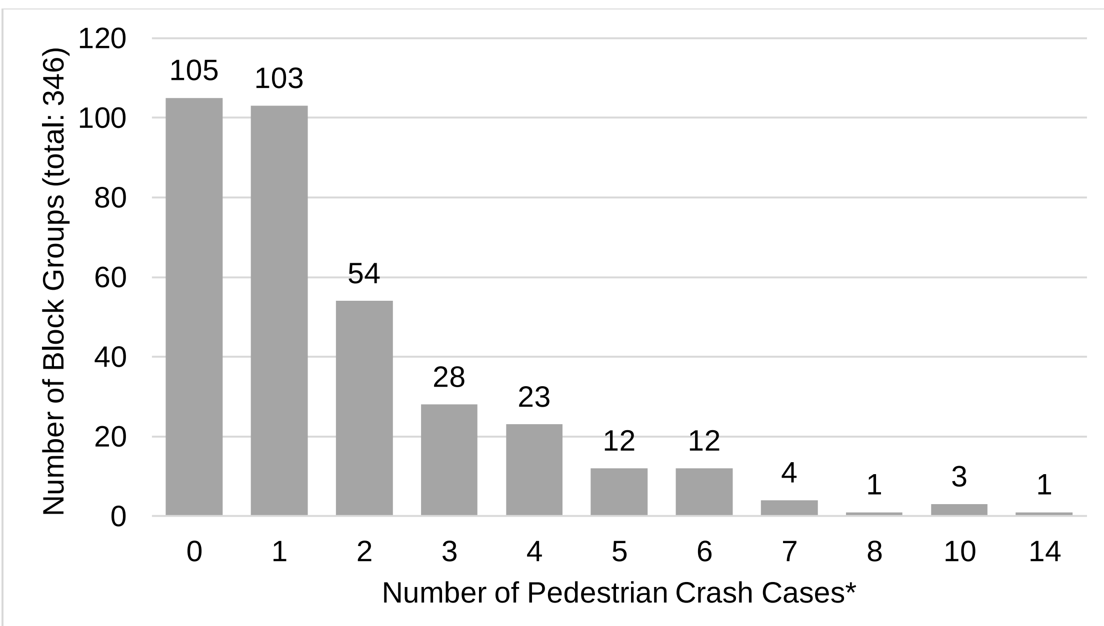
Based on spatial and tempoal analysis units, zero-valued cases of pedestrian crashes that occurred for five years (2018-2022) and three years (2020-2022) were not excessive, as shown in the following histograms (Figure 5-2**,** Figure 5-3) although many block groups have zero cases of pedestrian crashes for one year, 2022 (Figure 5-4).

Figure 5-2 Pedestrian Crashes by Census Block Group: 5-year (2018-2022)



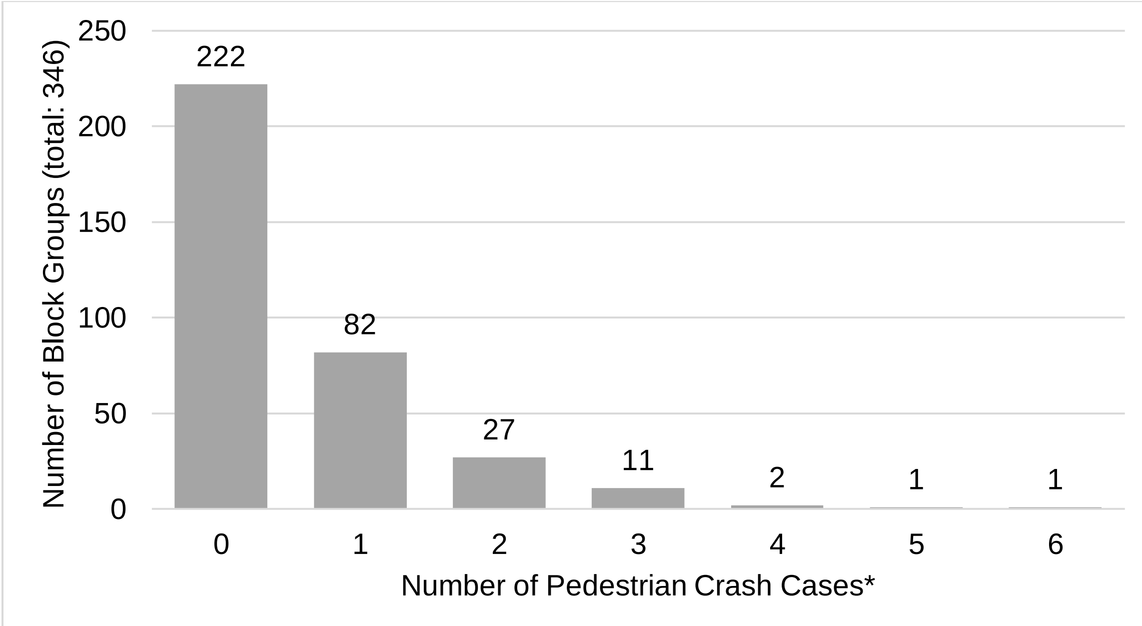
* Average of pedestrian crash cases by Census Block Groups: 3.69 (standard deviation: 3.99)

Figure 5-3 Pedestrian Crashes by Census Block Group: 3-year (2020-2022)



* Average of pedestrian crash cases by Census Block Groups: 1.73 (standard deviation: 2.01)

Figure 5-4 Pedestrian Crashes by Census Block Group: 1-year (2022)



* Average of pedestrian crash cases by Census Block Groups: 0.54 (standard deviation: 0.90)

The Poisson and negative binomial families can deal with large numbers of zero values in the dataset, especially where the number of zero cases is less than the peak (one or more value cases) (Green, 2021; Warton, 2005; Xie et al., 2013). However, data distribution is difficult to use as a firm ground for model selection. So, the following strategy is used to select a better model.

To select better models, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) can be utilized. For both AIC and BIC, models with smaller values are better at predicting or explaining data. However, AIC and BIC values may tend to differ when comparing models. For example, one of the models with a smaller

AIC may have a larger BIC. In this case, a model with a smaller BIC was selected for this study. AIC determines how well a model can predict, while BIC determines how well a model can explain the data (Chakrabarti & Ghosh, 2011; Shmueli, 2010). Because this study aimed to determine how well the model explains pedestrian crashes using data and variables, a model with a smaller BIC was ultimately selected.

This study compared four different models: Poisson regression, negative binomial regression, zero-inflated Poisson regression, and zero-inflated negative binomial regression. Table 5-1 and Table 5-2 summarize the AIC and BIC of each model by period (year) and type. Table 5-1 summarizes the AIC and BIC of the models using the pedestrian count, and Table 5-2 summarizes the AIC and BIC of the models using the population density. Negative binomial regression models (one of the generalized linear regression models) of each period have smaller BIC; however, in only the case of the one-year model using population density, zero-inflated Poisson regression has smaller BIC. Note that pedestrian volume and motor vehicle traffic variables are used to predict excess zeros in two types of zero-inflated models. Although the zero-inflated Poisson model is a better fit in terms of BIC for a one-year model using population density, for the consistency of comparing models, the results of all models were compared using the results of negative binomial regression models.

Table 5-1 Model Selection: Pedestrian Count

Distribution	Model Type	5-year		3-year		1-year	
		AIC	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
Poisson	GLM*	1726	1764	1220	1258	673	711
	Zero-Inflated	1694	1744	1198	1248	666	716
Negative Binomial	GLM*	1556	1598	1169	1211	665	707
	Zero-Inflated	1550	1604	1163	1217	664	718

* Generalized Linear Model

Table 5-2 Model Selection: Population Density

Distribution	Model Type	5-year		3-year		1-year	
		AIC	**BIC**	**AIC**	**BIC**	**AIC**	**BIC**
Poisson	GLM*	1728	1766	1229	1267	674	713
	Zero-Inflated	1687	1737	1210	1260	649	699
Negative Binomial	GLM*	1556	1599	1175	1217	666	708
	Zero-Inflated	1555	1609	1170	1224	647	701

* Generalized Linear Model

5.3 Results

5.3.1 Descriptive Statistics (spatial unit: census block group)

Table 5-3 summarizes descriptive statistics of variables of 346 census block groups: pedestrian crashes, pedestrian count, population density, and motor vehicle traffic; have three values by time-period (five-year: 2018-2022, three-year: 2020-2022, and one-year: 2022). Other built environment factors each except actual speed in Table 5-4 were measured in a single time: intersections, public transit stops, three types of land use (park, mixed-use land area, and commercial land area), speed limit (weighted by road length and maximum), and actual speed (50^{th} and 85^{th} of vehicle speed) by time-period.

Table 5-3 Descriptive Statistics: Pedestrian Crash & Volumes

n=346

Statistics		Min.	Median	Max.	Ave.	Std. dev.
Pedestrian Crash	5 years	0	3	34	3.7	4.0
	3 years	0	1	14	1.7	2.0
	1 year	0	0	6	0.5	0.9
Pedestrian Count	5 years	5	251	1,207	379	314
	3 years	5	249	1,242	380	315
	1 year	5	250	1,250	379	313
Population Density (persons/mi^2)	5 years	5	5,074	79,206	6,539	7,898
	3 years	5	5,069	78,772	6,543	7,858
	1 year	5	5,042	77,690	6,505	7,761
Motor Vehicle Traffic	5 years	52	17,065	167,330	26,554	33,569
	3 years	54	17,503	165,460	26,173	32,618
	1 year	57	17,593	166,664	26,275	32,807

Table 5-4 Descriptive Statistics: Built Environment

n=346

Statistics		Min.	Median	Max.	Ave.	Std. dev.
Intersection		4	41	382	63.2	40.8
Transit Stop		0	5	83	7.9	9.2
Land Use (%)	Park	0	0	65	5.4	10.9
	Mixed-use	0	2	100	15.0	26.1
	Commercial	0	0	51	3.7	8.0
Speed Limit	Weighted*	18	27	62	28.4	7.0
	Maximum	20	45	70	43.9	11.8
Actual speed (50th) *	5 years	3	28	67	29.8	12.2
	3 years	6	28	69	30.3	12.2
	1 year	7	28	70	30.7	12.0
Actual speed (85th) *	5 years	4	31	72	33.2	12.5
	3 years	7	31	72	33.9	12.3
	1 year	9	32	72	34.2	12.2

* This speed limit is aggregated by road length weight.

5.3.2 Correlation Analysis: Pedestrian Crashes & Risk Factors

Table 5-5 summarizes the bivariate correlation between the cumulated pedestrian crashes over the past five years (2018-2022) and traffic volume-related variables. Table 5-6 shows the bivariate correlation between pedestrian crashes and the built environment.

Pedestrian count significantly and positively correlated with pedestrian crashes, and motor vehicle volume also positively correlated with pedestrian crashes, while population density did not. Population density was positively correlated with the pedestrian count and negatively correlated with motor vehicle traffic (Table 5-5).

Table 5-5 Bivariate Correlation: Pedestrian Crash & Volume

5-year (2018-2022)

Variable	Pedestrian Crash	Pedestrian Count	Population Density	Motor Vehicle Traffic
Pedestrian Crash	1			
Pedestrian Count	0.089*	1		
Population Density	-0.027	0.25***	1	
Motor Vehicle Traffic	0.18***	-0.015	-0.1*	1

‘ ’ p <1 ‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001

Table 5-6 shows that the built environment variables were also positively correlated with the pedestrian crashes including intersections, public transit stops, and all three types of land use (park, mixed-use land, and commercial land). Although speed-related variables were not statistically significantly correlated with pedestrian crashes, higher speed limits, and faster vehicle speeds were negatively correlated with pedestrian count and population density while they are positively correlated with motor vehicle traffic.

Table 5-6 Bivariate Correlation: Pedestrian Crash & Built Environment

5-year (2018-2022)

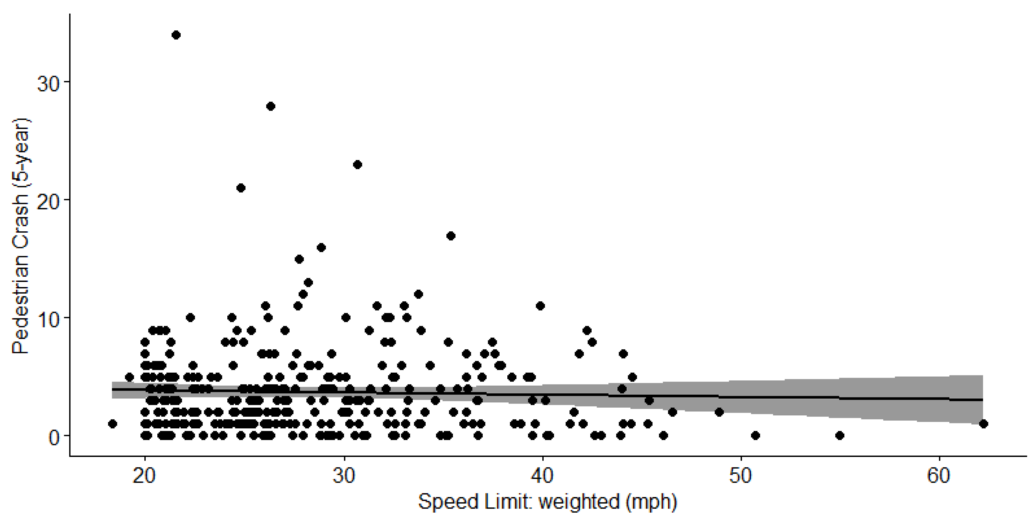
Variable		Pedestrian Crash	Pedestrian Count	Population Density	Motor Vehicle Traffic
Intersection	n	0.13*	-0.12*	-0.39***	0.04
	normalized by area: (n/mi^2)	0.13*	0.41***	0.69***	-0.12*
	normalized by road length: (n/mi)[1]	0.063	0.30***	0.53***	-0.25***
Public Transit Stop	n	0.43***	0.05	-0.12*	0.24***
	normalized by area: (n/mi^2)	0.29***	0.28***	0.53***	0.0014
	(normalized by road length: n/mi)[1]	0.32***	0.25***	0.41***	0.05
Park (%)		0.17**	0.06	-0.09	0.10^{+}
Mixed-use (%)		0.27***	0.21***	0.6***	0.15**
Commercial (%)		0.16**	-0.18***	-0.13*	0.03
Speed limit	Weighted	-0.033	-0.27***	-0.37***	0.29***
	Max	0.043	-0.26***	-0.4***	0.32***
Actual speed (50^{th})[1]		-0.030	-0.19***	-0.31***	0.20***
Actual speed (85^{th})[1]		-0.017	-0.18***	-0.31***	0.22***

‘ ’ *p* <1, ‘+’ *p* <0.1, ‘*’ *p* <0.05, ‘**’ *p* <0.01, ‘***’ *p* <0.001

[1] This variable value is normalized by road length.

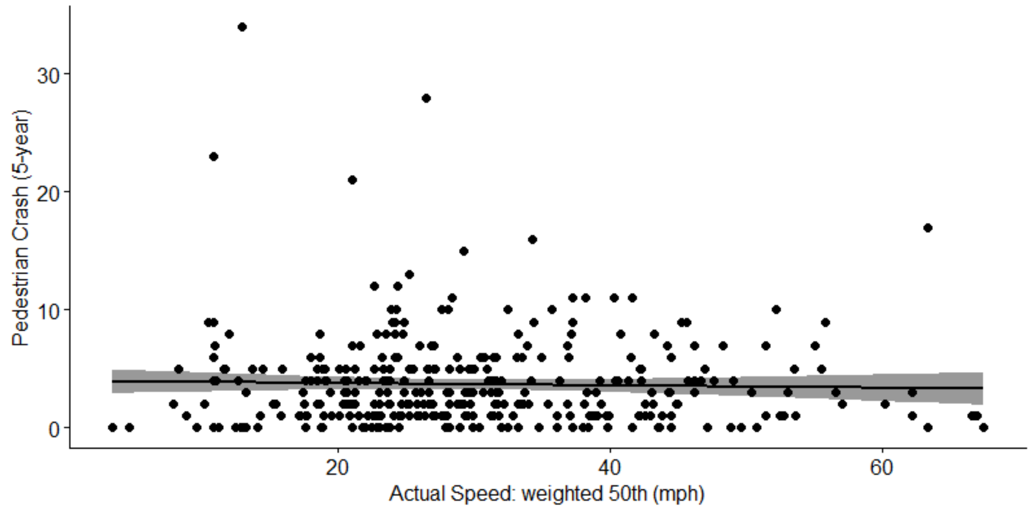
As shown in Figure 5-5 and Figure 5-6, pedestrian crashes have occurred at both speed limits and actual speeds, ranging from low to high. Considering that speed limits and actual speeds are influenced by road classification and motor vehicle traffic, it can be seen that pedestrian crashes occur in various classifications of roads. However, many pedestrian crashes occurred within the speed limit and actual speed range between 20 and 40mph (Figure 5-5 and Figure 5-6). This may imply that pedestrians mostly walk near roads with speed limits and actual speeds between 20 and 40mph, although they can access roads with higher speed limits and faster vehicles. This assumption is supported by the bivariate correlation results between pedestrian count and speed limit and between pedestrian count and actual speeds. In addition to the relationships between pedestrian count and speeds, population density negatively correlates with speed limits and actual speeds. This means more people lived in areas where vehicles moved at lower speeds.

Figure 5-5 Bivariate Correlation: Speed Limit & Pedestrian Crash (5-year)



γ= -0.033, p-value=0.54

Figure 5-6 Bivariate Correlation: Actual Speed (50th) & Pedestrian Crash (5-year)



γ= -0.03, p-value=0.58

5.3.3 Pedestrian Crash Estimation Models by Periods

Table 5-7 summarizes the results of negative binomial regression models using pedestrian count for three periods: five-year, thee-year, and one-year. In all three pedestrian crash models, motor vehicle traffic, the mixed-used land area ratio (%), and the commercial land area ratio (%) had significant relationships with pedestrian crashes.

The number of intersections, speed limit, and actual speed were not statistically significant (or marginally significant) in predicting pedestrian crashes in all three models. While the number of intersections was significantly positively correlated with the pedestrian crashes in the bivariate correlation analysis, it was not statistically significant in the negative binomial regression when controlled by other risk factors in the model. I also tested the normalized number of intersections by road length, which was also not statistically significant in all three models.

Overall, among the three models, the five-year and three-year models had almost the same significant variables and signs of the coefficients. However, the one-year model results slightly differed from the results of five-year and three-year models. The pedestrian count and public transit stop were not statistically significant in predicting pedestrian crashes for one year. The park area ratio was only significant in the one-year model.

Table 5-7 Negative Binomial Results with Pedestrian Count

coefficients estimate

Variables	**5-year Model**	**3-year Model**	**1-year Model**
Pedestrian Count (Ln)	0.127**	0.153**	0.097
Motor Vehicle Traffic (Ln)	0.141***	0.200***	0.227**
Intersection	0.001	0.001	0.004^{+}
Public Transit Stop	0.028***	0.021**	-0.001
Park area (%)	0.005	0.006	0.023***
Mixed-use area (%)	0.010***	0.009***	0.013***
Commercial area (%)	0.030***	0.026***	0.029**
Speed limit (weighted)	-0.016^{+}	-0.007	0.004
Actual speed (weighted 50^{th})	0.003	0.001	-0.004
n	346	346	346
pseudo-R^2	0.31	0.22	0.15

‘ ’ p <1‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001

Table 5-8 shows the results of the model using population density. Population density was significant in predicting five-year pedestrian crashes. However, this proxy was not statistically significant in three-year and one-year models. Regression results of other variables are similar to those of pedestrian count models. More motor vehicle traffic, mixed-use land area, and commercial land area significantly predicted more pedestrian crashes, while speed limit and actual speed did not. Unlike the models with the pedestrian count, the number of intersections significantly predicted pedestrian crashes in five-year and one-year (marginally) models.

Table 5-8 Negative Binomial Results with Population Density

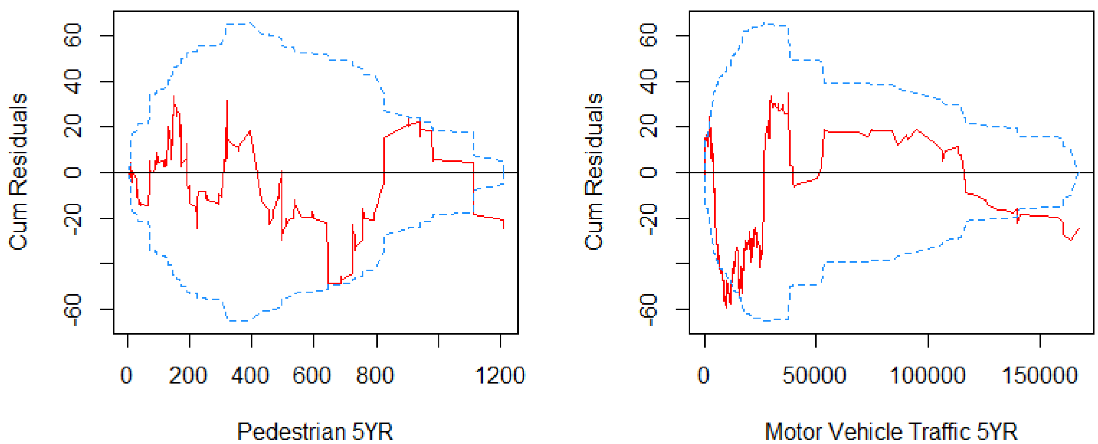
coefficients estimate

Variables	5-year Model	3-year Model	1-year Model
Population Density (Ln)	0.151**	0.071	0.083
Motor Vehicle Traffic (Ln)	0.144***	0.206***	0.229**
Intersection	0.003*	0.002	0.005^{+}
Public Transit Stop	0.028***	0.021***	-0.001
Park area (%)	0.007^{+}	0.008	0.025***
Mixed-use area (%)	0.009***	0.009***	0.013***
Commercial area (%)	0.025***	0.022***	0.026**
Speed limit (weighted)	-0.004	-0.004	0.010
Actual speed (weighted 50^{th})	0.003	0.001	-0.004
n	346	346	346
pseudo-R^2	0.31	0.20	0.15

‘ ’ p <1‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001

Figure 5-7 shows that the cumulated residuals (the red line) of the pedestrian count (number of pedestrians per day) and the motor vehicle traffic were mostly within the two-sigma of cumulated residuals (the blue dotted line). However, the left side plot in Figure 5-7 shows that the cumulated residuals of pedestrian count of more than 1,100 were beyond the range of two sigma. This means that more than 1,100 pedestrians may not predict cumulated pedestrian crash frequency by census block groups (Cameron & Trivedi, 1998). The right-side plot in Figure 5-7 shows that the cumulated residuals of motor vehicle traffic of more than 130,000 were not within the range of two-sigma. This also means that more than 130,000 motor vehicle traffic may not predict precisely cumulated pedestrian crashes by census block groups (Cameron & Trivedi, 1998).

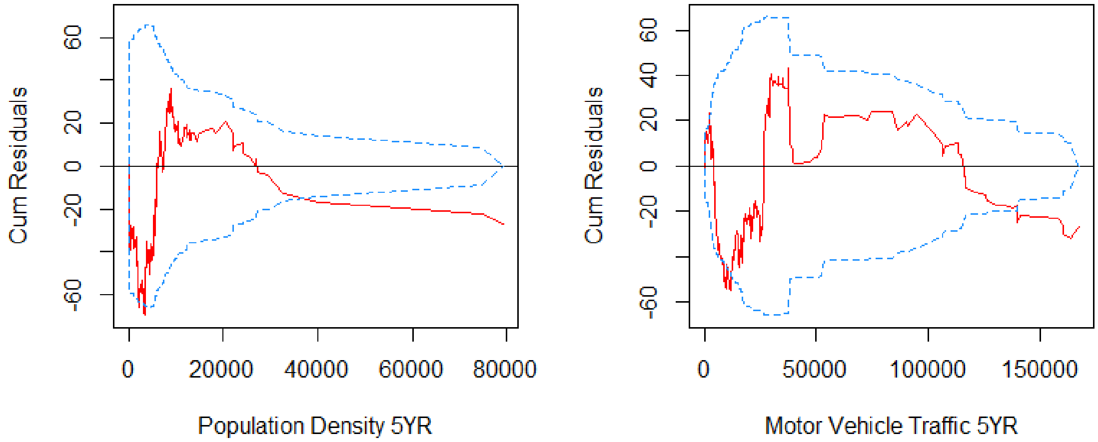
Figure 5-7 Cumulative Residual Plots (5-year model): Pedestrian Count



On the other hand, Figure 5-8 shows that, the cumulated residuals (the red line) of the population density of more than about 40,000 persons per square mile were off from the two-sigma of cumulated residuals (the blue dotted line). This means that more than about 40,000 population density may not precisely predict pedestrian crashes (Cameron & Trivedi, 1998) while the tendency of motor vehicle traffic cumulative residual plot (CURE plot) was almost the same as the result in Figure 5-7. Note that only three census block groups had over 40,000 population density in the sample. Although excessively high population density can be considered outliers in the sample, this still implies that a place with a higher population density than the surrounding places can expect fewer pedestrian crashes.

The CURE plots of other models, three-year and one-year, are almost the same as the plot of the five-year model; however, both pedestrian count and population density plots show that three-year and one-year models have slightly more ranges of pedestrian volume and motor vehicle traffic that may not precisely predict the pedestrian crashes. It can be implied that more accurate crash frequency predictions can be made by cumulating the number of pedestrian crashes over a longer period of time.

Figure 5-8 Cumulative Residual Plots (5-year Model): Population Density



5.4 Discussion

In this chapter, crash risk factors were tested to determine whether they can be statistically significant in explaining the cumulated pedestrian crashes. Three main points from the model results are as follows:

1. Pedestrian Volume: Pedestrian count explained pedestrian crashes better than population density.
2. Intersections and speeds: Intersections are likely places where pedestrians can encounter vehicles, and other research has found that the higher the vehicle speed, the greater the likelihood of crashes with pedestrians. However, these are not statistically significant in explaining the number of cumulated pedestrian crashes in this chapter.
3. Public transit stop and land use: Public transit stops and land use types explained the pedestrian exposures and the likelihood of their crashes that other variables did not cover.

First, higher pedestrian counts were significantly related to more pedestrian crashes in five-year and three-year models. This is consistent with findings in the previous studies (Al-Mahameed et al., 2019; Gill et al., 2022; Mahmoud et al., 2021). On the other hand, the population density was significant in predicting pedestrian crashes only in the five-year model. Although this pedestrian count data was collected in only two days, it can explain two different time periods of cumulated pedestrian crashes. This result may implty that the pedestrian count is better to explain the cumulated the number of pedestrian crashes for more than one year at the macro level with using the same explanatory variables. However, this does not mean that population density cannot explain the probability of pedestrian crashes. Several previous studies used population density as a proxy for measuring pedestrian volume and found significant results with the population density (Chimba et al., 2018; Raford & Ragland, 2004; Ukkusuri et al., 2012).

There are likely to be more pedestrians in densely populated areas; however, this does not mean that higher population density necessarily causes more pedestrian crashes. Population density may relate more to other factors, especially residential land areas, which are less likely to be destinations by walking. In addition, higher population density may relate to road classification, with fewer motor vehicle traffic. This can be supported by the fact that higher population density correlates with less motor vehicle traffic (Table 5-5), another essential crash predictor. In other words, the reduced motor vehicle traffic in places with higher population density may reduce the effect of pedestrian exposure that causes pedestrian crashes. Based on this result, I can conclude that pedestrian counts, which explain pedestrian activity more precisely, should be collected regularly at more sites, like motor vehicle traffic data (AADT or VMT). It helps to conduct more accurate pedestrian crash analysis, which is fundamental for improving pedestrian safety.

Next, intersection and speed-related variables are not statistically significant in explaining the number of cumulated pedestrian crashes, although previous studies referred to these as important crash risk factors (Hussain et al., 2019; Lee & Abdel-Aty, 2005; Lee et al., 2015, 2017; Schneider et al., 2004, 2021). Depending on road classification and surrounding land use, this may be due to the relationship between intersection and speed. For example, if local roads are connected with more intersections, they can be more accessible to pedestrians since they have fewer and slower vehicles because of the characteristics of the roads. In other words, increasing the number of intersections may imply improved pedestrian accessibility while inducing fewer vehicles and slower vehicle speeds. In addition, regarding speed, pedestrian crashes occur in a wide range of vehicle speeds and may cause speed variables to be not statistically significant in the model.

Lastly, public transit stops and land use variables, especially mixed-use land and commercial land areas, explained the pedestrian crashes. It is difficult to assert that more transit stops directly increased the number of pedestrian crashes. However, public transit stops can explain the exposure effect, which cannot be explained only by pedestrian and motor vehicle traffic. Previous studies have also referred to the importance of this factor (Chen & Zhou, 2016; Cho et al., 2009; Clifton et al., 2009; Mfinanga, 2014; Mukherjee & Mitra, 2019; Schneider et al., 2004; Zegeer & Bushell, 2012). In addition to the public transit factor, land use types also explained the exposure effect. More mixed-use land areas and commercial areas are expected to induce activities of both pedestrians and drivers (Chen & Zhou, 2016; Loukaitou-Sideris et al., 2007; Priyantha Wedagama et al., 2006; Pulugurtha & Sambhara, 2011; Ukkusuri et al., 2012).

Despite the unique findings from this first research question, several limitations could be improved upon in future research. First, although the number of pedestrians may differ by intersection, only one or two pedestrian counts represented the pedestrian volume of each census block group, which has multiple intersections. This measurement limitation can be overcome if it is possible to collect the pedestrian counts at more places in future research.

In addition, motor vehicle traffic in this study may not fully account for the amount of traffic volume that pedestrians may encounter. Since the maximum traffic volume within a unit was used in the final models, the detailed traffic volumes may not be considered in the model if traffic measured on interstates or freeways within or very close to the census block group was included. Considering pedestrians are less likely to access interstates or freeways, the maximum traffic volume may not perfectly represent the traffic volume that pedestrians usually encounter. Therefore, if there are methods that can offset these measurement errors, it will be possible to more accurately measure the amount of traffic that pedestrians may encounter, thereby predicting pedestrian crashes more accurately and improving the safety of road users with different speeds. Rather than directly measuring traffic counts, traffic volume may be measured by road classification, number of road lanes, road width, etc. In particular, the number of road lanes at an intersection where pedestrians cross may correlate with road classification and traffic volume. Instead of relying on measuring traffic volume at a specific location, it is possible to indirectly measure traffic volume with road segment length or the number of road lanes by road classification.

Next, this study includes pedestrian crashes during the COVID-19 pandemic. Slight inconsistencies between model results may come from the influence of the pandemic. In models, motor vehicle traffic reflected changes in volume due to the pandemic, but pedestrian counts were only measured in 2022. The number of pedestrians from 2018 to 2021 may differ from the actual number of pedestrians because it was scaled from the population changes by city, and this estimation may affect model results. This limitation can be overcome when pedestrian volumes are regularly measured in more places.

6 Factors Affecting Perceived Safety

6.1 Research Question 2: Perceived safety

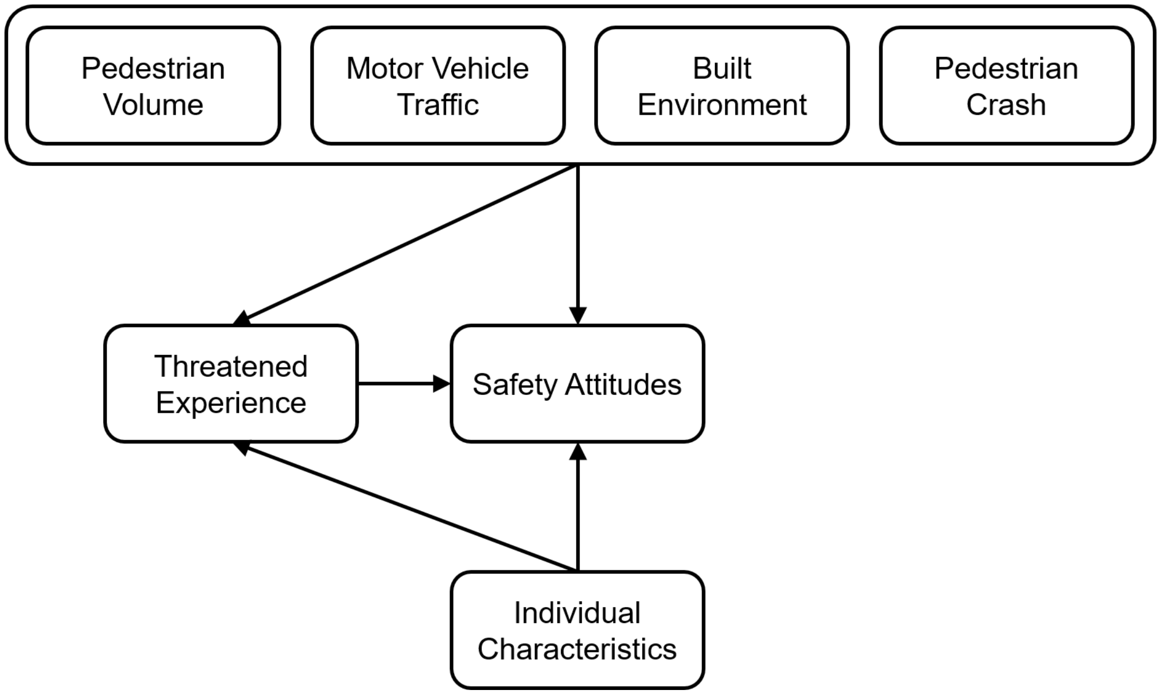
This research aims to examine whether pedestrians accurately perceive crash risk factors and whether these perceptions affect their walking behavior. In the previous chapter, I tested whether crash risk factors can predict actual pedestrian crashes in Oregon. Following this test, I investigated how crash risk factors and crashes affect pedestrians' perceived safety. The next chapter completes the analysis by testing how perceived safety affects walking behavior.

For this analysis, I assume that actual crashes could indirectly measure possible risks that are not measured by other crash risk factors, such as interactions between road users and micro-level facility influence (Chaurand & Delhomme, 2013; Cho et al., 2009). I subdivided pedestrians' perceived safety into threatened experiences and safety attitudes. Terminology and measuring methods of perceived safety vary depending on researchers. However, as I previously defined, the perceived safety in this study includes awareness of external stimuli and judgment of possible risks based on possibilities of controlling those risks. Threatened experiences in this study refer to pedestrians' experiences in which they perceive a dangerous situation while walking that may occur due to uncontrolled surrounding circumstances, especially a possible crash with a vehicle. This is an experience that pedestrians recognize may be more dangerous than the permitted risk (Proske, 2019) defined in the section 2.1. Safety attitudes refer to pedestrians' attitudes about their safety when walking in their neighborhood.

Threatened experiences while walking are measured by adding scores of 15 items related to pedestrian facilities and the behavior of other road users. Note that 15 items are listed in Figure 4-9 and Figure 4-10 in section 4.4.3. Safety attitudes are measured by asking about people's thoughts on nine items affecting walking safety. After factor analysis, seven items among nine were made into one latent variable. Survey items are listed in Figure 4-11 in section 4.4.3.

The accumulation of personal experience influenced by various external environmental or personal factors may affect safety attitudes (Johansson et al., 2016; Liao et al., 2022; Lyu & Forsyth, 2021; Mukherjee & Mitra, 2019; van der Vlugt et al., 2022). Thus, I divided pedestrians' perceived safety concept into 'threatened experiences' and 'safety attitudes' and measured them. I assume these are affected by external crash risk factors and individual characteristics. In terms of individual characteristics, individual-level factors can influence perceptions and behaviors as confounding factors (Cho et al., 2009; Mesch, 2000). It is also possible that individual characteristics can be considered moderators of relationships between crash risk factors and perceptions. Although they were tested as moderators in models, the data of this research did not fit well when selected individual characteristics were moderators to explain the relationships between risk factors and perceptions in the model. So, individual characteristics, including age, gender, etc, control two perceived safety concepts, threatened experiences and safety attitudes, as confounding factors. Figure 6-1 shows the part of the overall conceptual framework that covers my second research question.

Figure 6-1 Research Question 2 Conceptual Framework



The main research question for this chapter is: do pedestrian and motor vehicle traffic, built environment, and crashes affect pedestrians' threatened experiences and safety attitudes? More specifically:

1. Can crashes, in addition to crash risk factors, predict the pedestrian's threatened experiences and safety attitudes?
2. Do pedestrians' threatened experiences affect their safety attitudes?
3. Besides the crash risk factors and crashes, how do individual characteristics affect the perceived safety?

6.2 Analysis Methods

6.2.1 Modeling Method & Possible Issue

In this section, I explain the analysis method and spatial unit of analysis for the second research question, which differs from the previous chapter. This section also explains how I solve the possible issues in analysis because of the spatial unit and analysis method. Lastly, I explain why I estimated four different model types by crash variables.

6.2.1.1 Structural Equation Modeling (SEM)

Structural equation modeling (SEM) allows the testing of various statistical models, including regression, path, and confirmatory factor analysis (Kline, 2012, 2016; Schumacker, 2016). Since estimators are normally distributed but have some missing data in the data sample, the full information maximum likelihood (FIML) method is used to compute each set of cases with the same unique pattern of missing values (Arbuckle, 1996). Estimating the model requires more than 400 cases (Savalei & Bentler, 2005). In the SEM, various combinations of exogenous variables are possible, including crash risk, actual crash frequency, and personal characteristics. The final model was decided based on the assumption of relationships between variables, model fit, and multicollinearity. The combination of exogenous variables in SEMs will be explained in more detail in section 6.2.3 after the bivariate correlation results.

6.2.1.2 Spatial Unit of Analysis and Possible Issue in Path Analysis

For the second and third research questions, I defined a neighborhood as a space within a half-mile from one’s mailing address. Because of this spatial analysis unit, ‘crash event’ is not a path analysis (or SEM) mediator. When the pedestrian crash is a mediator in the path model, it causes an issue based on the data bias since crash cases in the same areas will be considered different observations multiple times in crash prediction. Multiple survey responses can be sent from the same street address. For example, multiple adults can answer my survey in the same household, or adults from different house units in the same apartment can participate.

The following two figures schematize the possible issue when the crash variable becomes a mediator in the path analysis (Figure 6-2 and Figure 6-3). In Figure 6-2, the relationships within the grey dash round square show the partial regression model estimating pedestrian crashes. The dependent variable in this model can be duplicated, as shown in Figure 6-3, because of the spatial unit. On the other hand, the dependent variable, i.e., perceived safety (experiences & attitudes) of the other partial part in the path analysis (within the black-lined round square) in Figure 6-2, is not duplicated since these observations are from individual answers. Therefore, I tested the crash as an exogenous variable rather than a mediator in the final model to investigate whether crash risk factors and crash cases affect pedestrians' perceived safety. In the following paragraphs, I will discuss another possible issue in path analysis (measuring speed in macro-level analysis) and an alternative way to deal with this possible problem.

Figure 6-2 Possible Issue in Path Analysis with Duplicated Observations

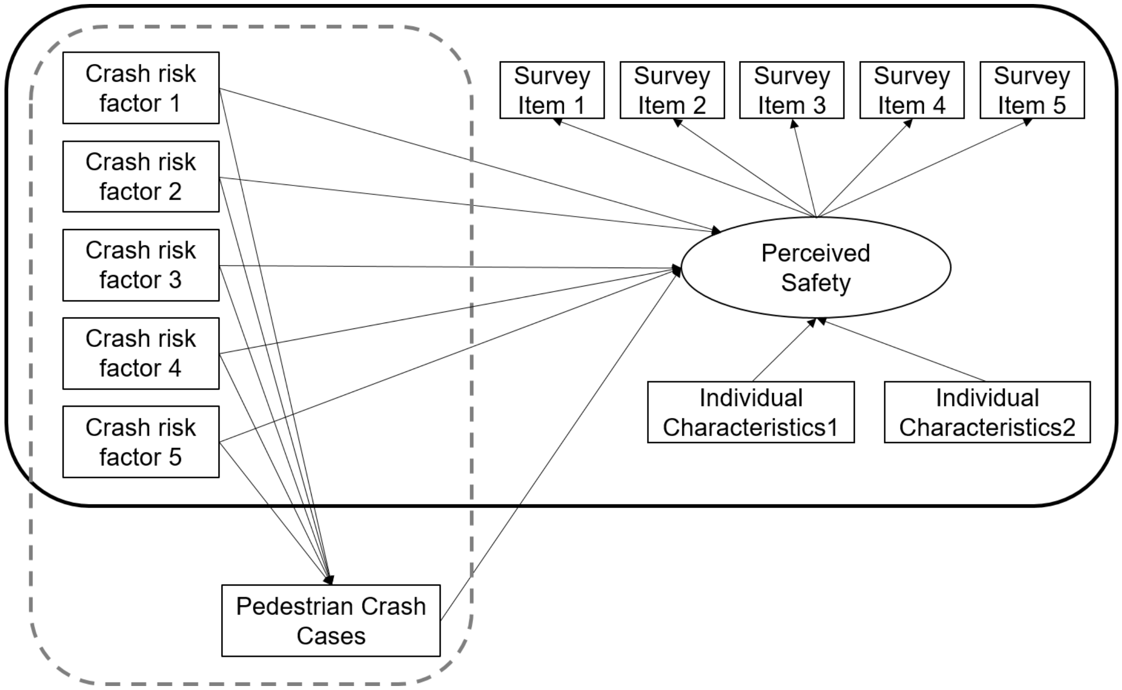


Figure 6-3 Duplicated Observations in Dataset Example

Survey ID	Site ID	Ped. count	AADT	Mixed-use area	Ped. crash	Survey Item 1	Survey Item 2	Survey Item 3	Age	Disability
A001	TG55001	100	3000	15	7	3	3	3	36	0
A002	TG55001	100	3000	15	7	4	3	4	45	0
A003	TG55001	100	3000	15	7	1	2	2	27	0
A004	TG55002	50	2000	3	1	4	4	4	30	0
A005	TG55002	50	2000	3	1	2	1	2	29	0
A006	TG55003	200	5000	25	5	3	4	3	58	1
A007	TG55003	200	5000	25	5	1	2	1	70	0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

6.2.2 Using Actual Speed Rather Than Speed Limit for Estimating Perception

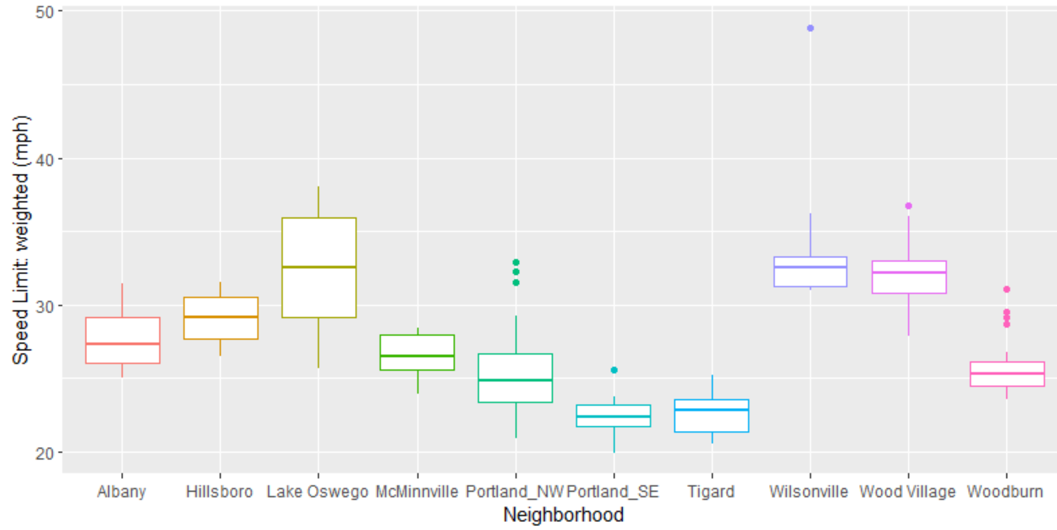
Vehicle speeds, which vary by vehicle, time of day, and road classification, can significantly affect the likelihood of a crash and the severity of injuries (Clifton et al., 2009; Davis, 2001; Haleem et al., 2015; Hussain et al., 2019; Monsere et al., 2017; Rosén et al., 2011; Rosén & Sander, 2009). Posted speed limit and actual speed can be used to measure aggregated vehicle speed at a spatially macro-level. However, it is difficult for pedestrians to accurately perceive the speed of passing vehicles or accurately perceive the speed difference between vehicles (Kwon et al., 2022; Papić et al., 2020; Shi et al., 2020; Sudkamp & Souto, 2023). Because of these reasons, I used only the actual speed in the final model for the second and third research questions. In the following paragraphs, I explain why posted speed limits were not included in the model, but actual vehicle speeds were included in the model for the second and third research questions.

6.2.2.1 Reasons for Excluding Posted Speed Limits

Using speed limit in structural equation models predicting perceived safety had two problems: leading to misinterpretation of model results and multicollinearity. As shown in Table 4-16, the speed limit can be measured in three ways for the half-mile straight-line buffer spatial unit: weighted by road length, maximum speed limit within the unit area, and nearest speed limit from the survey resident's address. Using the weighted speed limit and the nearest speed limit in structural equation models did not show any statistically significant results, as they were not statistically significant for the first research question models in the previous chapter. However, in the models, the maximum speed limit within the half-mile buffer area significantly and negatively correlated with pedestrians' threatened experiences. This result runs counter to my assumption and other research (Aceves-González et al., 2020; Kwon et al., 2022). This result may be due to the spatial unit for measurement (possible measurement error) or due to differences in individual perceptions in each neighborhood (perception mismatch). First, the spatial unit, a half-mile buffer area from the survey respondent's address, can include some roads with higher speed limits that can be less accessible for pedestrians. For example, NW Portland is close to Interstate I-405, but the actual pedestrian paths or sidewalks that residents can walk on are separated from high-speed roadways. In the case of Tigard, the neighborhood is surrounded by arterial roads, but pedestrian paths or sidewalks that residents can walk on are also separated. In these cases, the individual observations in the dataset can have higher maximum speed limits in their neighborhoods, while survey respondents may answer that they feel safer walking on the separate path adjacent to the road with lower speed limits.

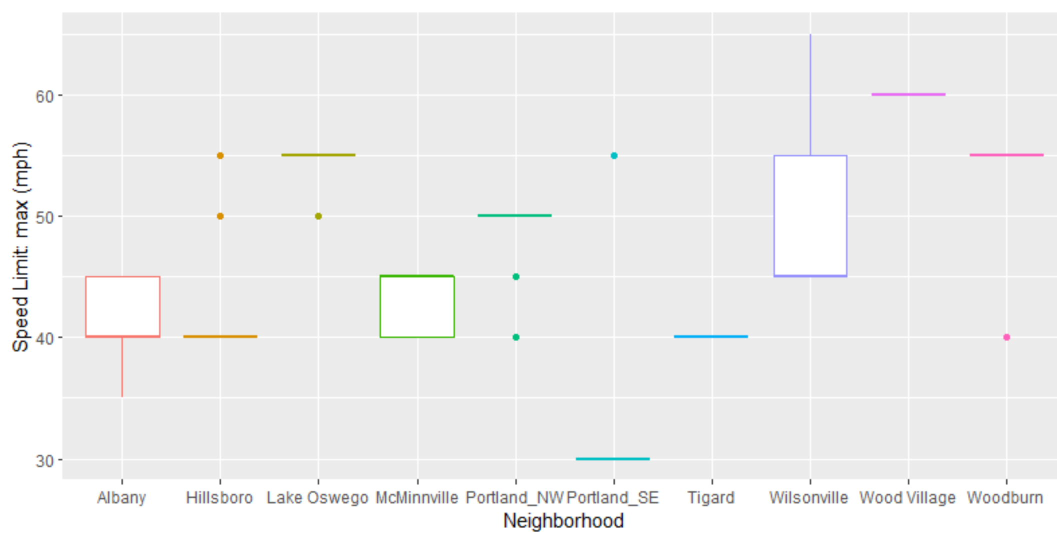
Next, the speed limit variable's result from ten all neighborhoods may differ from the result of each neighborhood since each neighborhood had a different speed limit range (Figure 6-4, Figure 6-5, Figure 6-6). The ANOVA test result shows that the speed limits were significantly different by neighborhood (weighted speed limit: F=189.4, p-value<0.001; max of speed limit: F=329, p-value<0.001; nearest speed limit: F=32.26, p-value<0.001).

Figure 6-4 Speed Limit Range by Neighborhoods: Weighted*



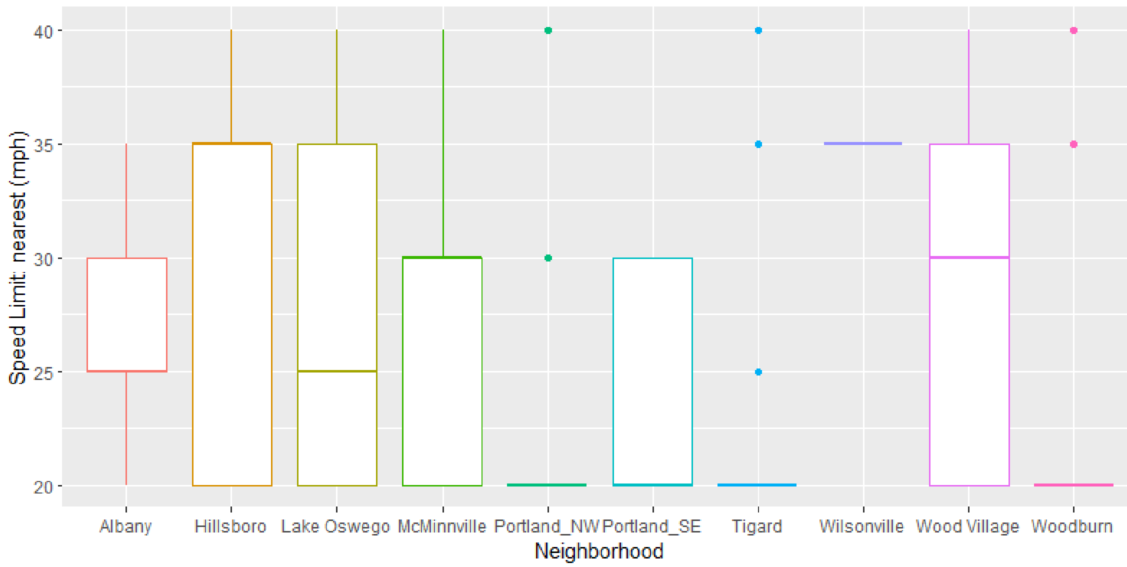
* In this figure, each boxplot shows the 25th percentile to 75th percentile range and the bold line in the middle, which means the median. Whiskers (vertical lines) stand for the rest of the percentile (minimum to 25th percentile and 75th percentile to maximum). Dots in the boxplot mean the outliers.

Figure 6-5 Speed Limit Range by Neighborhoods: Maximum*



* Since this figure shows the maximum speed limit range, several neighbhorhoods can have only the median (bold horizontal line) and outliers (dots). If the neighborhood does not have the observation stands for the 25th percentile or 75th percentile value in the range, the boxplot can show only the lower quartile, upper quartile, or neither.

Figure 6-6 Speed Limit Range by Neighborhoods: Nearest*



* Since this figure shows the nearest road speed limit range, several neighborhoods can have only the median (bold horizontal line) and outliers (dots). If the neighborhood does not have the observation stands for the 25th percentile or 75th percentile value in the range, the boxplot can show only the lower quartile, upper quartile, or neither.

Table 6-1 summarizes bivariate correlation results between the posted speed limit and perceived safety. Bonferroni correction was applied to the test since three data sets were used and compared for each neighborhood. The Bonferroni correction is used to adjust the significance level, α (i.e., 0.05) (Zielstra & Hochmair, 2012). Using Bonferroni correction, most of the relationships were not statistically significant. In addition, the correlation coefficients were weak (mostly less than 0.3).

Table 6-1 Bivariate Correlation: Speed Limit & Perceived Safety

Types of Speed Limit Meausrement	Speed Limit					
	Weighted		**Maximum**		**Nearest**	
Perceived Safety	Threatened Experience	Safety Attitude	Threatened Experience	Safety Attitude	Threatened Experience	Safety Attitude
Expected Sign Direction[1] (+ vs. -)	+	-	+	-	+	-
Ten Neighborhoods	-0.045	-0.013	-0.110	0.041	-0.004	-0.089
By Neighborhoods						
Albany	0.230	-0.023	0.098	-0.311	0.330	-0.191
Hillsboro	0.190	-0.052	-0.026	-0.183	0.012	-0.191
Lake Oswego	0.240	-0.467	0.080	-0.176	0.200	-0.195
McMinnville	-0.140	0.091	-0.210	0.182	-0.120	-0.008
NW Portland	0.190	0.115	0.220	-0.177	0.023	0.066
SE Portland	0.140	-0.273	-0.038	-0.074	0.320	-0.309
Tigard	0.210	-0.263	na[2]	na[2]	-0.034	-0.062
Wilsonville	0.011	-0.315	-0.250	-0.100	na[2]	na[2]
Woodburn	-0.110	-0.072	0.210	-0.261	0.061	-0.341
Wood Village	0.200	-0.311	na[2]	na[2]	-0.190	-0.278

[1] The sign of the assumption is to help understand the direction of the correlation. This research question assumes that speed limits and actual speeds will have a negative relationship with safety attitudes and a positive relationship with threatening experiences.

[2] There are no correlation coefficients when the speed limit has one value (the speed limits are the same in some neighborhoods depending on the measurement methods of the speed limit).

The bivariate correlation results on speed limits by neighborhood may be because of the contrast of the surrounding road environment which can affect pedestrians' speed perception. In other words, pedestrians do not perceive the absolute posted speed limit as low or high, but they may perceive the relative speed difference compared to the surrounding environment (Sudkamp & Souto, 2023). When measuring speed as speed limit, there is a risk of misinterpreting the results of the perceived safety analysis if the analysis is not conducted separately for each neighborhood or road network.

In addition to possible misunderstanding of the result, when the model was estimated using both the speed limit and the actual speed, the crash risk factors estimating pedestrian's threatened experiences have unacceptable variance inflation factor (VIF) values (five or higher). In the previous chapter, the speed limit and the actual speed were used in the model answering the first research question, but the VIF values of all variables were less than two. However, in this chapter, models answering the second research question with both the speed limit and the actual speed variables or with only the speed limit showed high multicollinearity.

6.2.2.2 Reasons for Including Actual Speed in SEM

Table 6-2 and Table 6-3 show the bivariate correlation results between actual speed. Bonferroni correction was also applied to the test and perceived safety by neighborhood were not statistically significant and the coefficients are small (mostly less than 0.3).

Table 6-2 Bivariate Correlation: Actual Speed (weighted) & Perceived Safety

Types of Actual Speed Measurement	Actual Speed			
	50th percentile (weighted by road length)		85th percentile (weighted by road length)	
Perceived Safety	Threatened Experiences	Safety Attitude	Threatened Experiences	Safety Attitude
Expected Sign Direction[1] (+ vs. -)	+	-	+	-
Ten Neighborhoods	-0.100	0.032	-0.100	0.031
By Neighborhoods				
Albany	0.190	-0.100	0.025	-0.104
Hillsboro	0.030	-0.220	0.043	-0.220
Lake Oswego	0.100	-0.230	0.100	-0.234
McMinnville	-0.150	0.152	-0.100	0.116
NW Portland	0.070	0.176	0.082	0.183
SE Portland	-0.040	-0.025	0.002	-0.043
Tigard	-0.280	0.322	-0.270	0.262
Wilsonville	-0.089	-0.244	-0.092	-0.238
Woodburn	-0.170	0.043	-0.170	0.044
Wood Village	0.011	-0.131	-0.002	-0.111

[1] The sign of the assumption is to help understand the direction of the correlation. This research question assumes that speed limits and actual speeds will have a negative relationship with safety attitudes and a positive relationship with threatening experiences.

Table 6-3 summarizes the bivariate correlation between the nearest actual speeds (50th and 85th percentile), threatened experiences and safety attitudes. Bonferroni correction was also applied to the test. As the results in Table 6-2, there were no statistically significant correlation reults.

Table 6-3 Bivariate Correlation: Actual Speed (nearest) & Perceived Safety

Types of Actual Speed Meausrement	Actual Speed			
	50th percentile (nearest)		85th percentile (nearest)	
Perceived Safety	Threatened Experiences	Safety Attitude	Threatened Experiences	Safety Attitude
Expected Sign Direction[1] (+ vs. -)	+	-	+	-
Ten Neighborhoods	-0.016	0.026	-0.006	0.016
By Neighborhoods				
Albany	0.240	-0.213	0.230	-0.256
Hillsboro	0.009	-0.180	0.046	-0.188
Lake Oswego	0.015	-0.221	0.032	-0.247
McMinnville	0.046	0.042	0.180	0.011
NW Portland	-0.033	0.295	-0.034	0.300
SE Portland	0.008	-0.123	0.011	-0.100
Tigard	0.025	-0.148	0.038	-0.128
Wilsonville	0.056	-0.092	0.022	-0.198
Woodburn	-0.140	-0.004	-0.120	-0.041
Wood Village	0.290	-0.380	0.290	-0.380

[1] The sign of the assumption is to help understand the direction of the correlation. This research question assumes that speed limits and actual speeds will have a negative relationship with safety attitudes and a positive relationship with threatening experiences.

Considering the results of the above analyses, the probability that actual vehicle speed significantly predicts perceived safety in the structural equation model seems low. However, in the case of actual vehicle speed, unlike the posted speed limit, it did not cause serious multicollinearity problems with other explanatory variables in the model. In addition, the model fits the model using only actual speed than the model using both speed limit and actual speed since the model result has a lower Akaike information criterion (AIC), the Bayesian Information Criterion (BIC). Especially the model with both actual speed and the maximum speed limit has higher BIC (more than 6) than the model with only using the nearest actual speed from the respondent's address. This means that the model with only the actual speed explains better with the sample data for this research (Bauldry, 2015). Therefore, final structural equation models were estimated that included the actual vehicle speed variable.

6.2.3 Four Structural Equation Models by Crash Variables

Four different models were tested using different crash data variables based on bivariate correlation results (Table 6-4):

1. Without crash cases: I estimated a model without crash cases to compare its results with those of other models, including other crash variables.
2. Including all types of crashes: All-type crashes significantly correlated with threatened experiences and safety attitudes (Table 6-4). So, I tested all types of crashes in the model to confirm whether the results differed from those of a model that included pedestrian crash cases.
3. Including pedestrian crashes: The model with pedestrian crash cases is the main model to answer my second research question, and the following result section explains this in detail.

4. Including pedestrian fatal crashes: Although pedestrian fatal crashes do not significantly correlate with two perceived safety variables, I also tested the model with pedestrian fatal crash cases for model comparison.

Table 6-4 also shows the bivariate correlation results of variables that I used in SEMs. Intersections, transit stops, sidewalks, and mixed-use land areas inducing pedestrian activities significantly positively correlate with threatened experiences. Although the park area negatively correlates with threatened experiences, it positively correlates with safety attitudes. In other words, more park areas relate to fewer threatened experiences and make people feel safer walking in their neighborhoods. On the other hand, public transit stops negatively correlated with their safety attitudes but positively correlated with threatened experiences. This means that people were threatened more often in the neighborhood with more transit stops and felt less safe. Regarding individual characteristics, the older people were, the fewer threats they experienced while walking, and they felt relatively safer walking. On the other hand, people with disabilities feel less safe about walking. People with children (under 18 years old) in their household responded that they experienced more threatening situations while walking, although the correlation with attitude was not significant. In the following paragraph, I will discuss how these correlation analysis results are similar to or different from the results of structural equation models.

Table 6-4 Correlation Between Crash Risk Factors and Perceived Safety

Variables		Perceived Safety	
Crash Risk Factors & Individual Characteristics		Threatened Experience	Safety Attitude
Pedestrian Count		0.110**	-0.032
Motor Vehicle Traffic[1]		0.045	-0.043
Actual Vehicle Speed	(weighted 50^{th})	-0.100*	-0.061
	(nearest 50^{th})	-0.016	0.308
Intersection	(n)	0.110**	-0.023
	(n/mile) [2]	0.049	-0.002
Transit Stop	(n)	0.210***	-0.157***
	(n/mile) [2]	0.093*	-0.111*
Sidewalk (mile)		0.120**	-0.021
Park (square mile)		-0.088*	0.139**
Mixed-use area (square mile)		0.160***	-0.077
Commercial area (square mile)		-0.034	0.005
All-type Crash (5-year)		0.230***	-0.166***
Pedestrian Crash: All-type (5-year)		0.210***	-0.125**
Pedestrian Fatal Crash (5-year)		0.064	-0.025
Age		-0.190***	0.149**
Gender		-0.071	0.047
Disability		0.023	-0.093^{+}
Kids		0.098*	-0.070

‘ ’ p <1‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001

1 Motor Vehicle Traffic is divided by 1,000 as it is used in the following final struactural equation model.

2 This value is normalized by road length as it is used in the following final struactural equation model.

Different combinations of land use, pedestrian facility, and individual characteristics factors were used to predict pedestrians’ threatened experience and safety attitudes in the model. First, to predict pedestrians’ threatened experiences, crash risk factors inducing pedestrian activities were used: intersection, public transit stop, areas of park, mixed-use land, and commercial land area. Next, to predict safety attitudes, factors that are relatively easily recognized by pedestrians or may affect their perceived safety were used: pedestrian crash cases, sidewalks, intersections, and areas of the park. Pedestrian exposure variables, including pedestrian count and motor vehicle traffic, actual speed, age, gender, disability, and kids, were commonly used as predictors for both endogenous variables. Between two endogenous variables, threatened experiences (cumulated score) were used to predict the pedestrian's attitudes toward safety. The final variable combination was selected based on model fit and multicollinearity.

6.3 Results

There are four different model results: without crash cases, a model including all types of crashes, a model including pedestrian crashes, and a model including pedestrian fatal crashes. For the third model, including pedestrian crashes, I cumulated five years of crashes. The three-year and one-year models were also tested, but the five-year model had the best fit and explanatory power. In this result part, I discuss the model with all-type pedestrian crash cases that occurred for the last five years (2018-2022). The other three models, which have almost the same results as the pedestrian crash model, are shown in Appendix D RQ2: Comparison of Structural Equation Models.

I used one latent variable, including seven items accessing safety attitudes (Table 6-5), and two modification indices as follows:

1. Correlation in the error terms between 'safety from traffic during the day' and 'safety from traffic at night'

2. Correlation in the error terms between ‘feeling unsafe while crossing the intersections during the day’ and ‘feeling unsafe while crossing the intersections at night.’

Factor loadings of all seven items measuring pedestrian attitudes toward safety are more than the acceptable standardized loading value (greater than 0.4) suggested by Hair et al. (1998). However, before applying the modification indices, the Comparative Fit Index (CFI) did not reach the standard (greater than 0.95). This is because the survey respondents’ answers to similar questions in different time zones, ‘during the day’ or ‘at night,’ may not be completely independent. Therefore, the correlation between the 4th and 5th items and the 6th and 7th items in Table 6-5 was added after the modification indices test. Adding these two indices improved the model fit in all the following structural equation models.

Table 6-5 shows that all seven items have acceptable standardized loading values (> 0.4) (Hair, 1998). The seven items assessing traffic speeds, street lighting, walking on rainy or snowy days, traffic amount during the day or at night, and intersections during the day or at night had acceptable standardized loadings on the factor in the all-type pedestrian crash model.

Table 6-5 Factor Loadings of Safety Attitudes (research question 2)

Items	Standardized Coefficient	Standard Error	p-value
Traffic speeds on most nearby streets are slow enough	0.663		<0.001***
Street lighting makes me feel safe at night	0.530	0.089	<0.001***
Walking on rainy or snowy days	0.570	0.075	<0.001***
Safety from traffic during the day	0.714	0.058	<0.001***
Safety from traffic at night	0.764	0.085	<0.001***
Intersections make me feel unsafe while crossing during the day[1]	0.575	0.109	<0.001***
Intersections make me feel unsafe while crossing at night[1]	0.593	0.117	<0.001***

‘ ’ p <1‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001

[1] reversely coded item

The model results are summarized and plotted as shown in Table 6-6 and Figure 6-7. The chi-square value was significant, χ^2 (107) = 225.240, p-value <0.001, suggesting a poor fit to the data. This is because the chi-square statistic tends to increase with increasing sample size; this model with a sample size of more than 400 easily rejects the null hypothesis that the observed covariance matrix and the covariance matrix predicted by the model are the same. The Comparative Fit Index (CFI) and Standardized Root Mean Square Residual (SRMR) showed acceptable model fits (CFI = 0.973, SRMR = 0.028), because the both CFI and SRMR reached standards (CFI greater than 0.95 and SRMR less than 0.08) suggested by Hu and Bentler (1999) for a good fitting model (Hu & Bentler, 1999).

Table 6-6 Regression Results of SEM: Crash Risk Factors & Perceived Safety

Regression			Standardized Coefficient	Standard Error	p-value
Threatened Experience (R-square :0.087)	←	Pedestrian Count	-0.105	0.002	0.100
		Motor Vehicle Traffic (n/1,000)	0.053	0.008	0.346
		Intersection (n/mi)	0.187	0.201	0.002**
		Public transit (n/mi)	0.079	0.356	0.156
		Park (mi^2)	-0.014	5.734	0.798
		Mixed-use area (mi^2)	0.184	2.855	0.015*
		Commercial area (mi^2)	-0.042	4.667	0.470
		Actual Vehicle speed: nearest 50^{th} (mph)	-0.057	0.03	0.298
		Age	-0.163	0.014	0.001**
		Gender (0: Female, 1: Male)	-0.064	0.448	0.135
		Disability (0: No, 1: Yes)	0.073	0.68	0.100
		Kids (0: No, 1: Yes)	0.079	0.593	0.107
Safety Attitudes (R-square :0.555)	←	Threatened experience	-0.726	0.007	<0.001***
		Pedestrian Crash: all-type, 5-year (2018-2022)	0.033	0.004	0.476
		Pedestrian Count	-0.008	<0.001	0.904
		Motor Vehicle Traffic (n/1,000)	0.006	0.001	0.897
		Sidewalk (mi)	0.057	0.005	0.535
		Intersection (n/mi)	-0.025	0.028	0.723
		Park (mi^2)	0.083	0.567	0.057^{+}
		Actual Vehicle speed: nearest 50^{th} (mph)	0.046	0.003	0.236
		Age	0.046	0.001	0.286
		Gender (0: Female, 1: Male)	-0.004	0.047	0.913
		Disability (0: No, 1: Yes)	-0.095	0.083	0.036*
		Kids (0: No, 1: Yes)	0.019	0.056	0.628

‘ ’ p <1‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001

The most important finding of this model was that more threatened experiences affected by several crash risk factors and individual characteristics significantly predicted less positive safety attitudes toward walking. Moreover, the threatened experience was this model's strongest predictor of safety attitudes. Although not all crash risk factors tested in the previous chapter can predict threatened experiences and safety attitudes, more detailed results of significant factors are explained in the following paragraphs.

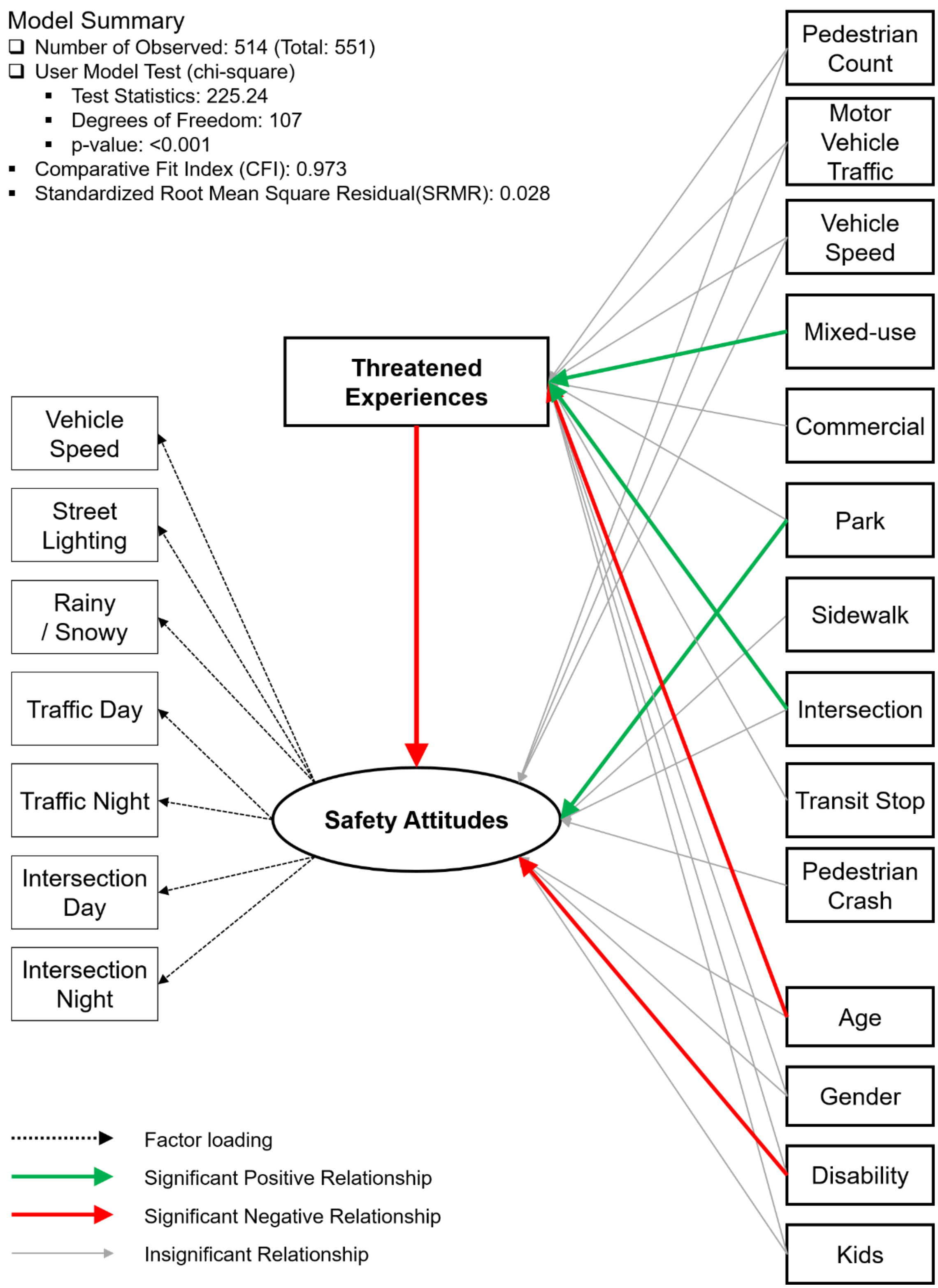
Three significant predictors of pedestrians' threatened experiences were intersection density normalized by road length, the mixed-use land area, and age. Higher intersection density and more mixed-use land area can predict more often threatened experiences. Older people had fewer experiences of being threatened. This was possible because older pedestrians tend to walk on routes, at certain times of day, or in weather conditions they consider safer based on their previous (or lifetime) experiences. The fact that age positively correlated with the period of living in the neighborhood (γ=0.47, p-value <0.001) can support this assumption. Age was positively correlated with safety attitudes, while it was not a significant predictor of attitudes in the structural equation model. This means that threatened experience in the path model fully mediated the relationship between age and attitudes. The model with these significant predictors can explain pedestrians' threatening experiences by 8.7% (R^2= 0.087).

Two more variables significantly predicted safety attitudes in addition to threatened experiences: park and disability. Park areas positively impacted safety attitudes, while other built environment and facility factors did not. Although age significantly predicted the threatened experiences, it did not significantly predict safety attitudes. Disability was significantly related to safety attitudes. People with disabilities were less positive about walking. The model with these significant predictors can explain pedestrian safety attitudes by 55.5% (R^2= 0.555).

Regarding the results of bivariate correlation analysis and SEM analysis (Table 6-4, Table 6-6, Figure 6-7), threatened experiences only mediated one relationship between age and attitudes toward safety. It fully mediated the relationship between age and safety attitudes (direct effect = 0.046, indirect effect = 0.118, total effect = 0.164). When age alone predicted safety attitudes, it was significantly positive. However, when the mediator, the threatened experiences, was included in the path, only the indirect effect was significant, and the threatening experience influenced by age is significant in predicting the safety attitudes.

The results shown in the Table 6-6 are schematized in the Figure 6-7. Several of the crash risk factors that were significant in previous research question 1 also significantly explained the frequency of threatened experiences. On the other hand, safety attitudes were influenced by the frequency of previous threatened experiences, the area of the park, and the presence of disability rather than crash risk factors. Regardless of how I measure crashes, crash variables did not statistically significantly predict safety attitudes (Appendix D RQ2: Comparison of Structural Equation Models). All types of crashes and pedestrian-involved crashes were significant only in bivariate correlation results (Table 6-4).

Figure 6-7 Structural Equation Model Result: 5-year Pedestrian Crash



6.4 Discussion

To answer the second research question, crash risk factors in the previous chapter were examined whether they affect pedestrians' threatened experiences and safety attitudes. Three main points from the model results are as follows:

1. Threatened experience: Threatened experience was a powerful predictor of pedestrians' safety attitudes.
2. Intersection density: Intersection density statistically significantly explained pedestrians' threatened experiences, although it did not statistically significantly predict pedestrian crashes.
3. Pedestrian crashes: While crash risk factors influenced safety attitudes mediated by threatened experiences, the cumulative number of pedestrian crashes did not explain safety attitudes.

First, pedestrians' threatened experiences, which are affected by crash risk factors and individual characteristics, significantly predict safety attitudes. As direct experiences can predict following attitudes (Fazio et al., 1978) and perceived experiences can affect attitudes toward a walking environment (Johansson et al., 2016), I assumed that safety-related experiences predict safety attitudes and confirmed it in model results. Although not all crash risk factors significantly predict threatened experiences, higher intersection density and wider mixed-use land areas increase threatened experiences, and more threatened experiences predict negative safety attitudes.

Next, among facility factors, the number of intersections normalized by the road length significantly predict the threatened experiences after being controlled by other factors. Higher intersection density can increase pedestrian's threatened experiences. This may be because of the increased probability that vehicles and pedestrians can encounter (Chen & Zhou, 2016; Cho et al., 2009; Clifton et al., 2009; Lee & Abdel-Aty, 2005; Mfinanga, 2014; Mukherjee & Mitra, 2019; Schneider et al., 2004, 2021; Zegeer & Bushell, 2012). However, intersection density did not directly predict safety attitudes as it did not statistically significantly predict pedestrian crashes in the previous chapter. It can be interpreted that people do not have negative safety attitudes simply because of the higher intersection density. However, when they experience and perceive more threats at intersections, those experiences negatively impact their safety attitudes.

The relationship between cumulative crashes and safety attitudes was not statistically significant in structural equation analysis. I assumed that the actual crashes could explain the parts of the safety attitudes that the crash risk factors cannot explain, but all three crash variables were not statistically significant in the models. It can be explained that pedestrians' attitudes toward safety change through threatened experiences related to other crash risk factors rather than being directly affected by the cumulated number of actual crashes.

Two individual characteristics, age, and disability, also significantly explained pedestrians' perceived safety. Regarding age, older pedestrians had fewer threatened experiences, and the relationship between age and safety attitudes was fully mediated by threatened experiences. In other words, only when older pedestrians had fewer experiences of being threatened, they had more positive safety attitudes. It is also possible that the older pedestrians are, the more likely they choose to walk in safer places, as previous research shows that they tend to stick to their previously chosen routes, especially when crossing the streets (Abdullah et al., 2019; Campbell et al., 2004; Oxley et al., 2005). On the other hand, pedestrians with disabilities had more negative attitudes toward safety. Disability significantly predicted safety attitudes but not threatened experiences. Thus, pedestrians with disabilities may have more negative safety attitudes without the threatened experiences.

In conclusion, this chapter's results show that pedestrians' experiences influenced by external factors predict their attitudes. In particular, when pedestrians have more chances to encounter vehicles at the intersection or mixed-use land area, they can expect more threatening experiences and less positive attitudes toward pedestrian safety.

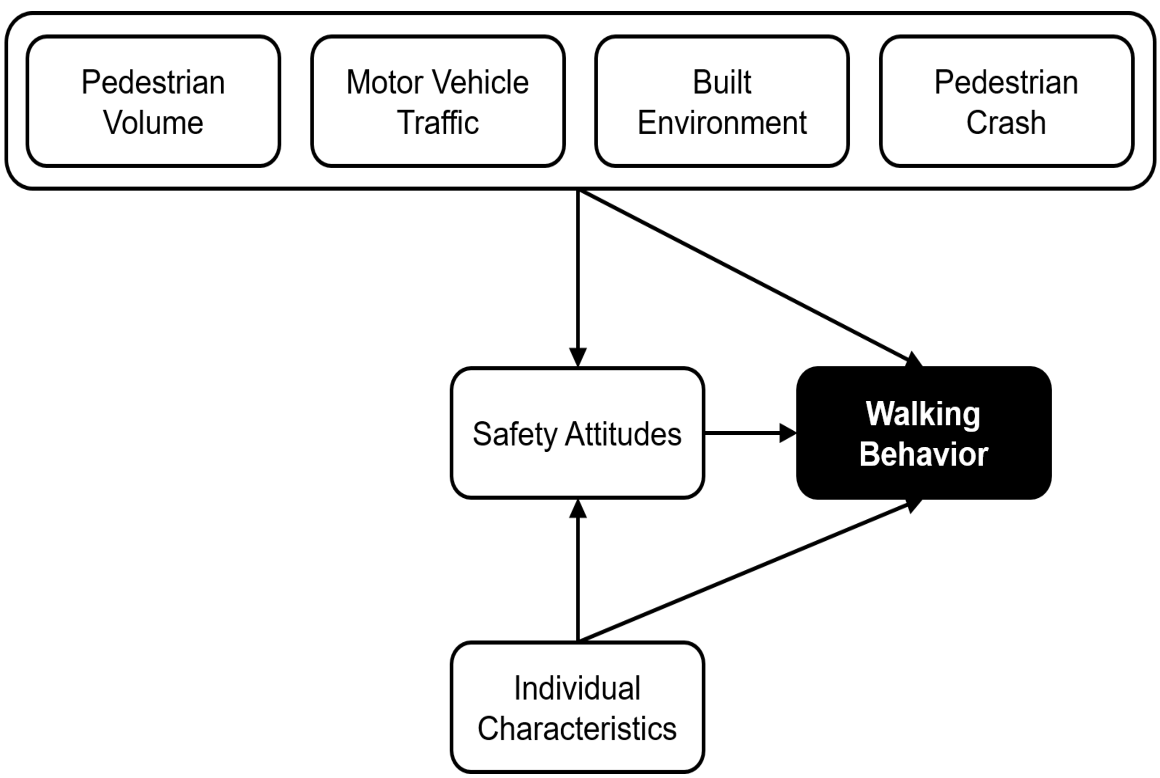
Despite the above meaningful statistical results regarding pedestrian safety, this analysis has several limitations. First, the macro-level spatial aggregation of data, especially speed, can make capturing subtle differences of crash risk factors and psychological factors difficult. Since people's walkshed is wider than a single intersection or short road segment, spatial data aggregation is necessary for analysis. However, this means that other crash risk factors were not included in the model, including specific ranges of vehicle speeds, road classification, intersection types, weather, or street light conditions. In addition, because of the overlapped spatial unit of each observation, the crash variable cannot be a mediator in the path model. If it is possible to collect survey answers from residents who live apart enough from each other, the pedestrian crashes can be tried to predict perceived safety as a mediator. Overcoming these limitations can explain how more detailed crash risk factors have influenced pedestrians’ perceived safety.

7 Factors Affecting Walking Behavior

7.1 Research Question 3: Walking Behavior

The last research question is how safety attitudes, which are influenced by the crash risk factors, affect walking behavior, as shown in Figure 7-1. Walking behavior in this study refers to the walking frequency, and it was measured by the annual average weekly walking days of more than five minutes in the survey respondents' neighborhood (within a half mile from respondents' street addresses). Perceived safety for this research question refers to pedestrians' attitudes toward safety while walking. In the previous chapter, I investigated how crash risk factors affect pedestrians' safety attitudes and how safety attitudes affect people's walking frequency in this chapter (Figure 7-1).

Figure 7-1 Conceptual Framework of Research Question 3



More detailed research questions for this chapter are as follows:

- How do pedestrian crash risk factors and individual characteristics affect the walking frequency mediated by safety attitudes?

In this third research question, the threatened experience did not mediate the relationship between crash risk factors and safety attitudes. This is because when threatened experiences are included in the model, the order of events may be reversed in path analysis. The method part below will explain this possible issue in more detail.

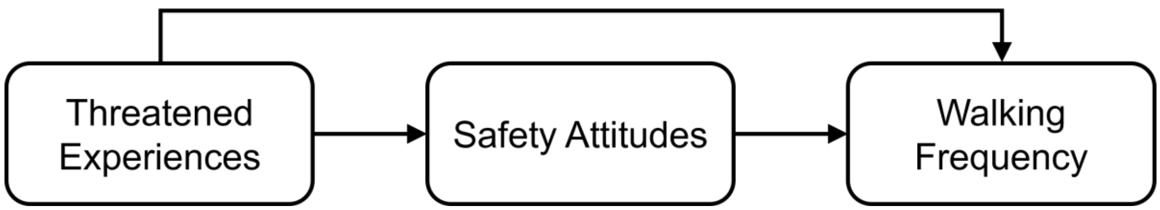
7.2 Analysis Methods

7.2.1 Possible Issue in Path Analysis: the matter of sequence

The structural equations model assumes probabilistic causal relationships (Kline, 2016). Causal relationships assume that there is a sequential relationship between events, so the temporal order of events within a path should be reasonable. However, some sequential relationships could be unclear when measuring variables in social science research (Bohrnstedt & Knoke, 1988). One example is the relationship between threatened experiences and walking frequency in this study.

In the previous chapter for the second research question, pedestrians' perceived safety was measured by experience and attitude. The analysis showed that pedestrians' threatened experiences had a negative impact on safety attitudes. Based on these results, my third research question begins with the assumption that perceived safety measured by safety attitudes can influence walking frequency. However, the temporal order problem can arise when a model includes all three variables, experience, attitude, and behavior, in a recursive model, which does not have direct or indirect feedback loops in the path. As shown in Figure 7-2, when three variables are connected, the temporal order between experience and behavior can be reversed. The path model shown in Figure 7-2 assumes that previous threatened experiences may decrease the walking frequency. However, on the contrary, it is possible that people may have more threatened experiences since they walk frequently. This is because in this study, threatened and walking frequency were measured simultaneously in one survey.

Figure 7-2 Possible Issue of Temporal Order in Recursive Path



The scatter plot of the relationship between the two variables also shows that some people who rarely walk in a week had a high level of threatening experience in addition to a generally positive correlation between them (Figure 7-3). Table 7-1 compares the results of simple linear and simple nonlinear regression analysis of the relationships between threatened experiences and walking frequency. The threatened experiences significantly increased as the walking frequency increased in simple linear regression relationship and vice versa. In addition, the threatened experiences also significantly increased as the square of walking frequency increased in the simple nonlinear regression relationship but not vice versa. Figure 7-3 and Table 7-1 support that if I estimate the path model as shown in Figure 7-2, both types of cases are in the same model: cases where people who have had a lot of threatened experiences tend to walk less often and cases where people who walk more often have had a lot of threatened experiences.

Figure 7-3 Bivariate Correlation: Threatened Experience & Walking Frequency

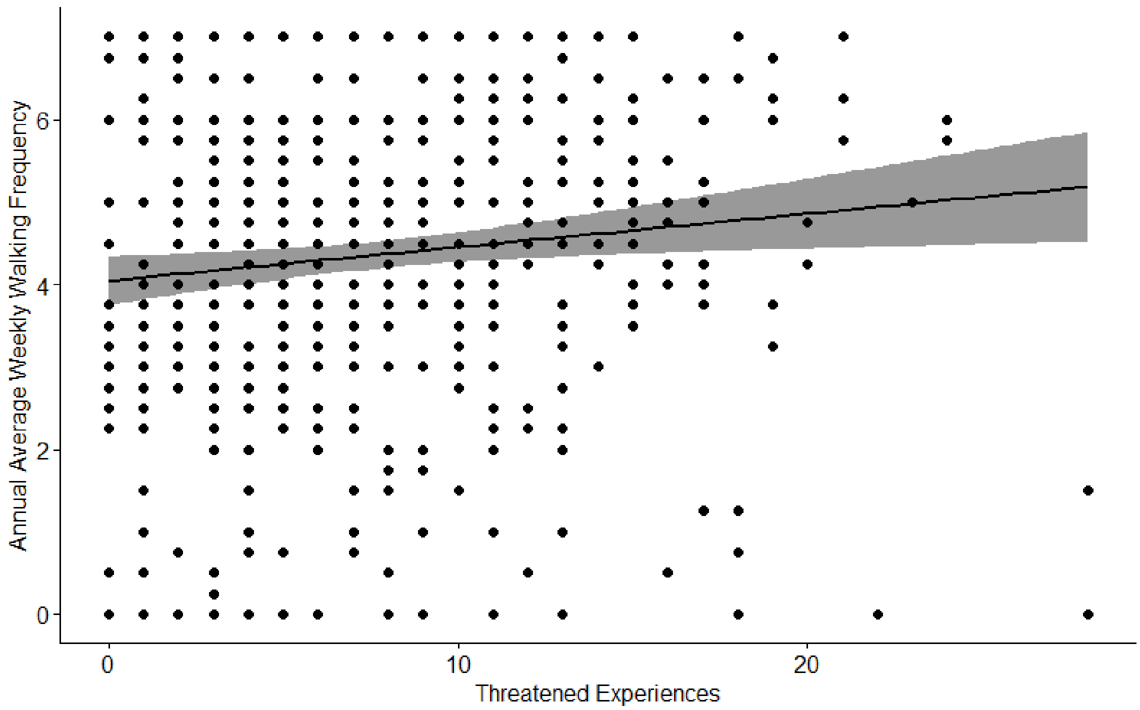


Table 7-1 Threatened Experiences & Walking Frequency

Regression	Dependent (y)	Independent (x)	Intercept	Coefficient	p-value
Linear	Walking Frequency	Threatened Experiences	4.05	0.04	0.012*
	Threatened Experiences	Walking Frequency	6.36	0.28	0.012*
Nonlinear	Walking Frequency	Square of 'Threatened Experiences'	4.30	0.00065	0.407
	Threatened Experiences	Square of the 'Walking Frequency'	6.84	0.03	0.02*

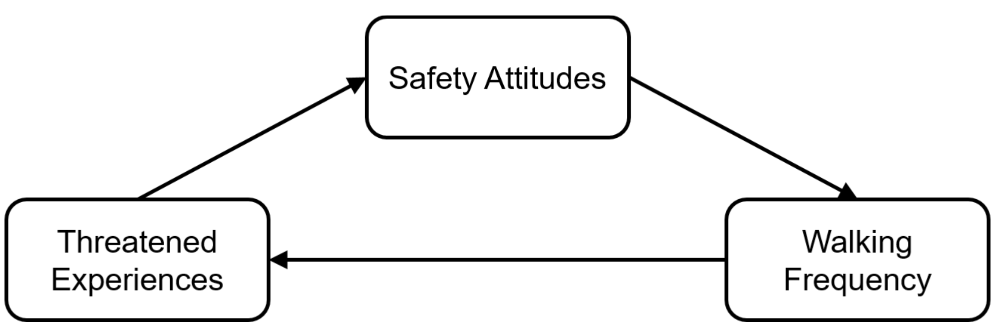
' ' p <1'+' p <0.1 '*' p <0.05 '**' p <0.01 '***' p <0.001

In the previous chapter, the direction of the path was not a problem in interpreting the results in the relationship between threatened experiences and safety attitudes because, considering the time order, the direction of the assumption that experience affects attitude is reasonable (Fazio et al., 1978). However, in this chapter, the model interpretation may be misunderstood because the respondent's increased walking frequency may cause the increased frequency of threatened experiences. In other words, if all three variables, experience, attitude, and behavior, are connected in a recursive model, as shown in Figure 7-2, a relationship that does not match the temporal order may be derived, and the results from this model may be misunderstood. Thus, this study did not use threatened experiences to predict walking frequency.

7.2.2 Recursive vs. Non-recursive Structural Equation Modeling

To address the temporal order problem, a non-recursive model, including an indirect feedback loop in which walking frequency affects the threatened experience, can be considered an alternative to the previous recursive model (Figure 7-4). However, this model is not a framework that structures the research question I want to answer and raises the following problems.

Figure 7-4 Indirect Feedback Loop in Non-recursive Path



Identifying causal relationships in the non-recursive model with feedback loops with cross-sectional data is difficult, and there is a high possibility of severely biased estimates (Kaplan et al., 2001; Kline, 2016). Because of these problems, non-recursive models are used to test causal relationships with short-time lags, such as reciprocal relationships between parents and their children, or in longitudinal studies with panel data (Finkel, 1995; Kline, 2016; Wong & Law, 1999). Thus, in this study, only the relationship between pedestrians' safety attitudes and walking frequency was estimated using a recursive model, as shown in Figure 7-1.

7.3 Results

7.3.1 Bivariate Correlation Analysis: Crash Risk Factors & Walking

Table 7-2 summarizes the bivariate correlation analysis results between annual average walking frequency and other variables. Safety attitudes, sidewalks, and the number of public transit stops were significantly and positively correlated with walking frequency. On the other hand, commercial land area, actual vehicle speed, and number of household motorized vehicles negatively correlated with walking frequency. Mixed-land area and several facilities inducing pedestrian's activities, including the number of intersections, and public transit stop density, had weak and marginally significant (p-value < 0.1) correlation with walking frequency.

Table 7-2 Crash Risk Factors & Walking Frequency

Variables			**Annual Average Weekly Walking Frequency**
Safety Attitudes			0.115*
Sidewalk (mile)			0.170***
Intersection	n		0.082^{+}
	n/mile		0.046
Public Transit Stop	n		0.160***
	n/mile		0.076^{+}
Park (mi^2)			0.033
Mixed-use land (mi^2)			0.075^{+}
Commercial land (mi^2)			-0.130**
Actual Vehicle speed (mph)	weighted	50^{th}	-0.170***
		85^{th}	-0.170***
	nearest	50^{th}	-0.130**
		85^{th}	-0.130**
Age			0.037
Gender			-0.067
Disability			-0.068
Kids			-0.079^{+}
Motorized Vehicles			-0.150***

‘ ’ p <1‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001

7.3.2 Structural Equation Model Results: Annual Weekly Walking Frequency

Table 7-3 shows the factor loadings of the latent variable measuring pedestrian’s safety attitudes are more than the acceptable standardized loading value (greater than 0.4) suggested by Hair et al. (1998). I also used two modification indices: the correlation between safety from traffic during the day and safety from traffic at night and the correlation between feeling unsafe while crossing the intersections during the day and unsafe while crossing the intersections at night.

Table 7-3 Factors Loading of Safety Attitudes (research question 3)

Items	Standardized Coefficient	Standard Error	p-value
Traffic speeds on most nearby streets while I walk in my neighborhood are slow enough to make me feel safe	0.660		<0.001***
Street lighting in our neighborhood makes me feel safe while I walk at night	0.507	0.096	<0.001***
I feel safe while walking in my neighborhood on rainy/snowy days	0.579	0.084	<0.001***
I feel safe from traffic while I walk in my neighborhood during the day	0.715	0.069	<0.001***
I feel safe from traffic while I walk in my neighborhood at night	0.799	0.109	<0.001***
There are some intersections in my neighborhood where I feel unsafe while crossing during the day[1]	0.536	0.110	<0.001***
There are some intersections in my neighborhood where I feel unsafe while crossing at night[1]	0.575	0.127	<0.001***

‘ ’ p <1‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001

[1] reversely coded item

The regression results of structural equation model are summarized in Table 7-4 and they are plotted in Figure 7-5. The number of used observations is 512 out of 551. The chi-square value of this model was significant, χ^2 (116) = 243.697, p-value <0.001, suggesting poor fit to the data. However, the Comparative Fit Index (CFI) and Standardized Root Mean Square Residual (SRMR), showed the acceptable model fits (CFI = 0.97, SRMR = 0.031) (Hu & Bentler, 1999).

The model’s significant predictors of safety attitudes were park area, age, and disability. Although the significance of the park area was marginal (p-value=0.097), it predicts positive attitudes toward safety, as it did in the path model of the previous research question. While disability predicted negative safety attitudes, older age significantly predicted more positive attitudes. In the previous path model for the second research question, age was not statistically significant in predicting safety attitude because of the mediator, threatened experiences, in the model. However, age was significant in predicting the safety attitudes without the mediator effect. These factors are explained only by 6.7% of the variation in safety attitudes (R-square: 0.067). This explanatory power is reduced from 55.5% of the SEM model result in Chapter 6 because of the absence of the threatened experiences.

To predict walking frequency, safety attitudes, weighted sidewalk length, actual vehicle speed, and the number of motorized vehicles in the household were significant. However, the land use variables were not. More positive attitudes toward safety and more sidewalks in the respondents' neighborhoods predicted more frequent annual average weekly walking. On the other hand, faster vehicle speeds (50^{th} percentile) on the nearest road from the respondent's address predicted less walking frequency. I also tested other actual vehicle speeds, the nearest 85^{th} percentile, and 50^{th} and 85^{th} weighted actual vehicle speeds by road length. The speeds measured on the nearest road were significant for predicting walking frequency, not the weighted one. Between two speeds, 50^{th} percentile speeds and 85^{th} percentile speeds, the 50^{th} percentile speeds variable made the model fit better than the 85^{th} percentile speeds. This may be because people were influenced by the speed of vehicles on the nearby road when they started walking. Depending on how speed was measured, it might have different significance and influence on walking frequency in the model. However, what is clear is that the high speed of vehicles around a residence can significantly impact walking frequency as much as safety attitudes did, considering the standardized coefficient in the model result.

Among the three land use variables, park and mixed-use land areas were not statistically significant in predicting walking frequency. Many survey respondents answered that they mostly walk for entertainment and exercise. In addition, some respondents answered that they enjoyed going to the park and walking. For this reason, I assumed that the park was one of their primary destinations. Moreover, more areas of the park affected more positive safety attitudes. However, the park's size in their neighborhood did not significantly encourage actual walking as a physical activity. On the other hand, the commercial land area was marginally significant in predicting the lower walking frequency.

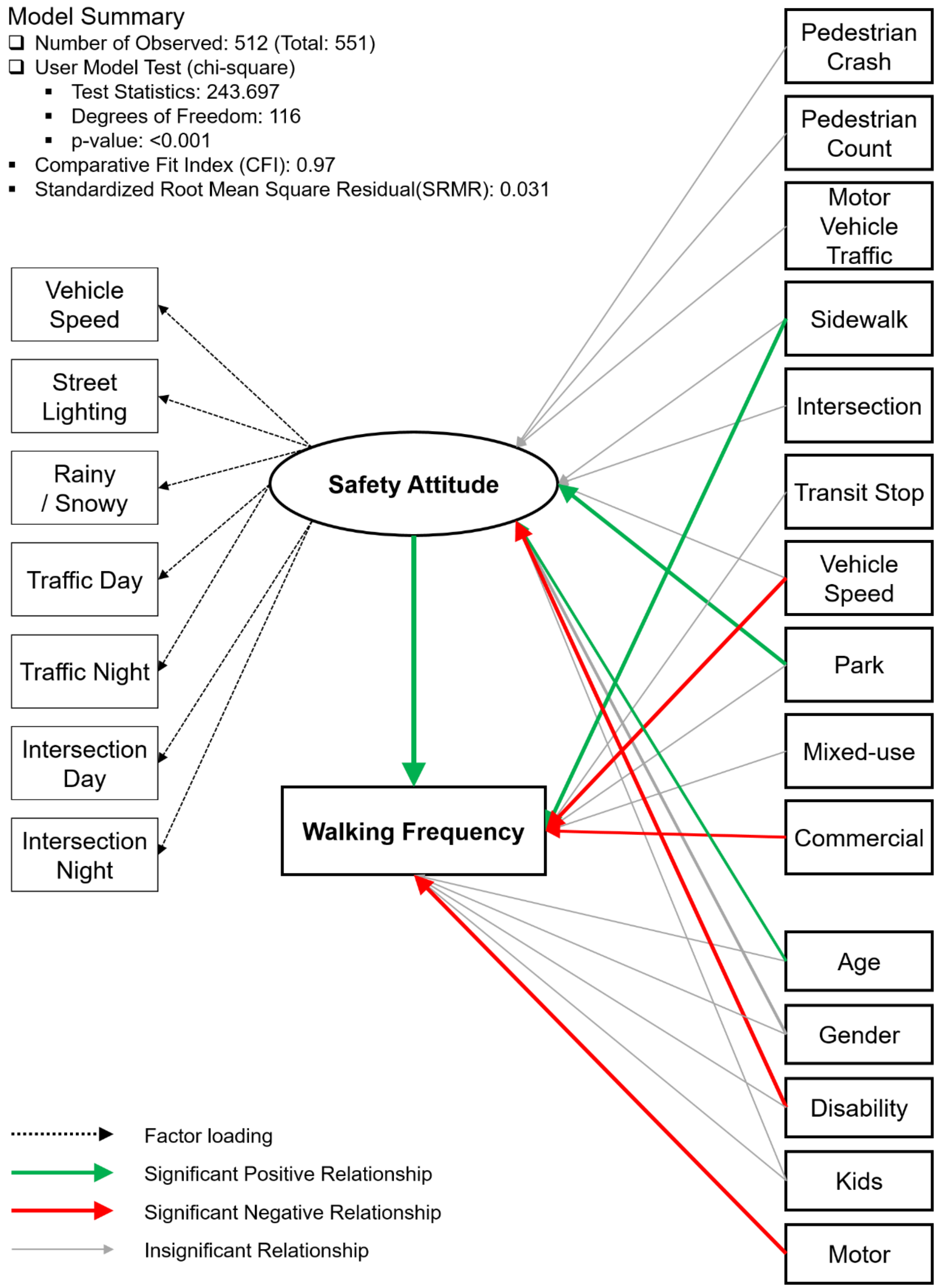
In addition to these external factors, the number of motorized vehicles in households also significantly predicted walking frequency. More motorized vehicles in their household affected less frequent weekly walking. Other personal characteristics, including age, gender, disability, and whether children are in the household, did not statistically significantly predict weekly walking frequency. These factors explained the waking frequency of about 10% (R-square: 0.097).

Table 7-4 Regression Results of SEM: Safety Attitudes & Walking

Regression			Standardized Coefficient	Standard Error	p-value
Safety Attitudes (R-square: 0.067)	←	Pedestrian Crash Frequency: all-type, 5-year (2018-2022)	-0.090	0.006	0.155
		Pedestrian count	0.037	0.000	0.646
		Motor Vehicle Traffic (n/1,000)	-0.016	0.001	0.764
		Sidewalk (mi)	0.040	0.007	0.734
		Intersection (n/mi)	-0.055	0.037	0.546
		Park (mi2)	0.095	0.735	0.097+
		Actual Vehicle speed: nearest 50th (mph)	0.047	0.003	0.372
		Age	0.156	0.002	0.006**
		Gender (0: Female, 1: Male)	0.043	0.062	0.386
		Disability (0: No, 1: Yes)	-0.138	0.100	0.012*
		Kids (0: no, 1: yes)	-0.033	0.078	0.545
Walking Frequency (R-square: 0.097)	←	Safety Attitude	0.118	0.185	0.036*
		Sidewalk (mi)	0.126	0.010	0.016*
		Public transit (n/mi)	0.08	0.132	0.133
		Park (mi2)	0.018	2.279	0.737
		Mixed-use area (mi2)	-0.022	0.862	0.708
		Commercial area (mi2)	-0.100	1.610	0.052+
		Actual Vehicle speed: nearest 50th (mph)	-0.115	0.009	0.006**
		Age	0.019	0.006	0.710
		Gender (0: Male, 1: Female)	-0.043	0.174	0.315
		Disability (0: No, 1: Yes)	-0.071	0.304	0.164
		Kids (0: no, 1: yes)	-0.037	0.207	0.403
		Motor	-0.097	0.101	0.048*

‘ ’ *p* <1‘+’ *p* <0.1 ‘*’ *p* <0.05 ‘**’ *p* <0.01 ‘***’ *p* <0.001

Figure 7-5 Regression Results of SEM: Safety Attitudes & Walking



7.4 Discussion

The model results in this chapter show relationships between safety attitudes and walking behavior influenced by the surrounding physical environment and personal characteristics. Three main points from the model results are as follows:

1. Safety attitudes and walking: Safety attitudes significantly predicted walking frequency.
2. Importance of sidewalks and land use: Although sidewalks did not significantly predict positive safety attitudes, sidewalks and commercial areas were significant predictors of walking frequency.
3. Actual speed: Speed significantly predicted walking frequency and, like the sidewalks, should be considered an essential factor in encouraging people to walk.

First, more positive safety attitudes predict more frequent walking, which is supported by previous studies on the relationships between perceived safety and walking behavior (Alton et al., 2007; Kwon et al., 2022; Lyu & Forsyth, 2021). While only the area of the park (among crash risk factors) significantly explains safety attitudes, several other factors can significantly explain walking frequency.

Next, longer sidewalks significantly predicted more frequent walking while commercial areas decreased it. This finding of positive relationship between the sidewalk and walking amount is supported by previous research results (McCormack et al., 2012; Saelens & Handy, 2008). However, my result of negative correlation between commercial land areas and walking frequency differs from the results of several previous studies (Nathan et al., 2012; Seong et al., 2021). In other words, people's frequent walking appears to be encouraged by pedestrian-friendly facilities rather than various nearby destinations. At least in my sample, this result may imply that there was no destination worth walking to within the commercial area, or it may mean that the commercial area was not a place people wanted to pass by for exercise. Also, the increase in the ratio of the commercial area may mean that the proportion of residential areas as the starting point for walking decreased.

Additionally, faster vehicle speeds on the nearest road decreased the walking frequency. Since the higher speeds of vehicles in the surrounding environment were likely to impede walking for pedestrians, the speed limit and traffic speed are important indicators in determining walkability, as well as in previous research (Fonseca et al., 2022; Guzman et al., 2022).

In conclusion, pedestrians, influenced by the surrounding environment and their characteristics, routinely walked more often when they felt safe. Furthermore, safe walking network connections separated from faster-speed vehicles were more important for encouraging walking frequency than the diversity of nearby destinations. Despite the above meaningful results related to pedestrian perceived safety and walking frequency, this study has the limitation of using cross-sectional data. Due to this limitation, I could not test the paths through which experience influences attitudes, and then those attitudes, in turn, influence behavior. If it is possible to obtain panel data, meaningful results can be obtained about individuals' active transportation mode choices, which are complexly influenced by the external environment and personal characteristics.

8 Conclusion

8.1 Key Findings & Practical Implications

The study starts by examining whether individuals are aware of the potential dangers in their surroundings as they navigate their neighborhood and whether this awareness impacts their safety attitudes. It also seeks to explore how these influences can affect walking behavior. I confirmed that crash risk factors can shape pedestrians' perceived safety and that their safety attitudes can ultimately impact behavior.

Previous studies on crash risk factors from the perspective of pedestrians or on their cognition and behavior had small spatial analysis units of study, such as intersections or short roads (Ihssian & Ismail, 2023; Mukherjee & Mitra, 2019). However, in this case, there is a possibility that the context of pedestrians' surrounding environment cannot be sufficiently captured due to the spatial unit of analysis being too small. Since a pedestrian's walking range is likely more extended and broader than a limited space, such as an intersection or a short road segment, it is necessary to analyze spatial units of a possible walkshed. Suppose we can understand the intertwined relationships between road networks, land use, traffic volume, and vehicle speed within that space. In that case, we can identify risk factors that pose real threats from a pedestrian's perspective. In addition, it will be possible to understand how each complex factor can affect an individual's perception of safety. Therefore, I set the research spatial unit to be within a half-mile straight-line buffer from the survey respondent's address. Before analyzing the relationship between risk factors and perceived safety in the half-mile buffer space, I first investigated pedestrian crash risk factors by census block group, a statistical geographic unit based on the number of people and households.

For the first research question, several variables related to the effect of pedestrian exposure on vehicle flow were tested. Two models estimating pedestrian crashes were compared using the pedestrian count and the population density. I confirmed that the pedestrian count data could better predict pedestrian crashes than the proxy population density, although the number of pedestrians was counted for two days. This can support the need for pedestrian counts to continue to be counted in various places to develop road safety plans and policies based on pedestrian safety research. Additionally, land use variables that induce the activities of pedestrians and drivers were significant risk factors for pedestrian crashes. In particular, mixed-use and commercial land areas relate to more pedestrian crashes, as there is a possibility that various transportation mode users may share the space simultaneously.

In the model result of the first research question, the significance of intersections, speed limits, and actual vehicle speeds were mainly not statistically significant, and they were also inconsistent across models. This inconsistency may be due to the correlation between explanatory variables and spatial characteristics. In particular, the number of intersections or intersection density may relate to speed limits and actual speeds. For example, a larger number of intersections or intersection density, where the smaller size of blocks, may lead to lower road classification and fewer motor vehicle traffic. In this case, denser intersections may decrease speed limits and actual vehicle speeds, affecting the possibility of pedestrian crashes.

Regarding the public transit stops, in the sample of this study, the number of them was significantly related to population density and land use (especially mixed-use land and commercial land areas). It may relate to pedestrian crashes. Even though public transportation stops are not the direct cause of crashes, they may explain pedestrian crashes, which other pedestrian exposure factors cannot explain (Diogenes & Lindau, 2010; Monsere et al., 2017; Pulugurtha & Sambhara, 2011). This model result implies the importance of the appropriate transit stop design and location (Zegeer & Bushell, 2012), avoiding the interaction between road users at stops. Avoiding interaction between road users may be related to securing sufficient visibility for each road user (Craig et al., 2019), enough space to avoid each other in case of unavoidable interactions, and facilities such as ramps, curbs, or signage to reduce the speed difference when interactions occur.

The model results for the second research question show that the threatened experience influenced by the surrounding environment influenced safety attitudes. Pedestrians' threatened experiences were influenced by the density of the intersection and the mixed-use land area, while the park's size positively affected their safety attitudes rather than their experiences. Interestingly, although the intersection factor was not statistically significant in predicting actual pedestrian crashes if pedestrians encounter intersections more frequently while walking, they perceived that they have had more threatened experiences. These threatened experiences decreased with age, which may be because they knew safe routes based on longer experiences in their neighborhood. Another significant personal characteristic was disability. Although disability had no significant effect on the threatened experiences, it had a negative effect on safety attitudes. Another interesting finding was that the actual pedestrian crashes did not affect safety attitudes on the path model. However, the bivariate correlation results showed that pedestrian crashes negatively correlate with safety attitudes. This can be interpreted that pedestrians' safety attitudes were mainly determined by their perceived experiences in a given environment rather than an actual crash probability.

This difference between the actual likelihood of crash risk and the perception of risk or safety should be considered important in transportation planning. While reducing actual crashes is one of the top priorities in transportation safety, perceived safety based on individual experiences and attitudes is also important because it can influence pedestrians' subsequent behaviors (Kwon et al., 2022; Lyu & Forsyth, 2021).

Since these two concepts, pedestrian safety and perceived safety were differently defined and measured in this study, the approaches and methods for improving pedestrian safety and perceived safety should be different. In particular, intersections should be designed to make pedestrians aware that higher density of them may not be dangerous. In urban design and transportation planning, smaller block designs may relate to denser intersections associated with lower levels of road classification, fewer road lanes, slower speed limits (or actual vehicle speeds), and fewer motor vehicle encounters. It may be difficult to make pedestrians intuitively aware of this, especially for those who have had threatened experiences at intersections. However, improving facilities, such as expanded curbs and medians, may induce the idea that a space with a high intersection density may not be too dangerous for pedestrians.

The third result about the relationship between safety attitudes and walking behaviors is also important for urban planners, designers, and transportation planners. Positive safety attitudes and nearby sidewalks increased walking frequency. On the other hand, larger commercial areas, faster vehicle speeds, and more vehicles in their households reduced walking frequency. In other words, people may walk more often when pedestrians feel safer in the surrounding walking environment. They walk more often in places with more sidewalks, fewer commercial land areas, and slower vehicle speeds.

One interesting result is that although survey respondents answered that they walk mostly for their physical exercises or entertainment, the area of the park was not statistically significant in predicting more frequent walking. It was only statistically significant in predicting more positive safety attitudes. Instead of the area of the park, more sidewalk length encourages more frequent walking. This may imply that respondents in this study sample enjoy walking along the sidewalk rather than walking to visit specific places. This may be the reason why the lower commercial land area and slower vehicle speed near the house can encourage more frequent walking.

In this third result, the importance of the intersection density was not directly shown. However, considering the previous result, intersection density can be an important factor affecting walking frequency since it affects safety attitudes mediated by threatened experiences. For pedestrians who enjoy walking along the sidewalk, frequently encountering intersections can make them hesitant to walk frequently. Thus, it is important to plan and design intersections that do not look dangerous to cross, with fewer road lanes and wider visibility (G. Lee et al., 2016). So, it will make people not hesitate to cross the intersection and allow them to keep walking.

8.2 Limitations & Future Research

As previously mentioned in the discussion section of each research question chapter, this study has several limitations. First, one or two pedestrian count places should represent a neighborhood pedestrian volume. Although pedestrian count significantly explained the number of cumulated pedestrian crashes, it is difficult to assume that this pedestrian count at intersections, collected over two days, can perfectly represent the annual average pedestrian volume or their exposure to traffic flow. This limitation can be overcome if pedestrian counts are collected at more intersections and paths is necessary.

In addition, due to the nature of the spatial analysis unit, some built environment factors were aggregated. This made accurate measurement of crash risk factors difficult. The maximum value of the motor vehicle traffic by spatial unit was applied to the models. Although the maximum traffic value significantly predicted pedestrian crashes, the measurement cannot fully describe the traffic volume pedestrians usually encounter. Since measuring traffic volume at all road points is virtually impossible, avoiding measurement errors in aggregating traffic volume in macro-level spatial units is challenging. Measuring the traffic volume using weights based on the road length for each road classification can be one approach instead of directly measuring and aggregating the traffic volume for each spatial unit of analysis. Additionally, if the number of road lanes is also considered, more accurate traffic volume measurement using proxies can be achieved. In this study, the physical characteristics of the intersection, such as whether there is a marked crossing, whether there is a traffic signal, and what the shape of the intersection is, were not included in the crash models. These characteristics of roads and intersections can be included in future research. If so, it would be possible to explain in more detail how each roadway characteristics affects the risk of pedestrian crashes and the perceived safety of pedestrians.

Next, the number of crashes was cumulated spatially and temporally (by year). This makes it challenging to investigate the characteristics of individual crashes, such as weather and lighting conditions. As the visibility of each road user can significantly impact pedestrian crashes, changes in actual crash probabilities and perceived safety due to weather and lighting are also important topics that should be studied in the future. In particular, in this study's survey, people walked least frequently before sunrise. In addition, regarding safety attitudes, they responded that they considered intersections at night the most unsafe. If the length of day, weather by season, and the quality of street lights in each neighborhood were also investigated, it would help to understand the actual and perceived safety of pedestrians and their walking behavior. This will help with better traffic safety planning and designing a safer walking environment.

This study also has limitations since it is a cross-sectional study. If longitudinal research with panel data is possible, examining how people's safety attitudes and behavior change due to threatened experiences would be possible. In addition, research using panel data can help evaluate or predict the outcomes of transportation safety plans, projects, and facilities that each city or county has attempted or will attempt. Future research could overcome these limitations by acquiring and analyzing panel data. This could have meaningful implications for improving pedestrian safety in future transportation plans.

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Appendix A Paper Questionnaire

PART 1 Please tell us about your walking in your neighborhood
(OR within a 20-minute walk distance from your home)

1. During the **last 7 days**, how many days did you walk, jog, or run outside for more than 5 minutes in your neighborhood? *Please write the number between 0 – 7.* ________ **Day(s)**

2. During the **last 7 days**, how often did you walk, jog, or run outside for more than 5 minutes in your neighborhood?

	Never / Rarely	Sometimes	Often
Morning, before sunrise	☐	☐	☐
Morning, after sunrise, but before noon	☐	☐	☐
Afternoon	☐	☐	☐
Evening, before sunset	☐	☐	☐
Evening, after sunset	☐	☐	☐

3. On average, how many **weekdays (Monday - Friday)** do you walk, jog, or run outside for more than 5 minutes in your neighborhood in the following four seasons?

	# of days during Weekday (Monday - Friday)					
	0 (None)	1	2	3	4	5 (All days)
Spring (March - May)	☐	☐	☐	☐	☐	☐
Summer (June - August)	☐	☐	☐	☐	☐	☐
Fall (September - November)	☐	☐	☐	☐	☐	☐
Winter (December – February)	☐	☐	☐	☐	☐	☐

4. On average, how many days during **weekends (Saturday - Sunday)** do you walk, jog, or run outside for more than 5 minutes in your neighborhood in the following four seasons?

	# of days during Weekends (Saturday - Sunday)		
	0 (None)	1	2 (Sun. & Sat.)
Spring (March - May)	☐	☐	☐
Summer (June - August)	☐	☐	☐
Fall (September - November)	☐	☐	☐
Winter (December – February)	☐	☐	☐

5. What are the main reasons you walk? **Please check all that apply.**

- [ ] Commuting to/from work
- [ ] Commuting to/from school
- [ ] Going to/from a transit or bus stop
- [ ] Required for my job
- [ ] Walk the dog or other pet
- [ ] Drop off/Pick up someone, including children at school
- [ ] Personal errands (to/from the store, post office, and so on)
- [ ] Recreational pleasure
- [ ] Exercise/for my health
- [ ] Visit a friend or relative
- [ ] Some other reasons (please specify) ______________________

6. When you walk, jog, or run, how often do you use the following type of path or road in your neighborhood?

	Usually	Sometimes	Rarely	Never
Sidewalks	☐	☐	☐	☐
Shoulders of paved roads	☐	☐	☐	☐
Paved roads, not on shoulder	☐	☐	☐	☐
Bike paths, walking paths, or trails	☐	☐	☐	☐
Unpaved roads (e.g., dirt, gravel, sand)	☐	☐	☐	☐
Grass or fields next to road	☐	☐	☐	☐

7. If you did **NOT** check the "**Usually**" for the "**Sidewalk**" in the above table, what are reasons that you **don't** usually use sidewalks? **Please check all that apply.**

- [ ] No sidewalk along the route I need to
- [ ] Not in good repair
- [ ] Too crowded
- [ ] Prefer softer surface
- [ ] Don't feel safe
- [ ] Other ______________________

PART 2 Please tell us about your walking experience in terms of safety in your neighborhood

(OR within a 20-minute walk distance from your home)
Here, your walking includes walking, jogging, or running outside.

8. Please indicate the extent to which you agree or disagree with each of the following statements on a scale from "strongly disagree" to "strongly agree."

	Strongly Disagree	Somewhat Disagree	Somewhat Agree	Strongly Agree	Don't know or Not Applicable
Traffic speeds on most nearby streets while I walk in my neighborhood are **SLOW enough** to make me **feel SAFE**	☐	☐	☐	☐	☐
Street lighting in our neighborhood makes me **feel SAFE** while I walk at **NIGHT**	☐	☐	☐	☐	☐
I **feel SAFE** while walking in my neighborhood on **RAINY/SNOWY** days	☐	☐	☐	☐	☐
Crime in our neighborhood makes it **UNSAFE** for me to go on walks alone during the **DAY**	☐	☐	☐	☐	☐
Crime in our neighborhood makes it **UNSAFE** for me to go on walks alone at **NIGHT**	☐	☐	☐	☐	☐

9. Please indicate the extent to which you agree or disagree with each of the following statements on a scale from "strongly disagree" to "strongly agree."

	Strongly Disagree	Somewhat Disagree	Somewhat Agree	Strongly Agree	Don't know or Not Applicable
I feel **SAFE** from traffic while I walk in my neighborhood during the **DAY**	☐	☐	☐	☐	☐
I feel **SAFE** from traffic while I walk in my neighborhood at **NIGHT**	☐	☐	☐	☐	☐
There are some **intersections** in my neighborhood where I feel **UNSAFE** while crossing during the **DAY**	☐	☐	☐	☐	☐
There are some **intersections** in my neighborhood where I feel **UNSAFE** while crossing at **NIGHT**	☐	☐	☐	☐	☐

10. Do you have a child(ren) under 18 years old in your household?

☐ Yes *(please go to the question 11)*

☐ No *(please go to question 12 on the next page)*

11. *<u>If you check "**Yes**" in the above question 10</u>,* Please indicate the extent to which you agree or disagree with each of the following statements on a scale from "strongly disagree" to "strongly agree" while you walk with your child(ren).

	Strongly Disagree	Somewhat Disagree	Somewhat Agree	Strongly Agree	Don't know or Not Applicable
I feel **SAFE** from traffic while I walk **with my child(ren)** in my neighborhood	☐	☐	☐	☐	☐
Street lighting in our neighborhood makes me feel **SAFE** while I walk **with my child(ren)** at **NIGHT**	☐	☐	☐	☐	☐
Traffic speeds on most nearby streets in my neighborhood while I walk **with my child(ren)** are **SLOW enough** to make me feel **SAFE**	☐	☐	☐	☐	☐
There are some intersections in my neighborhood where I feel **UNSAFE** while crossing **with my child(ren)**	☐	☐	☐	☐	☐
Crime in our neighborhood makes it **UNSAFE** for me to go on walks **with my child(ren)**	☐	☐	☐	☐	☐

PART 3 Please tell us more about your safety experience while walking in your neighborhood

(OR within a 20-minute walk distance from your home)

12. Do you ever **feel threatened** while you are walking, jogging, or running in your neighborhood because of any of the following?

	No	Yes, Sometimes	Yes, Often
Motorist (e.g., driver of car, motorcycle, truck) cutting me off	☐	☐	☐
Motorist entering intersection without looking	☐	☐	☐
Motorist driving very close to me	☐	☐	☐
Motorist honking at me	☐	☐	☐
Motorist disregarding traffic signal	☐	☐	☐
Motorist driving very fast	☐	☐	☐
Inattentive driving (e.g. using smartphone, talking with other)	☐	☐	☐
Other road users (e.g. cyclists, skateboarders, people on scooters) passing very close to me or other behavior that made me feel threatened	☐	☐	☐
Path or sidewalk crowded with bicyclists, pedestrians, and other people competing for space	☐	☐	☐
Potential for physical assault	☐	☐	☐

13. Do you ever **feel threatened** while you are walking, jogging, or running in your neighborhood because of any of the following?

	No	Yes, Sometimes	Yes, Often
Crosswalks too long to cross (or too many road lanes at intersections)	☐	☐	☐
Poorly lit sidewalk or path	☐	☐	☐
Sidewalk or path too close to motor vehicle traffic	☐	☐	☐
Structure of the road makes it difficult to recognize the approaching vehicles (e.g. bumpy road, steep curve, hillside)	☐	☐	☐
Obstacles blocking the path or sidewalk (e.g., parked vehicles, trash cans)	☐	☐	☐
Poorly maintained paths or roadway surfaces (e.g., cracks, potholes, broken glass)	☐	☐	☐

14. Please share any other experiences that made you feel threatened while walking…

PART 4 Please tell us about yourself

15. What year are you born? Please answer the year in 4-digit (e.g. 1988)

16. What is your gender identity?

- ☐ Female
- ☐ Male
- ☐ Non-binary or third gender
- ☐ Prefer to self-identify
- ☐ Prefer not to say

17. Do you consider yourself...? **Please check all that apply.**

- ☐ American Indian, Native American, Alaska Native
- ☐ Black, African American, African
- ☐ Asian/Asian American
- ☐ South Asian/Indian
- ☐ Hispanic/Latino/a/x
- ☐ Native Hawaiian, Pacific Islander
- ☐ Middle Eastern, North African
- ☐ Slavic, Eastern European
- ☐ White, Caucasian
- ☐ I prefer to identify as ____________________
- ☐ I prefer not to disclose

18. What is your annual household income?

- ☐ Less than $15,000
- ☐ $15,000 to less than $24,999
- ☐ $25,000 to less than $34,999
- ☐ $35,000 to less than $49,999
- ☐ $50,000 to less than $74,999
- ☐ $75,000 to less than $99,999
- ☐ $100,000 to less than $149,999
- ☐ $150,000 or over

19. In a typical week, how did you get around your neighborhood?

	No Trips	Some Trips	Most Trips
Drove a personal car or shared car (Zipcar, Enterprise, CarShare, etc.)	☐	☐	☐
Got a ride from a friend or family member	☐	☐	☐
Taxi / Uber / Lyft	☐	☐	☐
Public transit (bus, rail, etc.)	☐	☐	☐
Walking	☐	☐	☐
Bicycling - a personal or shared bike	☐	☐	☐
Other please specify	☐	☐	☐

20. Do you identify as having or living with a disability?

- ☐ Yes *(please also answer the following two questions 21 and 22)*
- ☐ No *(please go to the question 23 on the next page)*
- ☐ Prefer not to say *(please go to the question 23 on the next page)*

21. ***If you checked "Yes" to the above question 20,*** would you please share your disability? **Please check all that apply.**

- ☐ Mobility (e.g., walking, climbing stairs)
- ☐ Speech or communication
- ☐ Visual (e.g., blind, low vision)
- ☐ Invisible (e.g., diabetes, HIV, cancer)
- ☐ Deaf or hard-of-hearing
- ☐ Not listed, please describe ____________
- ☐ Mental health (e.g., anxiety, PTSD)
- ☐ Prefer not to disclose
- ☐ Cognitive (e.g., neurodivergent, autistic, TBI, learning disabilities)
- ☐ Intellectual or developmental (e.g., Down syndrome, fragile X syndrome)

22. ***If you checked "Yes" to the above question 20,*** do you require assistance from any of the following? **Please check all that apply.**

- ☐ Wheelchair (manually or power operated)
- ☐ Service animal
- ☐ Other power driven-mobility devices (e.g. golf cart)
- ☐ Not listed, please describe ____________
- ☐ Walkers / Canes / Crutches / Braces
- ☐ Prefer not to disclose

23. How long have you lived in your current neighborhood?

__________ **year(s)** __________ **month(s)**

24. Including yourself, how many people are there in your household?

__________ **adult(s)** __________ **child(ren)**

25. How many motor vehicles (e.g., car, pickup truck, SUV, motorcycle) are owned, leased, or available for regular use by members of your household?

____

Appendix B Ten Maps of Selected Research Sites

Figure B-1 Buffered Map of Albany

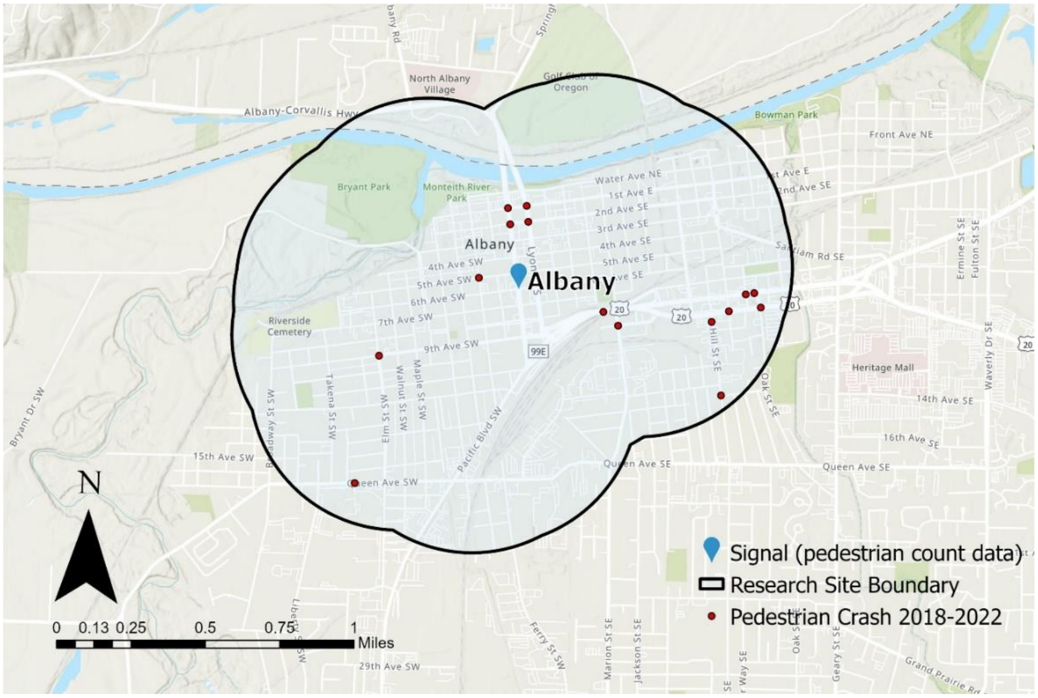


Figure B-2 Buffered Maps of Hillsboro

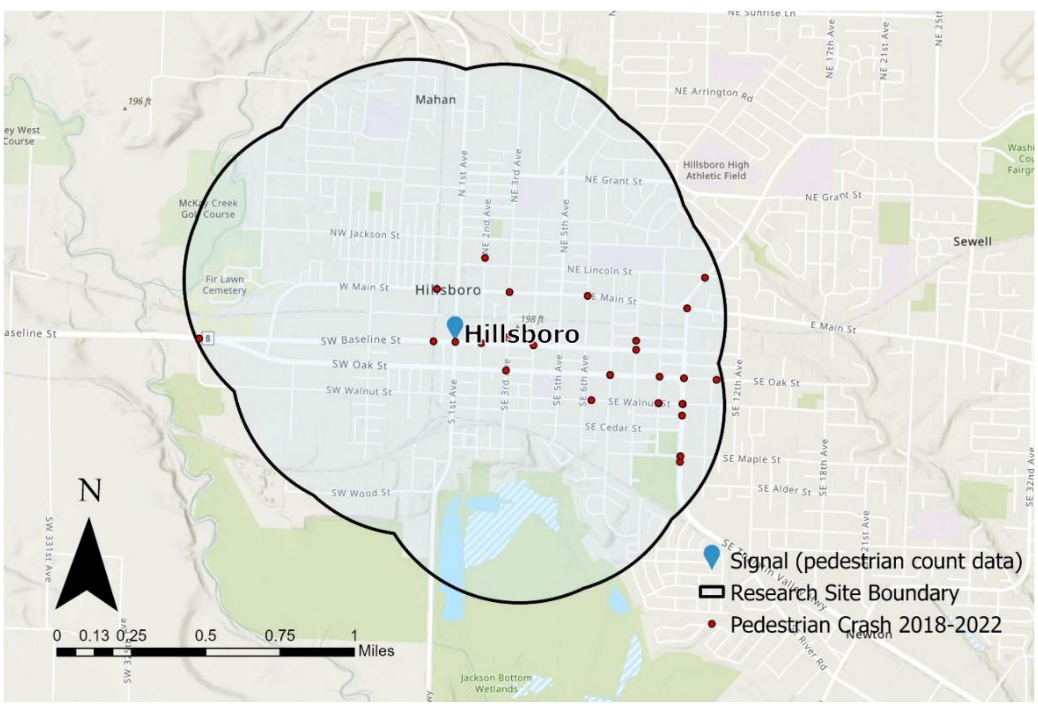


Figure B-3 Buffered Map of Lake Oswego

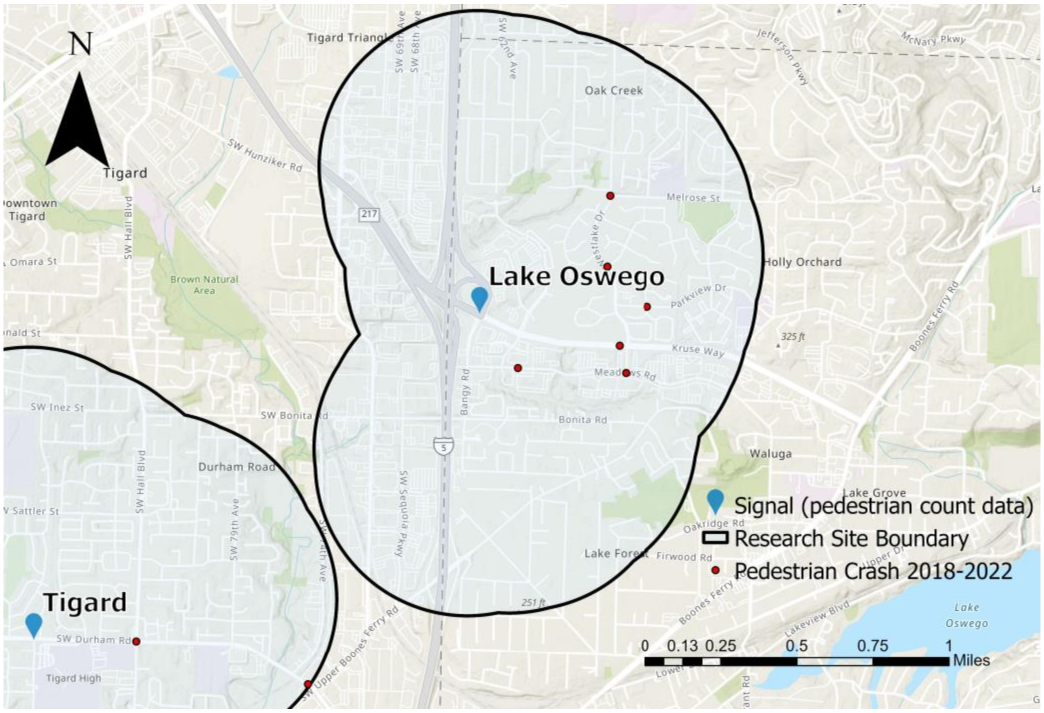


Figure B-4 Buffered Map of McMinnville

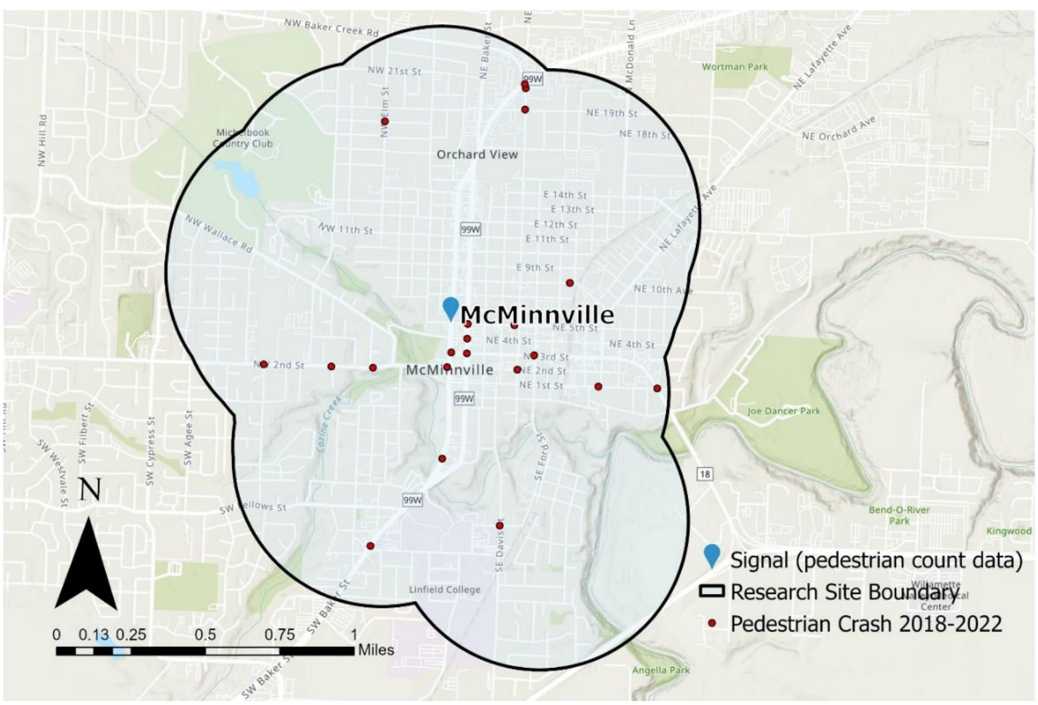


Figure B-5 Buffered Map of NW Portland

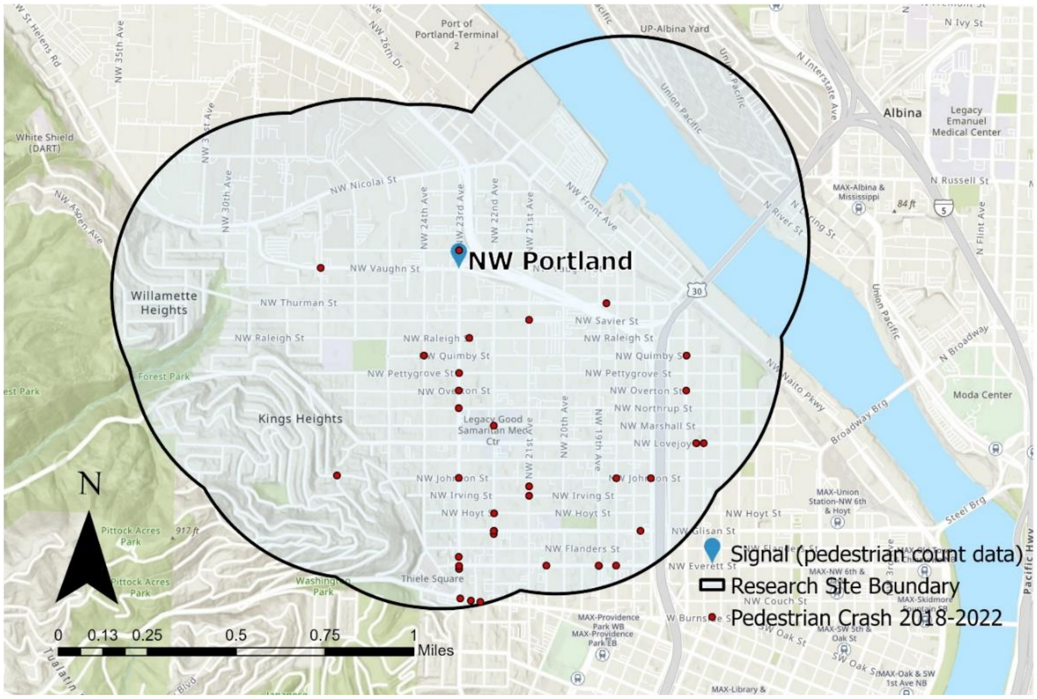


Figure B-6 Buffered Map of SE Portland

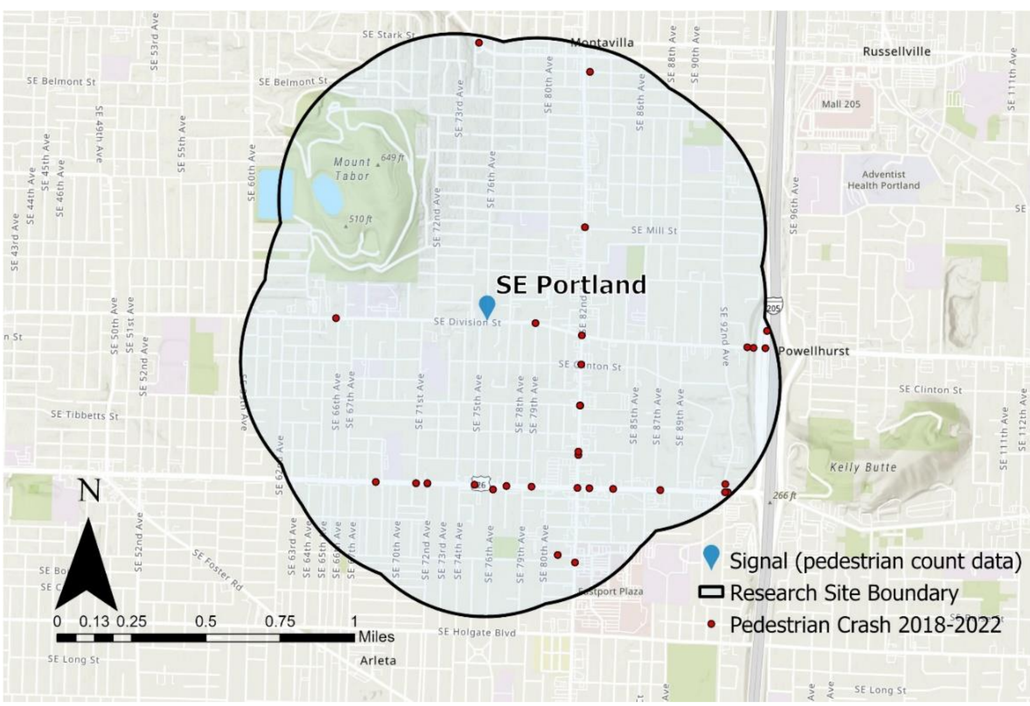


Figure B-7 Buffered Map of Tigard

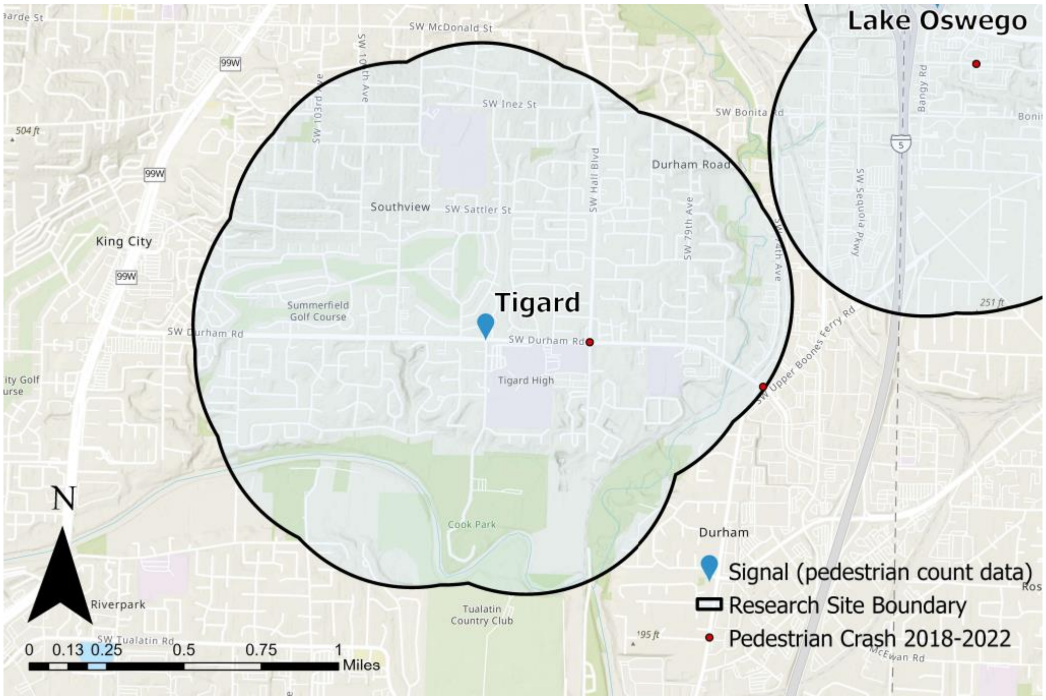


Figure B-8 Buffered Map of Wilsonville

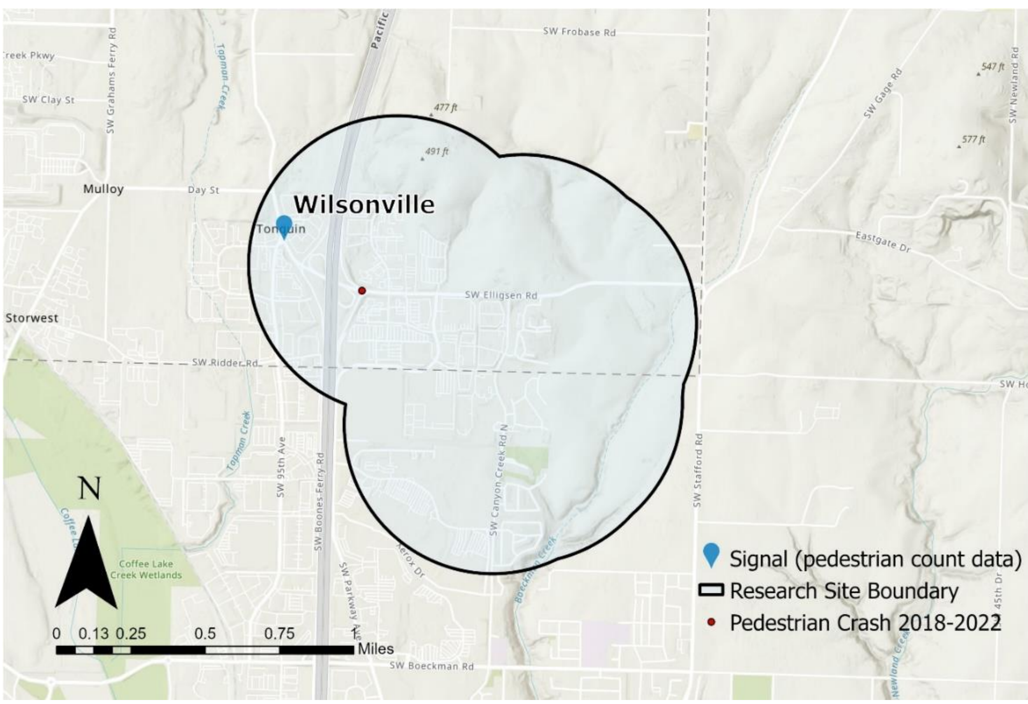


Figure B-9 Buffered Map of Wood Village

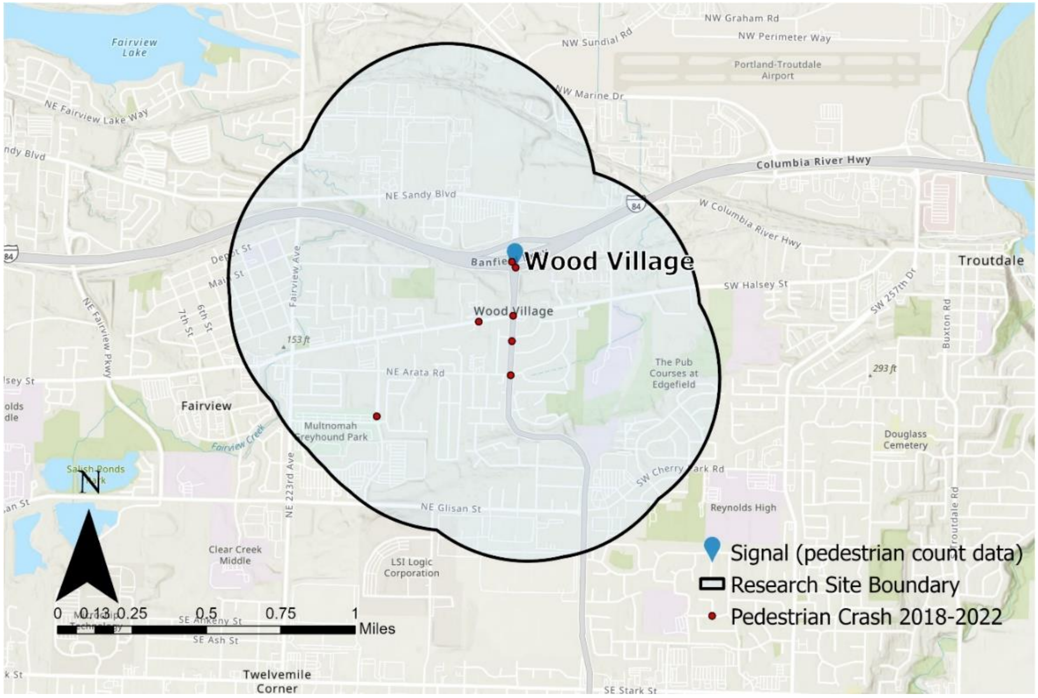
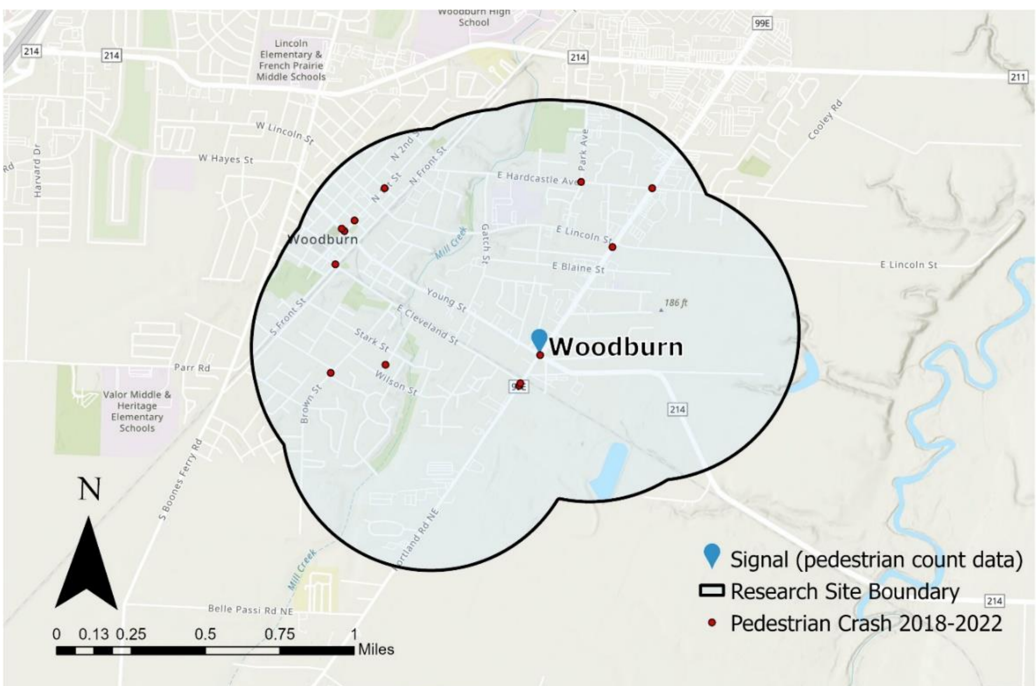


Figure B-10 Buffered Map of Woodburn



Appendix C RQ1: Cumulative Residual Plots (CURE Plots)

Figure C-1 CURE Plots (3-year Model): Pedestrian Count

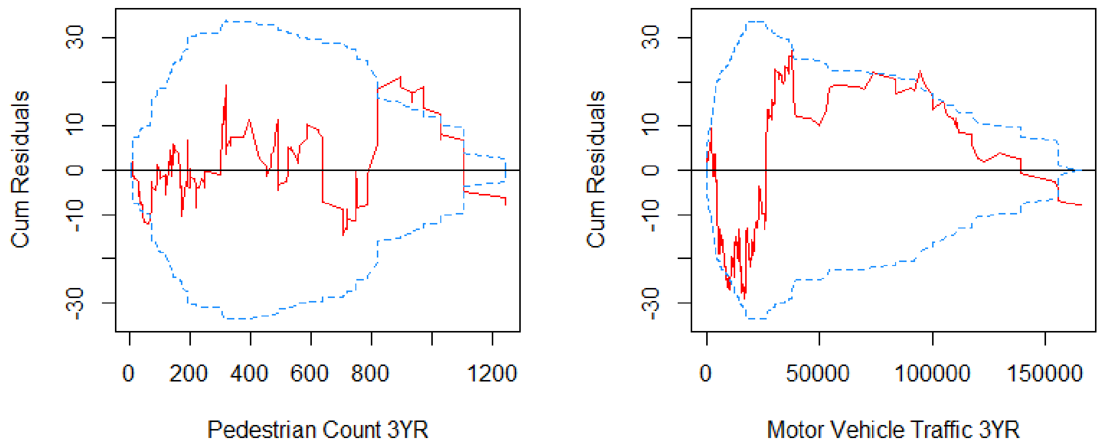


Figure C-2 CURE Plots (3-year Model): Population Density

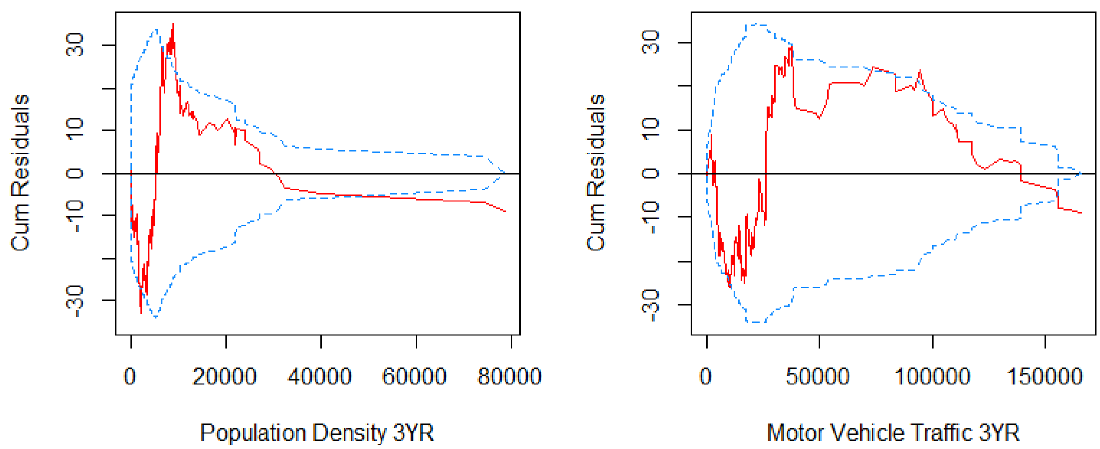


Figure C-3 CURE Plots (1-year Model): Pedestrian Count

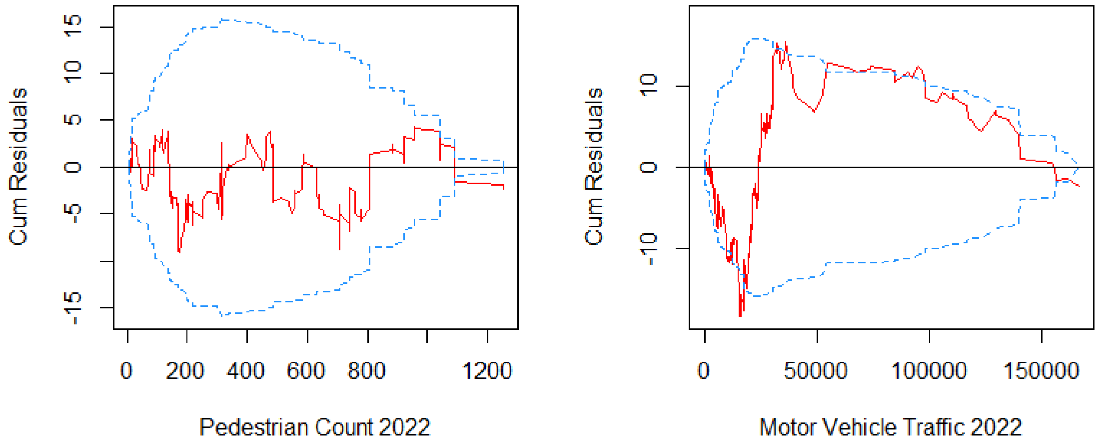
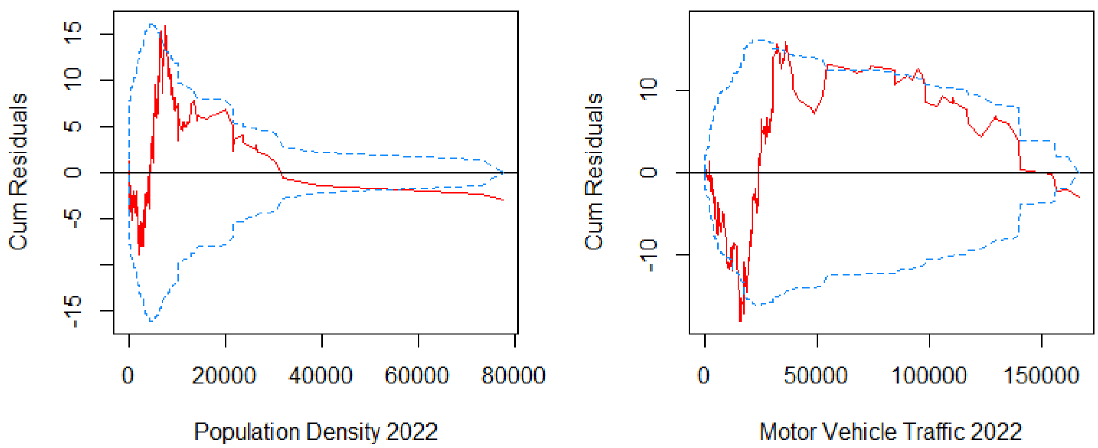


Figure C-4 CURE Plots (1-year Model): Population Density



Appendix D RQ2: Comparison of Structural Equation Models

Table D-1 Model Fit of SEM: Perceived Safety

Model	No Crash Variable	5-year All Crash	5-year Fatal Pedestrian Crash
Number of observed	551	551	551
Number of used	514	514	514
Model Fit			
Chi-test	218.048	234.364	222.651
Degree of freedom	100	107	107
P-value	<0.001	<0.001	<0.001
CFI	0.972	0.974	0.972
SRMR	0.028	0.028	0.028

Table D-2 Factor Loadings of Safety Attitudes

Items	No Crash Variable	5-year All Crash	5-year Fatal Pedestrian Crash
Traffic speeds on most nearby streets are slow enough	0.663***	0.663***	0.663***
Street lighting makes me feel safe at night	0.529***	0.529***	0.530***
Walking on rainy or snowy days	0.570***	0.570***	0.571***
Safe from traffic during the day	0.714***	0.714***	0.715***
Safe from traffic during at night	0.763***	0.763***	0.763***
Intersections make me feel unsafe while crossing during the day[1]	0.575***	0.575***	0.576***
Intersections make me feel unsafe while crossing at night[1]	0.592***	0.592***	0.593***

‘ ’ *p* <1‘+’ *p* <0.1 ‘*’ *p* <0.05 ‘**’ *p* <0.01 ‘***’ *p* <0.001

[1] reversely coded item

Table D-3 Comparison SEM Results by Crash Variable Type

Standardized coefficient

Variable \ Model			No Crash Variable	5-year All-type Crash	5-year Fatal Pedestrian Crash
Threatening Experience R-square			0.087	0.087	0.087
Threatening Experience	←	Pedestrian Volume	-0.105	-0.105	-0.105
		Motor Vehicle Traffic (n/1,000)	0.053	0.053	0.053
		Intersection (n/mi)	0.187**	0.187**	0.187**
		Public transit (n/mi)	0.079	0.079	0.079
		Park (mi^2)	-0.014	-0.014	-0.013
		Mixed-use area (mi^2)	0.184*	0.184*	0.184*
		Commercial area (mi^2)	-0.042	-0.042	-0.042
		Actual Vehicle speed (mph)	-0.057	-0.057	-0.057
		Age	-0.163**	-0.163**	-0.163**
		Gender (0: Female, 1: Male)	-0.064	-0.064	-0.064
		Disability (0: No, 1: Yes)	0.073	0.073	0.073
		Kids (0: No, 1: Yes)	0.079	0.079	0.079
Safety Attitude R-square			0.553	0.554	0.556
Safety Attitude	←	Threatened experience	-0.724***	-0.725***	-0.725***
		Crash Frequency	NA	0.008	0.038
		Pedestrian count	0.002	0.001	0.003
		Motor Vehicle Traffic (n/1,000)	0.006	0.003	0.008
		Sidewalk (mi)	0.07	0.068	0.068
		Intersection (n/mi)	-0.026	-0.028	-0.026
		Park (mi^2)	0.075^{+}	0.078^{+}	0.073^{+}
		Actual Vehicle speed (mph)	0.043	0.043	0.042
		Age	0.044	0.044	0.047
		Gender (0: Female, 1: Male)	-0.003	-0.003	-0.004
		Disability (0: No, 1: Yes)	-0.093*	-0.093*	-0.098*
		Kids (0: No, 1: Yes)	0.021	0.02	0.022

‘ ’ p <1‘+’ p <0.1 ‘*’ p <0.05 ‘**’ p <0.01 ‘***’ p <0.001