

## **Disparities in Pedestrian Crossing and Driver Yielding Behaviors: Evidence from a Large-Scale Observational Study at Urban Intersections**

### **Angela J. Haddad**

The University of Texas at Austin  
Department of Civil, Architectural and Environmental Engineering  
301 E. Dean Keeton St, Stop C1761, Austin TX 78712, USA  
Email: [angela.haddad@utexas.edu](mailto:angela.haddad@utexas.edu)

### **Emily A. Podnar**

The University of Texas at Austin  
Department of Civil, Architectural and Environmental Engineering  
301 E. Dean Keeton St, Stop C1761, Austin TX 78712, USA  
Email: [emilypodnar@utexas.edu](mailto:emilypodnar@utexas.edu)

### **Anna E. Beliveau**

The University of Texas at Austin  
Department of Civil, Architectural and Environmental Engineering  
301 E. Dean Keeton St, Stop C1761, Austin TX 78712, USA  
Email: [annabeliveau@utexas.edu](mailto:annabeliveau@utexas.edu)

### **Devina Sharma**

The University of Texas at Austin  
Department of Civil, Architectural and Environmental Engineering  
301 E. Dean Keeton St, Stop C1761, Austin TX 78712, USA  
Email: [devinasharma@utexas.edu](mailto:devinasharma@utexas.edu)

### **Chandra R. Bhat (corresponding author)**

The University of Texas at Austin  
Department of Civil, Architectural and Environmental Engineering  
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA  
Tel: +1-512-471-4535; Email: [bhat@mail.utexas.edu](mailto:bhat@mail.utexas.edu)

## **ABSTRACT**

Pedestrian safety remains a critical challenge in urban environments, marked by rising fatalities and persistent disparities across sociodemographic groups. Uncovering the drivers of these disparities requires a deeper understanding of both pedestrian and driver behaviors. This study examines how individual attributes, social context, and time-of-day/weather conditions shape pedestrian crossing and driver yielding decisions. We analyzed over 1,000 hours of video footage from two intersections in Austin, Texas, documenting over 20,995 pedestrian crossings and 3,124 pedestrian-vehicle interactions. Manual annotation of this footage enabled the estimation of two binary logit models: one predicting non-compliant pedestrian crossings (NCPC) and the other predicting driver failure to yield to pedestrians. The results indicate that male pedestrians, Black pedestrians, those displaying visible signs of housing insecurity, and individuals crossing solo are significantly more likely to cross non-compliantly and to encounter lower driver-yielding rates. Runners also exhibit higher NCPC rates than walkers, with peak non-compliance occurring during late night and dawn periods. On the driver side, pedestrian NCPC behavior is the strongest predictor of failure to yield. Driver non-yielding behavior is also more likely during morning periods and among drivers of personal (non-commercial) vehicles, and when the pedestrian in question is older, Black or Brown, and male. These findings highlight the importance of addressing social and behavioral factors in pedestrian safety interventions. By revealing how marginalization and context interact to shape risk, this research contributes to the transportation equity literature and supports interventions that go beyond infrastructure, such as education campaigns, bias reduction, and community-led safety initiatives.

**Keywords:** Pedestrian-vehicle interaction; pedestrian crossing violation; jaywalking; driver yielding; naturalistic video data collection; pedestrian safety

# 1. INTRODUCTION

## 1.1. Background and Context

Pedestrian safety remains a pressing concern in transportation research and practice, driven by persistently high and rising rates of injuries and fatalities, and the inequitable distribution of these risks across communities. An analysis of National Highway Traffic Safety Administration (NHTSA) records reveals a steady deterioration in pedestrian safety since fatalities hit a historic low in 2009. In 2022, pedestrian fatalities reached 7,593, representing a 1.6% increase from the previous year, and the highest annual toll since 1981 (NHTSA, 2024a). Although fatalities declined slightly to 7,314 in 2023, the number of non-fatal pedestrian crashes increased by 1.34% compared to 2022, reaching 68,244 incidents (NHTSA, 2024b). Overall, this long-term upward trend in pedestrian crashes and fatalities contrasts with trends in other developed nations, where pedestrian deaths have generally declined (Naumann et al., 2025). Moreover, pedestrians have become increasingly vulnerable relative to other road users, as reflected in the growing share of pedestrian deaths, which increased from 12.1% of all traffic fatalities in 2009 to 17.9% in 2023 (NHTSA, 2024b), despite relatively stable walking rates over the same period (McGuckin et al., 2018).

Demographic and socioeconomic characteristics further shape disparities in pedestrian safety. Men represent approximately 70% of pedestrian fatalities (NHTSA, 2024a), potentially reflecting gendered differences in travel behavior and risk-taking, such as more frequent violations of traffic laws (see Guo et al., 2011, Brosseau et al., 2013, Dommès et al., 2015, and Baker et al., 2022). Older adults also face heightened vulnerability due to mobility limitations, slower reaction times, and increased injury severity in the event of a crash (Smart Growth America, 2024). Racial minorities, particularly Black and Native American pedestrians, experience disproportionately high rates of severe and fatal crashes, with per-trip and per-capita fatality rates significantly exceeding those of white pedestrians (see Hamann et al., 2020, Sanders and Schneider, 2022, and Smart Growth America, 2024). These disparities are often attributed to differences in infrastructure quality and exposure to high-risk traffic environments (see Dadashova et al. (2024) for a comprehensive review of associations between pedestrian race and pedestrian crash propensity). Individuals experiencing homelessness also face an increased risk of being seriously injured or killed in traffic crashes, potentially due to greater reliance on walking and transit, frequent presence near high-speed, high-traffic roads, and elevated health-related vulnerabilities, including physical disabilities, mental health challenges, and substance use (see USDOT, 2024 for a comprehensive review). Income is another critical factor. Pedestrian fatality rates in census tracts with median household incomes below \$15,000 are nearly five times those in high-income areas (Smart Growth America, 2024), a disparity often linked to a combination of higher walking rates and insufficient pedestrian infrastructure, such as inadequate crosswalks, pedestrian signals, and lighting (Morency et al., 2012, Lee et al., 2019, and Yu et al., 2022).

Although infrastructure and exposure factors, as discussed above, have long dominated pedestrian safety research, they do not fully account for the persistent demographic disparities in crash outcomes. For example, studies have shown that racial and income-related disparities in pedestrian injuries and fatalities often persist even after controlling for infrastructure and exposure

variables (see Roll and McNeil, 2022, Dumbaugh et al., 2023, and Haddad et al., 2023), suggesting that additional behavioral and contextual mechanisms are at play. At the driver level, implicit biases have been documented, with studies showing differential yielding behavior and increased crash risk based on pedestrians' race, gender, and the socioeconomic status of the surrounding neighborhood (Goddard et al., 2015, Coughenour et al., 2017, and Schneider et al., 2018). However, while recent studies using real-world observational data have advanced our understanding of how built-environment and traffic-related stimuli shape individual behavior (see Ghomi and Hussein, 2022, for a comprehensive review), far less attention has been accorded to examining how pedestrian and driver behaviors intersect with sociodemographic characteristics or temporal contexts (see Feng et al., 2021, Ghomi and Hussein, 2022, and Gerogiannis and Bode, 2024). This research gap limits our understanding of how intersecting factors, such as race, housing status, social context and time-of-day, influence exposure to risk and contribute to persistent disparities in safety outcomes.

## **1.2. Research Objectives and Significance**

The discussion above motivates the research in the current paper, which seeks to uncover the often-hidden social and behavioral patterns in pedestrian safety and contribute to a more comprehensive understanding of pedestrian safety risks. Specifically, we focus on two central questions: (1) How do individual pedestrian attributes, social context, and time-of-day/weather conditions interact to influence pedestrian crossing behavior, especially non-compliant crossings (e.g., jaywalking or crossing against signals)? (2) What factors influence driver yielding behavior, and how does the combination of pedestrian characteristics, group dynamics, and temporal conditions shape drivers' decisions to yield?

To address these questions, we analyzed over 1,000 hours of intersection video footage from two locations in Austin, Texas. Trained analysts coded 20,995 pedestrian crossings and documented 3,124 pedestrian-vehicle interactions. These data informed two separate binary logistic regression models: one modeling the likelihood of non-compliant pedestrian crossing (NCPC), and the other modeling the likelihood of driver non-yielding behavior in contexts where statutory provisions impose a legal obligation on drivers to yield to pedestrians. By capturing real-world behavior across diverse contexts, this research contributes to the transportation literature by addressing the influence of individual and social factors on pedestrian safety. The findings have significant implications for urban planning and policy, underscoring the need for interventions that extend beyond infrastructure to address the broader social and behavioral aspects of street safety.

## **2. RELEVANT LITERATURE**

The literature on pedestrian safety is extensive, with most studies relying on historical crash data to examine both macro- and micro-level patterns, such as identifying high-risk groups and locations, or analyzing how individual pedestrian characteristics influence crash severity (see Mirhashemi et al., 2022, Shrinivas et al., 2023, and Kumar et al., 2025, for systematic literature reviews). These studies have been valuable for identifying patterns and disparities in safety outcomes; however, there is still a need to uncover, at a fine-grained behavioral level, the

mechanisms underlying those disparities. Recognizing this need, recent research has shifted toward examining the behavioral dimensions of pedestrian safety, focusing on the factors influencing (i) non-compliant pedestrian crossings (NCPC), and (ii) driver decisions to yield to pedestrians.

In studying pedestrian and driver behaviors, researchers commonly categorize influencing factors into four domains: human, traffic, built-environment, and environmental/temporal conditions (see Zhu et al., 2021, and Ghomi and Hussein, 2022). Human factors typically include the demographic and socioeconomic characteristics of pedestrians and drivers. Traffic factors refer to variables such as traffic volume, vehicle speed, and traffic composition. Built-environment factors encompass elements such as roadway geometry, pavement condition, lighting, and traffic control features. Lastly, environmental/temporal factors refer to weather conditions, ambient lighting, and the time-of-day during which pedestrian or driver behavior is observed.

A range of data collection methods has been used to study the influences of the above listed factors, including surveys (e.g., Deb et al., 2017 Mukherjee and Mitra, 2020), video-based stated-preference experiments (e.g., Liu and Tung, 2014), in-person road observations (e.g., Avineri et al., 2012, Dommes et al., 2015, Ferenchak, 2016, Aghabayk et al., 2021), analysis of recorded video footage either manually (e.g., Bella and Nobili, 2020, Zhu et al., 2021) or using computer vision algorithms (e.g., Anik et al., 2021, Chavis et al., 2023, Wan et al., 2023), field experiments (e.g., Goddard et al., 2015, Coughenour et al., 2017), and immersive virtual reality studies (e.g., Hübner et al., 2025, Nazemi et al., 2025). Of these methods, in-person road observations and the analysis of video footage are considered naturalistic approaches, as they capture real-world behavior in uncontrolled, everyday settings without researcher intervention. Such naturalistic approaches also allow for capturing pedestrian behavior and pedestrian-vehicle interactions over extended periods of time at one or more locations, allowing for the collection of a large number of pedestrian walking instances and vehicle-pedestrian interactions to facilitate an investigation of the social-behavioral mechanisms underlying pedestrian safety risk.

To align with this paper’s objective of specifically uncovering the social-behavioral mechanisms of pedestrian safety risk, our synthesis of the literature is confined to naturalistic observational studies and to an overview of pedestrian/driver behavior as a function of (a) pedestrian/driver sociodemographics, (b) pedestrian activity and social context, (c) time-of-day and weather factors, and (d) vehicle characteristics. That is, unlike many other studies that attempt to investigate the effects of built-environment and traffic characteristics (such as road width, number of lanes of crossing, neighborhood demographics, sidewalk availability, roadside parking, and traffic volumes/speeds) on pedestrian crash propensity, we focus directly on pedestrian/driver behaviors that constitute precursor factors affecting pedestrian crash propensity. Tables 1 and 2 serve to support such an overview. Specifically, Table 1 synthesizes naturalistic observational studies from the past decade on pedestrian crossing, while Table 2 similarly synthesizes naturalistic studies of driver yielding behaviors. Each table summarizes the study location, data collection duration, number of observation sites, sample size, behavioral outcomes, and the explanatory variables considered (grouped within the variable categories identified earlier). Table 2 includes an additional column for data collection methods, reflecting the more diverse

methodological approaches used in driver yielding research, including controlled field experiments that have proven invaluable for examining racial effects on yielding behavior. Together, the literature review and tabulated summaries highlight common themes and methodological approaches, while identifying critical gaps related to underexplored sociodemographic and behavioral dimensions influencing pedestrian/driver behaviors.

## **2.1. Pedestrian Crossing Behavior**

Several behavioral outcomes have been examined in the pedestrian safety literature to gain a better understanding of crossing patterns and decision-making processes. These include specific violation types, such as temporal violations (e.g., running a red light) and spatial violations (e.g., crossing outside a designated crosswalk or midblock), as well as distraction, crossing speed, waiting time, gap acceptance, and head-turn frequency, all used as proxies for risk awareness. These outcomes are highlighted in the comprehensive reviews by Theofilatos et al. (2021) and Ghomi and Hussein (2022), as well as in the “Measured Outcomes” column of Table 1.

### ***2.1.1. Pedestrian Sociodemographics***

Gender is one of the most commonly studied factors in pedestrian behavior (see Table 1), with many studies finding that men tend to take more risks than women. However, the evidence varies by region and behavior type. U.S.-based studies present mixed evidence on gender differences in pedestrian behavior. While some findings suggest that men are more prone to spatial violations (Russo et al., 2018; Rafe et al., 2025) and distraction (Russo et al., 2018), gender differences in temporal violations have often been found to be statistically insignificant (Russo et al., 2018; Rafe et al., 2025). Interestingly, Baker et al. (2022) found that gender differences in temporal violations were evident only in low-risk situations (where a concrete safety island was present), with men being more non-compliant, whereas these differences were not statistically significant in higher-risk environments (where there was no safety island present). Similarly, Schwebel et al. (2022) found no significant gender effects across multiple dimensions, including situational awareness, distraction, and general unsafe crossing behavior. In contrast, non-U.S. studies have more consistently associated male pedestrians with higher rates of temporal and spatial violations (Xie et al., 2018; Zhu et al., 2021; Aghabayk et al., 2021; Bendak et al., 2021; Zhang et al., 2023; Miladi et al., 2025). Some non-U.S. studies have also pointed to reduced situational awareness among male pedestrians, such as less frequent head-turning before crossing (Bendak et al., 2021).

With respect to age, recent U.S.-based studies have generally reported no statistically significant association between older age groups and pedestrian violations (Ivan et al., 2017; Russo et al., 2018; Rafe et al., 2025). However, some other age-related trends have been evident. For instance, Rafe et al. (2025) found that children and adolescents were more likely to engage in temporal violations, while Russo et al. (2018) identified elevated distraction levels among pedestrians aged 16 to 29. Findings from studies conducted outside the U.S. also highlight significant age-related trends, though results remain somewhat inconsistent. Older adults were frequently associated with safer pedestrian behavior, including a lower likelihood of temporal violations (Aghabayk et al., 2021; Bendak et al., 2021), reduced distraction (Bendak et al., 2021),

greater situational awareness (Aghabayk et al., 2021), and a higher tendency to wait on the curb rather than in the roadway (Dommes et al., 2015). However, several studies found no significant association between age and temporal violations (Dommes et al., 2015; Xie et al., 2018; Zhang et al., 2023), and only one study in Hong Kong reported that older adults were more likely to commit such violations (Zhu et al., 2021). Additionally, Miladi et al. (2025) noted that older adults were more likely to complete crossing during the red phase after starting on green, a behavior likely attributable to slower walking speeds rather than intentional non-compliance.

We are not aware of any naturalistic studies of pedestrian crossing behavior that examine pedestrian race-related variations, as we consider in our analysis (see last row of Table 1).

### ***2.1.2. Pedestrian Activity and Context***

Social context (first column under “pedestrian activity and context” in Table 1) is frequently examined in pedestrian behavior research, though it is defined in varying ways, including walking with companions or the presence or number of others crossing concurrently. Additionally, although pedestrian volume is typically treated as a traffic-related variable, it can also serve as a proxy for the presence of other pedestrians at a crossing. These differences in definition partly explain the mixed findings across the literature. Some social context variables are associated with safer behavior. For instance, Rafe et al. (2025) and Dommes et al. (2015) found that others crossing at the same time reduced spatial and temporal violations, while Zhu et al. (2021) and Bendak et al. (2021) reported fewer violations and technological distractions when pedestrians were accompanied, particularly by children. Compliance has also been found to increase with pedestrian volumes (Ivan et al., 2017; Miladi et al., 2025). However, other forms of social presence appear to encourage risk. Larger group sizes, especially three or more, were linked to higher violation rates (Russo et al., 2018; Zhang et al., 2023), and observing others engage in non-compliant behavior increased the likelihood of doing the same (Xie et al., 2018). Adding further nuance, Anik et al. (2021) documented gendered responses to group behavior, finding that women were more risk-averse when walking alone but more likely to follow a group in engaging in non-compliant crossings. These findings suggest that social context can either deter or promote risky crossing behavior, depending on how it is defined and the actions modeled by surrounding pedestrians.

With the growing prevalence of smartphones and personal technology, several studies have also examined the impact of technological distraction (second column under “pedestrian activity and context” in Table 1) on pedestrian crossing behavior. Despite increased interest in distraction, whether treated as an explanatory factor in violation models or as a behavior influenced by individual and environmental conditions, findings generally indicate inconsistent or limited effects on crossing behavior, with impacts varying by distraction type, violation type, and surrounding context. Texting, for instance, is frequently linked to reduced situational awareness. Aghabayk et al. (2021) found that pedestrians who were texting were less likely to scan for traffic, while Bendak et al. (2021) and Russo et al. (2018) reported an increased likelihood of spatial violations, such as crossing outside marked crosswalks, among texters, likely due to diminished attention to pavement markings. However, multiple studies found no significant association between texting and temporal violations (Russo et al., 2018; Aghabayk et al., 2021; Bendak et al., 2021; Miladi et al.,

2025). Similarly, pedestrians engaged in phone conversations were generally not associated with increased temporal violations (Russo et al., 2018; Aghabayk et al., 2021; Miladi et al., 2025), while headphone use was linked to a lower likelihood of such violations (Aghabayk et al., 2021). Schwebel et al. (2022) further demonstrated that the influence of distraction varied by location. In downtown areas, distraction was associated with a reduced risk of temporal violations but a higher risk of spatial violations and failing to scan for traffic. In contrast, in entertainment districts, distraction was associated with a lower risk of spatial violations.

Another contextual variable commonly examined in the pedestrian safety literature is the act of carrying or holding visible items. This factor has been studied more frequently in non-U.S. contexts, where it has generally shown no significant association with pedestrian violations (Bendak et al., 2021; Zhu et al., 2021; Zhang et al., 2023). A notable exception is Aghabayk et al. (2021), who found that pedestrians carrying items were more likely to look left and right for traffic before crossing, suggesting increased situational awareness. Other miscellaneous factors in this category include changes in walking speed, such as shifting from walking to running, which Rafe et al. (2025) found to have no significant effect. The same study also reported that individuals using mobility devices, such as wheelchairs, skateboards, scooters, or bicycles, were less likely to commit spatial violations but more likely to engage in temporal violations.

### ***2.1.3. Time-of-Day and Weather***

Time-of-day and weather have been shown to influence pedestrian crossing behavior. Rafe et al. (2025) found that overnight hours (00:00-05:59) were associated with elevated rates of both spatial and temporal violations relative to other times of day. Similarly, Fu et al. (2022) reported that pedestrians were less likely to cross in the presence of right-turning vehicles during nighttime hours (19:00-22:00) compared to daytime periods (10:00-16:00), while Liu and Tung (2014) observed increased caution at dusk, likely due to reduced visibility. Additionally, Ivan et al. (2017) noted decreased compliance during late afternoon hours (16:00-18:00) compared to earlier in the day, as well as on Fridays compared to other weekdays.

Regarding weather-related conditions, Bendak et al. (2021) found that higher temperatures were associated with increased temporal violations, whereas Rafe et al. (2025) reported a similar effect on spatial violations but found no significant impact on temporal violations. Both studies observed that precipitation was associated with fewer temporal violations, suggesting that rain may discourage risk-taking. Ivan et al. (2017) further found that cloudy conditions reduced crossing compliance. Seasonal variation was evident in Miladi et al. (2025), who reported that pedestrians were less likely to finish crossing on a red light in the fall than in the summer. However, during the early COVID-19 period (spring 2020), pedestrians were more likely to initiate and complete crossings during the red phase, likely due to decreased vehicle traffic.

## **2.2. Driver Yielding Behavior**

Similar to the case of pedestrian crossing, a variety of outcomes are used to study driver behavior in the context of pedestrian-vehicle interactions. These include driver yielding behavior, which is sometimes categorized into hard stops, soft yielding, or complete non-yielding, as well as surrogate



safety metrics such as stopping distance (e.g., Figliozi and Tipagornwong, 2016), vehicle deceleration rate (e.g., Bella and Nobili, 2020), Time to Collision (TTC) (e.g., Bella and Nobili, 2020; Pinnow et al., 2021), and Post-Encroachment Time (PET) (e.g., Pinnow et al., 2021; Das et al., 2023). This section, along with Table 2, focuses specifically on driver yielding behavior, as it directly corresponds to one of the most commonly reported precursor factors in pedestrian crashes -- drivers failing to yield at crosswalks.

### ***2.2.1. Pedestrian Sociodemographics***

Existing studies have consistently shown that drivers are more likely to yield to women (Anciaes et al., 2020; Coughenour et al., 2017; Demir et al., 2020; Zafri et al., 2022; Pechteep et al., 2024), with only two exceptions in Table 2 reporting no significant effect of pedestrian gender on yielding (Dileep et al., 2016; Schneider et al., 2018). In contrast, while many studies in Table 2 also examined the effect of pedestrian age, most found no significant age associations (Dileep et al., 2016; Schneider et al., 2018; Anciaes et al., 2020; Demir et al., 2020; Zafri et al., 2022). An exception was Pechteep et al. (2024), who reported that drivers were more likely to yield to older pedestrians.

Since 2015, there has been growing interest in the U.S. in examining the effect of pedestrian race on driver yielding behavior, particularly through staged field experiments. Studies by Goddard et al. (2015), Coughenour et al. (2017), and Coughenour et al. (2020) found that Black pedestrians experienced lower yielding rates and longer wait times at crosswalks compared to white pedestrians. These findings are also supported by in-person observational research by Schneider et al. (2018), which reached similar conclusions. However, Schneider et al. (2018) reported no significant associations between driver yielding and site-level racial composition, such as whether the majority of pedestrians or drivers were white. Similarly, Anciaes et al. (2020) found no significant differences in yielding behavior toward pedestrians using a wheelchair or walking stick.

### ***2.2.2. Pedestrian Activity and Context***

Beyond demographic traits, specific pedestrian behaviors and contextual cues also affect driver responses. Social context (especially group presence and group walking) has generally been associated with higher yielding rates (see Zafri et al., 2022, and Pechteep et al., 2024), with the exception of Dileep et al. (2016) and Schneider et al. (2018), who reported insignificant findings. Additionally, all studies that examined assertiveness-related variables found that assertive pedestrian behaviors, such as brisk movement toward the crosswalk, hand gestures, or making eye contact with the driver, increased the likelihood of yielding (Dileep et al., 2016; Schneider et al., 2018; Zafri et al., 2022).

In contrast, drivers were less likely to yield to non-compliant or jaywalking pedestrians, often demonstrating sharper deceleration and shorter stopping distances (Bella and Nobili, 2020). However, Zafri et al. (2022) reported that whether or not a pedestrian used a designated crosswalk while crossing an intersection had no significant impact on driver yielding behavior. Their findings

also indicate that drivers were more likely to yield when pedestrians carry baggage, and are not distracted by mobile devices (Zafri et al., 2022).

### **2.2.3. *Driver Sociodemographics***

Relatively few studies have examined the influence of driver gender and age on yielding behavior. Most of these studies reported no significant differences based on driver gender (Hirun, 2016; Schneider et al., 2018; Demir et al., 2020). However, Demir et al. (2020) noted that gender effects were significant only among middle-aged drivers, suggesting that generational shifts may be reducing gender disparities in yielding decisions. Findings on driver age are similarly inconsistent. Hirun (2016) observed that older drivers were more likely to yield, while Demir et al. (2020) found the opposite in a Turkish context, and Schneider et al. (2018) did not report a significant association between driver age and yielding behavior.

In addition to demographic characteristics, other factors such as social cues in the form of the behavior of other drivers and formal education attainment have also been found to impact yielding behavior. For instance, drivers were more likely to yield when they observed a preceding vehicle yielding or witnessed a yielding event in an adjacent lane (Figliozi and Tipagornwong, 2016), while Hirun (2016) found that drivers with a bachelor's degree and greater awareness of right-of-way laws were more likely to yield.

### **2.2.4. *Time-of-Day and Weather***

The effects of time-of-day and weather conditions on driver yielding behavior have also received limited attention, and the few studies that have addressed them report mostly insignificant findings (Anciaes et al., 2020; Demir et al., 2020; Fu et al., 2022).

### **2.2.5. *Vehicle Characteristics***

Coughenour et al. (2020) observed that drivers in expensive, high-status vehicles, often serving as a proxy for social class, were less likely to yield to pedestrians, with yielding rates decreasing by approximately 3% for every \$1000 increase in vehicle price. However, Greitemeyer (2023) presented a contrasting view, noting that vehicle status was not significantly related to whether a driver yielded or drove through a crosswalk when a pedestrian was waiting. Studies have also found that drivers of larger or more powerful vehicles, such as SUVs, pickup trucks, and heavy vehicles, are generally less likely to yield to pedestrians (see Dileep et al., 2016, and Figliozi and Tipagornwong, 2016). These patterns may reflect visibility differences, a sense of greater protection, or potentially different driving attitudes associated with these vehicle types.

**Table 1. Summary of Literature on Pedestrian Crossing Behavior**

Reference	Country/ Region	Data collection duration	Locations (Type/ Number)	No. of Obs.	Measured Outcomes	Pedestrian Sociodemographics			Pedestrian Activity & Context			Time-of-Day/ Weather	
						Gender	Age	Race	Social context	Distraction	Carrying items/ Other*	Time-of-day	Weather
Studies conducted in the US.													
Rafe et al., 2025	Utah	24-60 hrs/site	39 signalized intersections	5,589	• Spatial violation • Temporal violation	×	×		×		×	×	×
Baker et al., 2022	Campus of a southern American university	Two-weeks (~5 hrs/day/site)	1 signalized intersection crossing	2,707	• Temporal violation	×							
Schwebel et al., 2022	Alabama	~ 1 hr/site	112 intersections	3,248	• Pedestrian unsafe crossing (did not look left/right; crossed against walk signal or outside crosswalk) • Pedestrian distracted crossing	×	×		×	×	×		
Russo et al., 2018	New York and Arizona	3 hrs/site	4 signalized intersections	3,038	• Walking speed • Pedestrian distraction • Spatial violation • Temporal violation	×	×		×	×			
Ivan et al., 2017	Connecticut	216 hrs (~6 hrs/site)	42 intersections	14,838	• Temporal violation		×					×	×
Studies conducted outside the US.													
Miladi et al., 2025	Canada	9 hrs/site	24 signalized intersections	4,711	• Pedestrian crossing start on red • Pedestrian crossing finish on red • Pedestrian crossing finish on red/started on green • Pedestrian crossing completely on red	×	×			×	×		×
Zhang et al., 2023	China	0.5 hrs/site	6 4-lane two-way road segments	723	• Spatial violation	×	×		×		×		
Fu et al., 2022	China	54 hrs (9 hrs/site)	6 crosswalks adjacent to right-turning vehicles at signalized intersections	518	• Pedestrian crossing decisions: cross vs. not cross				×			×	
Aghabayk et al., 2021	Iran	4 hrs/site	2 signalized and 2 unsignalized intersection	552	• Temporal violation • Looking left-right for traffic before/while crossing	×	×		×	×	×		
Bendak et al., 2021	United Arab Emirates	0.5 hrs/site	5 signalized intersections and 5 signalized midblock crossings	708	• Temporal violation • Spatial violation • Looking left-right before crossing • Crossing speed	×	×		×	×	×		×
Zhu et al., 2021	Hong Kong	5 hrs/site	6 signalized crosswalks	6,320	• Temporal violation	×	×		×		×		
Xie et al., 2018	Hong Kong	1.5 hrs/site	7 signalized intersections	7,230	• Temporal violation	×	×						
Dommes et al., 2015	France	unspecified	6 signalized intersections	680	• Waiting position (curb vs. road) • Running during crossing • Situational awareness • Temporal violation	×	×		×		×		
This Study	Texas	432-864 hrs/site	2 signalized intersections	20,995	• Temporal or spatial violation	×	×	×	×	×	×	×	×

\*The “Other” category under “Pedestrian Activity & Context” corresponds to changes in pedestrian speed (change from walking to running) and use of mobility devices such as wheelchairs and scooters.

**Table 2. Summary of Literature on Driver Yielding Behavior**

Reference	Country/ Region	Data collection method	Data collection duration	Locations (Type/ Number)	No. of Obs.	Measured outcomes	Pedestrian Sociodemographics				Pedestrian Activity & Context			Driver Sociodemographics			Time-of-Day/ Weather		Vehicle Characteristics	
							Gender	Age	Race	Other*	Social context	Assertiveness	Non- Compliant crossings	Gender	Age	Other**	Time-of-day	Weather	Car Cost	Car Type
Studies conducted in the US.																				
Coughenour et al, 2020	Nevada	Controlled field experiment	2 hrs/site	2 non-signalized mid-block crosswalks	461	• Driver yielding	×		×										×	
Schneider et al., 2018	Wisconsin	In-person observation	2 hrs/site	20 uncontrolled intersections	364	• Driver yielding	×	×	×	×	×	×		×	×	×				
Coughenour et al, 2017	Nevada	Controlled field experiment	2 hrs/site	2 non-signalized midblock crosswalks	126	• Driver yielding			×											
Figliozi and Tipagornwong, 2016	Oregon	Video recording	1 hr	1 signalized intersection	116	• Driver yielding • Stopping distance					×					×				×
Goddard et al., 2015	Oregon	Controlled field experiment	88 crossing trials	1 unsignalized mid-block crossing	173	• Driver yielding			×											
Studies conducted outside the US.																				
Pechteep et al., 2024	Thailand	Video recording	4 hrs/site	4 midblock crosswalks	400	• Driver non-yield, soft-yield, and yield behavior	×	×			×									
Fu et al., 2022	China	Video Recording	54 hrs (9 hrs/site)	6 crosswalks adjacent to right-turning vehicles at signalized intersections	543	• Driver yielding (including full stops, yielding with rolling stops, and non-yielding)					×						×			×
Zafri et al., 2022	Bangladesh	Video recording	2 hrs/site	6 signalized or police-controlled intersections	314	• Driver yielding	×	×			×	×	×							
Anciaes et al., 2020	England	Video Recording	14-32 min/site	3 unsignalized zebra and 17 courtesy crossings	937	• Crossing design characteristics that affect driver yielding frequency	×	×		×	×						×			×
Bella and Nobili, 2020	Italy	Video recording and GPS on vehicle	--	4 signalized and 11 unsignalized zebra crossings	76	• Driver non-yield, soft-yield, and yield behavior							×							
Demir 2020	Turkey	In-person observation	18 hrs (3 hrs/day)	1 roundabout	1140	• Driver yielding	×	×						×	×		×	×		×
Dileep et al., 2016	India	Video recording, radar gun, manual recording	4 hrs (1 hr/site)	4 undivided mid-block locations	815	• Driver yielding	×	×		×	×									×
Hirun, 2016	Thailand	Survey	--	--	445	• Driver yielding								×	×	×				
This Study	Texas	Video recording	1,296 hrs	2 signalized intersections	3,124	• Driver yielding	×	×	×	×	×		×				×	×		×

\*The “Other” category under “Pedestrian Sociodemographics” includes the following variables: majority of pedestrians are White, majority of drivers are White, and presence of a visible disability.

\*\*The “Other” category under “Driver Demographics” includes witnessing yielding by other drivers, formal education levels, and knowledge of traffic rules.

## 2.3 The Current Paper

Overall, the existing literature provides valuable insights into the factors that influence pedestrian crossing compliance and shape pedestrian-driver interactions. However, significant gaps remain, particularly concerning the entire range of sociodemographic characteristics, pedestrian activity and contextual conditions, and time-of-day/weather factors in these behaviors. This study contributes to the literature by addressing several of these limitations and advancing empirical understanding in seven key ways.

First, as observed in Table 1, pedestrian crossing behavior remains relatively understudied in the U.S. Much of the existing evidence originates from international contexts, such as China, Hong Kong, and Iran, where dense urban design, high pedestrian volumes, and walk-oriented cultures create conditions that differ substantially from those in the U.S., thereby limiting the generalizability of the findings. In addition, the few U.S.-based studies that do exist often report varying results across key behavioral outcomes and demographic variables, including gender, age, and distraction, highlighting the need for further empirical research grounded in the U.S. context. Our study addresses this gap by providing detailed, real-world observational data from Texas, offering both a geographic contribution and a context-sensitive analysis that helps clarify and possibly reconcile conflicting findings in the literature.

Second, prior studies have often relied on short-duration data collection, frequently limited to a few hours or a single day per site (as indicated in the third column of Table 1 and the fourth column of Table 2). While this approach may simplify data management and annotation, it limits the ability to capture rare events, such as non-compliant pedestrian crossings (NCPC) or instances of driver non-yielding. In contrast, our study incorporates continuous video monitoring over periods exceeding two weeks at each of two intersection sites, resulting in a large and temporally diverse dataset of over 20,000 observations. To our knowledge, this is the first study to combine high-volume naturalistic footage with detailed pedestrian-, vehicle-, and context-level variables to examine interactions in shared spaces.

Third, while factors such as gender, age, and group size have received substantial attention in past research (see Tables 1 and 2), the effects of pedestrian race, and perceived housing insecurity on both non-compliant pedestrian crossings (NCPC) and driver yielding behavior remain largely underexplored. Although a few field experiments in the U.S. have investigated racial disparities in driver yielding, these studies have generally relied on staged crossings with limited variation in pedestrian characteristics and small sample sizes (see Table 2), constraining the scope and generalizability of their findings. Our large-scale naturalistic observational study highlights how race and social vulnerability intersect with pedestrian risk, offering evidence that can inform more equitable safety interventions and policy reforms.

Fourth, our study incorporates pedestrian activity factors, specifically whether individuals are walking or running, which have received limited attention in the existing literature. To our knowledge, only one prior study (Zhang et al., 2023) differentiated between walking and running activity and reported no statistically significant difference in crossing behavior. Accordingly, this study offers a more refined understanding of how pedestrian movement, whether walking or running, influences crossing behavior and driver response.

Fifth, the influence of time-of-day and weather conditions on pedestrian and driver behaviors remains insufficiently explored. Existing studies often focus on daytime or peak-hour data collection under favorable weather conditions, overlooking how risk-taking and activity patterns may vary across different temporal contexts. Our continuous 24/7 observation protocol enables us to examine behavioral variation across a range of time periods and weather scenarios, offering a more comprehensive view of pedestrian risk.

Sixth, most earlier studies examine exogenous variables in isolation, without adequately considering potential interaction effects. In this study, our large sample enables us to consider a number of interaction effects, such as whether there are gender/race, gender/time-of-day, and race/time-of-day interaction effects in both pedestrian crossing behavior and driver yielding behavior. Similarly, we not only consider the general impact of non-compliant crossing behavior on driver yielding behavior, but also whether, for example, male pedestrians who are non-compliant are yielded to differently than female pedestrians who are non-compliant. More generally, we consider a whole range of potential determinants of NCPC and driver yielding behavior relative to earlier studies, as well as their interactions, as should be clear from the ‘×’ markings (in the last row of Tables 1 and 2) identifying variables considered in the current study.

Lastly, much of the existing literature on pedestrian violations has focused on traditional four-way signalized intersections, while yielding behavior is typically examined at unsignalized intersections and midblock crossings (see the fourth column of Table 1 and the fifth column of Table 2). In contrast, we examine two locations featuring channelized slip lanes, which require more discretionary driver judgment in yielding decisions. This intersection design introduces greater complexity to pedestrian-driver interactions and offers novel insights into decision-making under ambiguous right-of-way conditions. To our knowledge, only Fu et al. (2022) have previously examined slip lanes in this way, making our contribution particularly distinctive.

### **3. DATA COLLECTION AND ANALYSIS METHODS**

#### **3.1. Study Sites and Context**

To examine pedestrian-driver interactions in naturalistic settings, video footage was collected from two signalized intersections in Austin, Texas. Figures 1 and 2 present detailed site characteristics, including annotated intersection layouts that show traffic flow patterns and pedestrian infrastructure, as well as field photographs that illustrate physical design features and operational conditions.

The first intersection (hereafter referred to as the MB intersection) is located in north Austin at the junction of the southbound Mopac (Loop 1) frontage road and West Braker Lane. Mopac is a major access-controlled highway running north-south, while Braker Lane is a three-lane, divided arterial road running east-west. As illustrated in Figure 1, this intersection features right-turn slip lanes accompanied by pedestrian refuge islands, and unprotected bike lanes along Braker Lane in both directions. The intersection is signalized and equipped with pedestrian push-button-activated crossing signals at all four corners. Each approach features a “Walk/Don’t Walk” display and a countdown timer indicating the remaining time for safe pedestrian crossing.

Additionally, each channelized right-turn slip lane is controlled by a “Stop Here for Pedestrians” sign, instructing motorists to stop for pedestrians crossing from the sidewalk to the refuge islands.

The second intersection (hereafter referred to as the DS intersection) is located in central Austin, within the University of Texas at Austin’s main campus. It connects East Dean Keeton Street, a four-lane east-west arterial divided by a raised concrete median, with San Jacinto Boulevard, a two-lane north-south local street, as shown in Figure 2. The intersection is signalized and features left-turn lanes on all approaches, along with channelized right-turn slip lanes (each equipped with a pedestrian refuge island) on the northbound and southbound legs. Pedestrian infrastructure includes push-button-activated pedestrian signals at all four corners, with “Walk/Don’t Walk” displays and countdown timers. “Yield” signs are also posted at each slip lane, directing motorists to yield to pedestrians within the crosswalks. Additionally, unprotected bike lanes on both sides of East Dean Keeton Street support substantial bicycle and e-scooter activity. This site experiences consistently high pedestrian volumes throughout the day due to the presence of university students, faculty, staff, nearby residents, and event attendees.

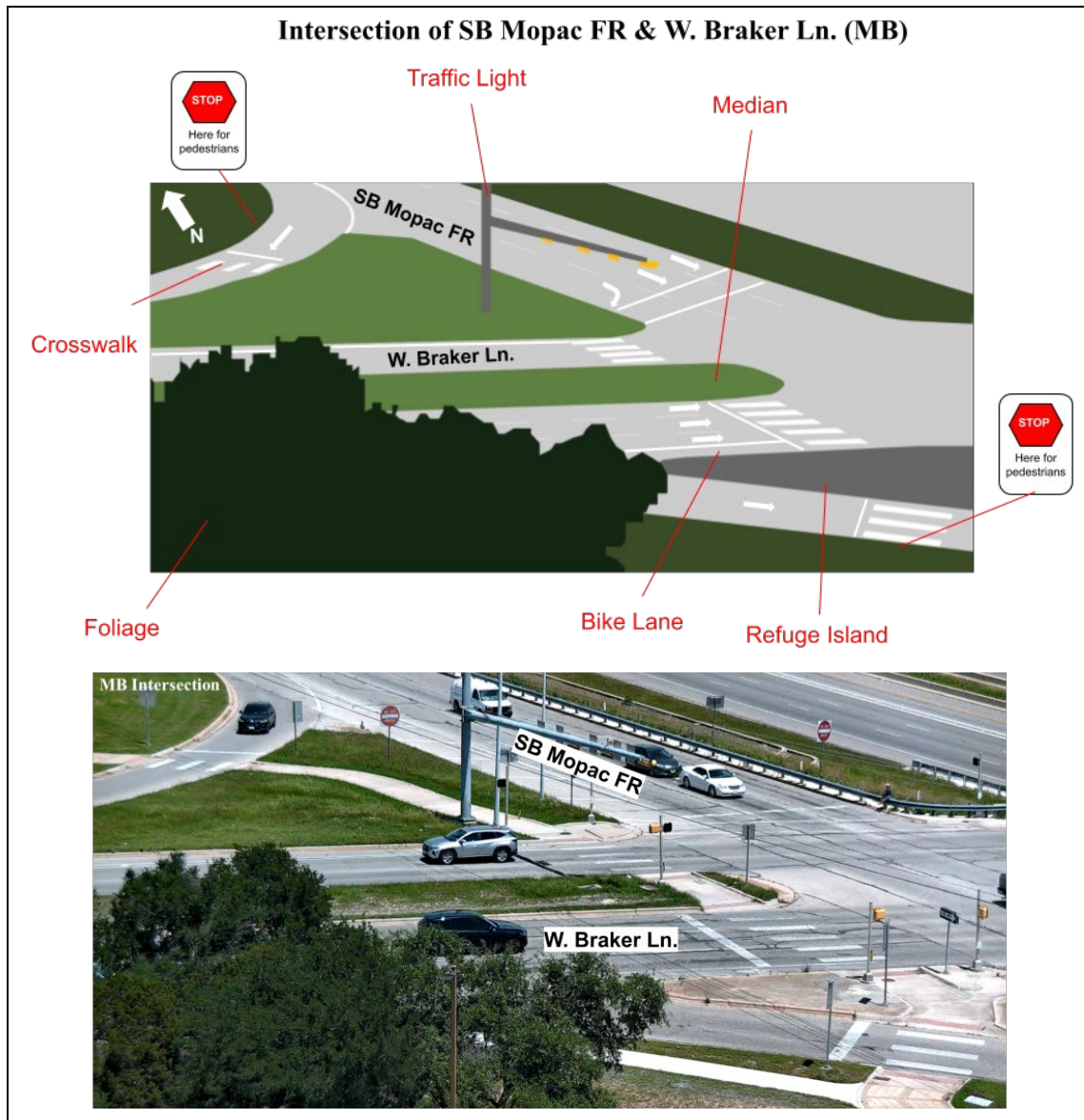
The Euclidean distance between the two sites is approximately 7.4 miles, providing spatial variation between central and north Austin. Site selection was guided by the availability of nearby university-owned property, which enabled the secure placement of cameras and equipment during the recording period, an approach commonly adopted in similar observational studies (e.g., Figliozzi and Tipagornwong, 2016; Wells et al., 2018; Baker et al., 2022; Piazza et al., 2022; Gerogiannis and Bode, 2024).

### **3.2.Video Setup and Data Collection**

A custom-built outdoor video recording system was developed to capture pedestrian and driver behavior at the selected intersections. As shown in Figure 3, the system utilized an off-the-shelf 4K Ultra High Definition, 360° PoE IP security camera with 16x optical zoom, housed in a weatherproof enclosure to ensure continuous operation during adverse weather conditions. Video footage was managed using the open-source *Shinobi* surveillance software, installed on a Raspberry Pi 3. *Shinobi* was selected for its ability to support continuous, high-resolution video capture, compatibility with IP cameras, and flexible configuration options, including scheduling and timestamping (Shinobi Systems, 2025). The recorded data were then stored locally on a 5TB hard drive. This low-power, cost-effective system enabled extended unattended monitoring, making it well-suited for detailed behavioral observation in naturalistic settings.

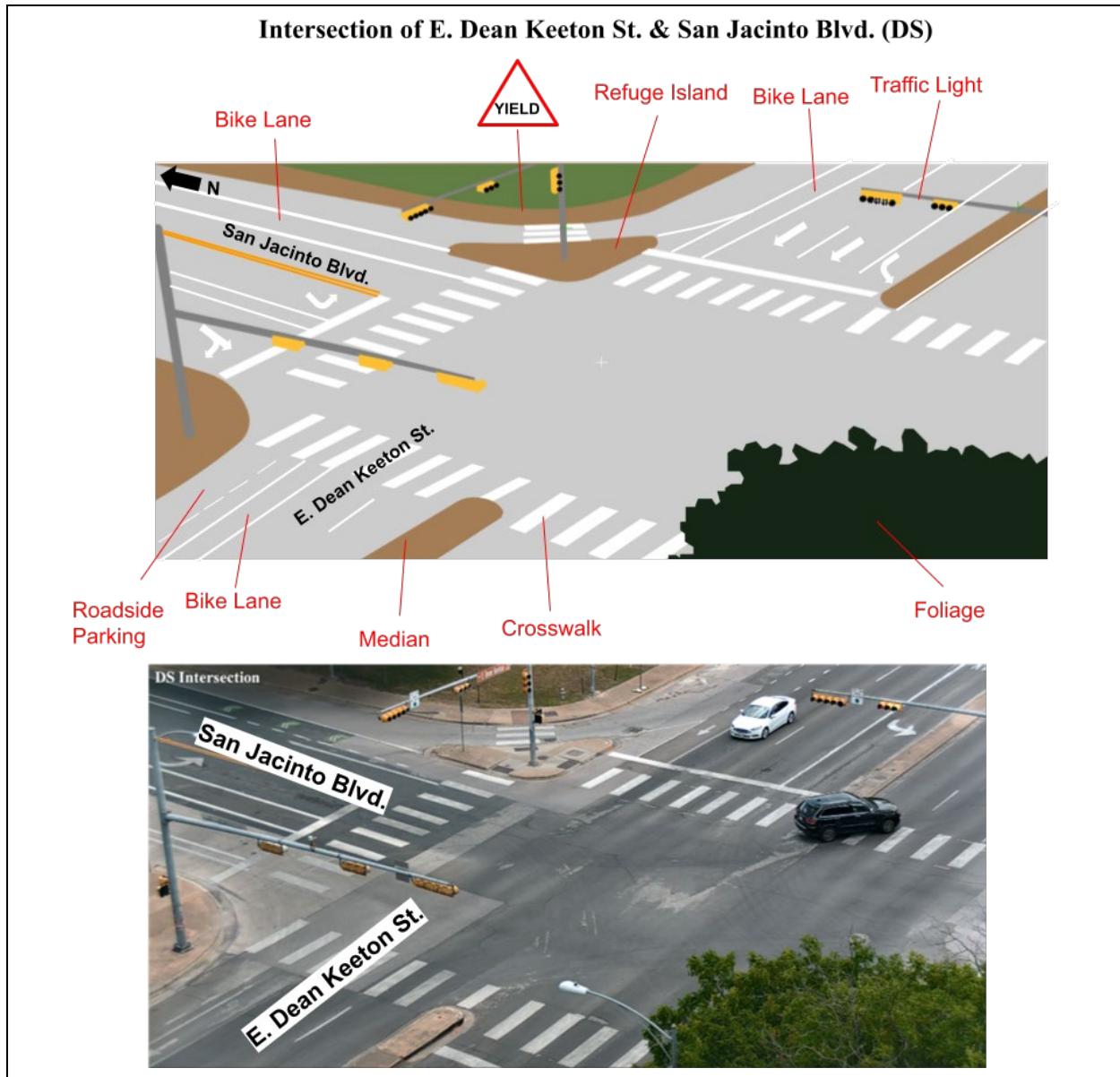
At each site, the camera was strategically positioned to maximize visibility of the intersection area. Only the crosswalks captured in the recordings are indicated on the annotated intersection layouts in the upper panels of Figures 1 and 2. The field photographs in the lower panel of each figure further illustrate the camera’s field of view at each site. At the MB intersection (Figure 1), the camera captured the eastbound crosswalk on Braker Lane and both crosswalks on the southbound Mopac Frontage Road. At the DS intersection (Figure 2), all crosswalks were within the camera’s view except the crossing on San Jacinto Boulevard at the southern end of the intersection, which was obstructed by vegetation.

Extended-duration, continuous video monitoring was implemented at both sites. The MB intersection monitoring period, which extended from April 19 to May 6, 2024, resulted in 18 days of continuous data acquisition, yielding 2,976 documented crossing observations. At the DS intersection, data collection took place from May 23 to June 27, 2024, resulting in 36 full days of footage and 18,019 recorded pedestrian crossings.



**Figure 1. MB Intersection Layout**

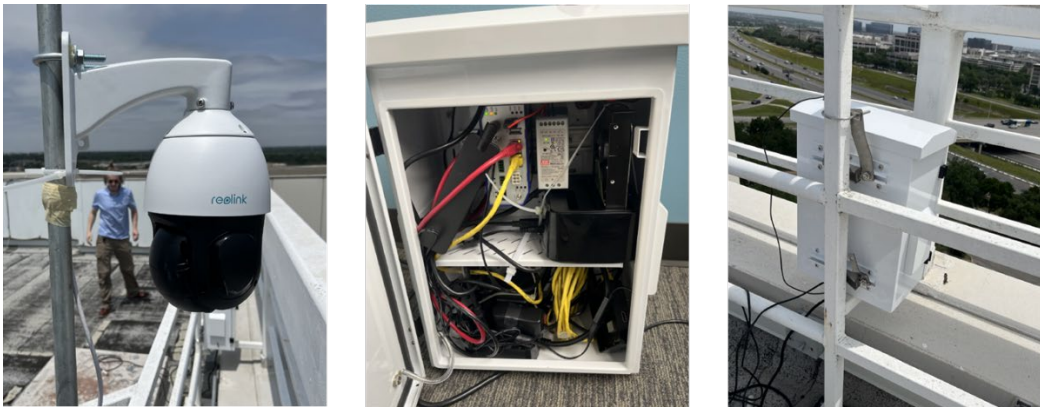




**Figure 2. DS Intersection Layout**

It is important to note that several contextual factors may have influenced the representativeness of the collected data. First, the DS intersection observation period fell outside the University of Texas at Austin's regular academic calendar. While this may have contributed to lower-than-usual pedestrian volumes at the DS site, the presence of summer classes ensured a consistent flow of student walking activity. Second, data collection occurred during late spring and early summer months, when elevated Texas temperatures may have introduced seasonal bias in pedestrian behavior. The average high temperature in Austin was 79.4°F during the MB intersection monitoring period and 93.6°F during the DS intersection observation period. Although the study avoided peak summer heat, elevated midday temperatures may have influenced pedestrian volume and temporal distribution patterns. In contrast, other meteorological conditions

had a limited impact. Precipitation occurred during only 27.5 hours of the total 1,296 recorded hours, more than half of which occurred during dawn or nighttime periods, minimizing potential disruption to daytime crossing behavior.



**Figure 3. Video Recording Setup**

### **3.3. Data Coding Process**

Upon completion of data collection, trained research assistants conducted systematic video analysis to extract key parameters from individual pedestrian crossings and vehicle-pedestrian interaction events. Each video recording was reviewed frame by frame to ensure the accurate identification and measurement of the variables of interest. These variables included a range of pedestrian characteristics, vehicle characteristics, other contextual factors, and dynamics of crossing situations.

Pedestrian demographic characteristics were coded through systematic observation, with gender classification determined through visual assessment of morphological features and coded as male, female, or unknown when classification was not possible due to image quality or other observational constraints. Additionally, pedestrian age was estimated through visual assessment and categorized into three distinct groups: individuals appearing to be under 18 years were classified as “minors,” those appearing to be 18-40 years were categorized as “young adults,” and individuals appearing to be over 40 years were classified as “older adults.” While visual estimation of age may introduce classification errors, this method has been used in prior observational studies and is considered acceptable for behavioral fieldwork where direct demographic data are unavailable (see, for example, Brosseau et al., 2013, Aghabayk et al., 2021, and Schwebel et al., 2022). Skin tone classification was performed using the Monk Skin Tone (MST) Scale, which was developed by experts in social psychology, social categorization, and underrepresented communities (Monk, 2022). The scale captures socially meaningful variation in skin tone within a framework focused on social inequality, making it particularly well-suited for behavioral research on demographic disparities in pedestrian-vehicle interactions. The MST Scale consists of ten skin tone categories (Monk, 2022), each represented by a standardized color swatch, which served as a visual reference for evaluating pedestrians’ skin tone in the video footage. However, to minimize classification error, particularly given that the video footage captured pedestrians from a distance,

skin tone was categorized using broader groupings of the MST Scale: MST 1-2, MST 3-8, and MST 9-10, corresponding approximately to individuals with light (White), medium (Brown), and dark (Black) skin tones, respectively. Additionally, annotators flagged pedestrians exhibiting visual indicators of housing insecurity (VHI). Specifically, they were instructed to identify a set of observable visual cues previously documented in the literature as associated with homelessness, or the perception thereof, including untidy or layered clothing, possession of multiple bags or belongings, use of makeshift containers such as shopping carts, prolonged presence in public spaces (e.g., sitting for extended periods), and displaying signs soliciting donations from passing vehicles. For a more in-depth discussion of the aesthetics and visibility of people experiencing homelessness, see Goldfischer (2018), Speer (2019), and Long (2024).

Additional contextual variables related to pedestrian behavior and environmental conditions were also recorded. Pedestrian activity level was categorized as either walking or running. Pedestrian distraction was recorded and defined as visibly engaging with a smartphone, such as texting or using phone applications while crossing, with limited attention directed toward the roadway. The social context of group crossing dynamics was also assessed by identifying instances in which two or more individuals simultaneously occupied or queued for crosswalk access.

Time-of-day data were extracted from video timestamps and converted to standardized time-of-day categories during post-processing: Dawn (04:00-05:59), Morning (06:00-11:59), Noon (12:00-13:59), Afternoon (14:00-17:59), Dusk (18:00-19:59), Evening (20:00-21:59), and Night (22:00-03:59). Weather conditions, specifically precipitation, were also documented to account for potential weather-related influences on crossing behavior.

In instances where pedestrians crossed in the presence of a vehicle, the vehicle type was recorded as SUV, sedan, pickup truck, commercial (including box-trucks, company-branded cars and vans, garbage trucks, and city buses), or “other,” (encompassed motorcycles, emergency vehicles, and any vehicles that could not be clearly identified).

Lastly, crossing dynamics variables, which constitute the primary outcome measures examined in this study, included pedestrian crossing compliance and vehicle yielding behavior. Non-Compliant Pedestrian Crossing (NCPC) behavior was defined as a composite measure indicating that the pedestrian violated at least one of two statutory conditions. A temporal violation occurred when a pedestrian entered the roadway against a steady red, steady yellow, “Don’t Walk,” or “Wait” signal, as prohibited under Sections 552.001(c) and 552.002(c) of the Texas Transportation Code (2023). A spatial violation occurred when a pedestrian crossed outside a marked or unmarked crosswalk (Section 552.005(a)), or crossed midblock between adjacent signalized intersections where no marked crosswalk was present (Section 552.005(b)). Driver non-yielding behavior was assessed through systematic observation of pedestrian-vehicle interactions and was defined more broadly than statutory right-of-way violations to reflect both legal and safety considerations. A driver was coded as non-yielding if they either (1) violated a legal obligation to yield, such as failing to yield to a pedestrian lawfully crossing with a “Walk” signal (Section 552.002(b)) or at a location controlled by a Stop or Yield sign (Section 545.153(b)), or (2) failed to exercise reasonable care to avoid a pedestrian already in the roadway, consistent with the general

duty of due care under Section 552.008. This broader operationalization allows non-yielding behavior to be recorded even when a pedestrian was in violation of crossing laws, reflecting real-world instances in which both parties may contribute to conflict risk.

To ensure inter-rater reliability and data quality, all research assistants underwent standardized training protocols designed to promote consistent variable categorization across the coding process. Regular calibration meetings were conducted throughout the data collection period to maintain coding consistency and address emerging classification challenges. Additionally, for ambiguous cases requiring subjective interpretation, a consensus-based approach was implemented whereby multiple observers provided independent assessments before reaching final coding decisions. When consensus could not be achieved for variables with inherent classification difficulties (e.g., gender, age, or skin tone), observers were instructed to record “unknown” classifications. These instances were subsequently coded as missing values during data processing to maintain analytical integrity.

### 3.4. Analytical Approach

This study employs binary logit discrete outcome models to analyze two distinct behaviors: (1) pedestrian crossing behavior (Compliant Pedestrian Crossing (CPC) *versus* Non-Compliant Pedestrian Crossing (NCPC)) and (2) driver yielding behavior (yield properly to pedestrians *versus* fail to yield).

#### 3.4.1. Model Estimation

The binary logit model (sometimes also referred to as a logistic regression) is based on a latent variable framework, where the observed binary outcome is determined by an underlying continuous latent propensity (see Train, 2009). The model formulation is identical for both binary outcomes in our paper, but, for simplicity, we present it here for the pedestrian crossing outcome.

Let  $y_q^*$  denote the latent propensity for the pedestrian  $q$  to exhibit non-compliant pedestrian crossing (NCPC) behavior. The latent propensity  $y_q^*$  is modeled as:

$$y_q^* = \beta'x_q + \varepsilon_q \quad (1)$$

where  $x_q$  is a  $(K \times 1)$  vector of observed exogenous variables (including a constant term),  $\beta$  is a corresponding  $(K \times 1)$  vector of coefficients to be estimated, and  $\varepsilon_q$  is a random error term representing unobserved factors affecting the propensity. We assume that  $\varepsilon_q$  is independently and identically distributed (i.i.d.) following a Gumbel (Type I extreme value) distribution. Under this assumption, the probability that the individual  $q$  exhibits NCPC behavior (that is,  $y_q = 1$ ) is based on the logit formula:

$$P(y_q = 1 | x_q) = \frac{e^{(\beta'x_q)}}{1 + e^{(\beta'x_q)}}, \text{ and } P(y_q = 0 | x_q) = 1 - P(y_q = 1 | x_q) \quad (2)$$

The parameters  $\beta$  are estimated using the maximum likelihood method. In non-linear models such as the binary logit, the effect of each exogenous variable is dependent on the values of the other

variables. Thus, variable effects are different across individuals. However, to quantify the effect of each exogenous variable, we calculate average treatment effects (ATE) by determining the change in predicted share associated with each category of an explanatory variable relative to a specific reference group, thereby providing an overall magnitude of the effect of each variable. Specifically, for each individual in the sample  $q$ , we compute the predicted probability of exhibiting NCPC (or driver non-yielding behavior in the case of the second outcome) under two scenarios: (1) when a specific explanatory variable  $A$  is set to its base level, and (2) when  $A$  is set to an alternative (treatment) level, while holding all other variables at their observed values. We then average these predicted probabilities across all individuals  $Q$  to obtain the predicted share of individuals under both the base and treatment levels. To express the impact as a relative percentage, we finally compute the percentage average treatment effect (%ATE) as the percentage difference between the predicted share of individuals under the treatment level and the base level (taken with respect to the change from the base level). We return to the computation and interpretation of %ATE effects in Section 4.2.

## 4. EMPIRICAL RESULTS AND DISCUSSION

### 4.1. Sample Characteristics

Following data collection, a systematic data cleaning procedure was implemented to ensure data quality and analytical validity. Observations containing incomplete records or variables coded as “unknown” were excluded from the analysis. The final sample used in model estimation comprises 17,251 pedestrian crossing observations, of which 2,767 observations (16.0%) correspond to instances involving pedestrian-vehicle interactions. Table 3 presents the descriptive statistics for all outcome and explanatory variables included in the analysis. The table structure accommodates the hierarchical nature of the data, where pedestrian-vehicle interactions represent a subset of all observed pedestrian crossings. For each variable, four statistical measures are reported:

- (a) Total Number of Observations (Relative Frequency): The absolute frequency and relative frequency of each variable category. In calculating the relative frequency, the denominator varies based on variable applicability. Variables specific to pedestrian-vehicle interactions (such as yielding behaviors and vehicle type) are calculated based on 2,767 total interactions, while general pedestrian variables applicable to all crossings are calculated based on 17,251 total observations.
- (b) Vehicle Interaction Rate: The proportion of observations for each variable category that involved a pedestrian-vehicle interaction, computed as the number of observations with vehicle interaction divided by the total number of observations for that variable category.
- (c) Non-Compliant Pedestrian Crossing (NCPC) Rate: The proportion of observations for each variable category that exhibited NCPC behavior, calculated as the number of NCPC observations divided by the total number of observations for that variable category.
- (d) Non-Yielding Rate: The proportion of observations for each variable category where the driver failed to yield to the pedestrian, computed as the number of non-yielding instances divided by the total number of pedestrian-vehicle interactions for that variable category.

The analysis of outcome variables (top panel of Table 3) reveals distinct patterns in pedestrian crossing compliance and driver yielding behavior. NCPC behavior was observed in 8.1% of all pedestrian crossings (N = 17,251). Among pedestrians exhibiting NCPC behavior, 8.2% involved vehicle interactions. Regarding driver yielding behavior, non-yielding incidents occurred in 13.3% of all pedestrian-vehicle interactions (N = 2,767). Additionally, driver non-yielding was higher at 10.9% in vehicle-pedestrian interactions when the pedestrian exhibited NCPC behavior, compared to 3.1% when the pedestrian did not exhibit NCPC behavior.

The bottom panel of Table 3 summarizes the distribution of explanatory variables in the sample. In the category of pedestrian sociodemographic variables, male pedestrians accounted for a greater share of observations compared to female pedestrians (67.1% vs. 32.9%, respectively). While a slightly higher proportion of female pedestrians were involved in vehicle-pedestrian interactions, both the NCPC rate and the non-yielding rate were higher among male pedestrians. Regarding age, young adults were overrepresented in the sample, which is consistent with the study location on or near a university campus. The vehicle interaction rate and NCPC rate were comparable between young adults and older adults. However, the non-yielding rate toward older adult pedestrians was significantly higher, reaching 23.2%. Skin tone distribution analysis revealed that the majority of observed pedestrians had lighter skin tones, though pedestrians with dark (black) skin tones (MST 9-10) exhibited the highest rates of NCPC behavior (11.5%) and experienced the highest driver non-yielding rates (16.9%), indicating potential disparities in both pedestrian behavior and driver response patterns across different demographic groups. Although pedestrians exhibiting visual markers of housing insecurity (VHI) represented fewer than 2% of the total sample, this subgroup demonstrated disproportionately high rates of risky interactions. Specifically, 21.1% of individuals with VHI engaged in NCPC behavior, and 39.7% were subject to driver non-yielding behavior during vehicle-pedestrian interactions.

The statistics for pedestrian activity and contextual variables in Table 3 show that most pedestrians crossed alone rather than in groups. Descriptive statistics show that solo crossers had a vehicle interaction rate of 15.5%, compared to 20.8% for group crossers. However, solo crossers exhibited a higher NCPC rate (8.4%) than those crossing in groups (5.9%). The non-yielding rate was comparable across both categories, at approximately 13%. Distracted pedestrians made up only a small share of all crossers, and NCPC and driver yielding behaviors were largely comparable to those of non-distracted pedestrians. Also, the majority of observed pedestrians were walking, with runners comprising only 7.2% of the sample. However, runners exhibited a higher rate of NCPC behavior and were less likely to be yielded to by drivers.

The time-of-day and weather variable statistics in Table 3 indicate that the majority of pedestrian crossings occurred during the morning and afternoon periods. The data indicate notable temporal overlap between periods of heightened NCPC behavior and increased driver non-yielding. Specifically, both behaviors were more frequently observed during the morning, evening, and nighttime hours, indicating a potential convergence of risk during periods of low visibility and/or high traffic volume. Lastly, fewer than 1% of observations occurred during rainfall. Although the non-yielding rate appeared higher in these conditions compared to dry weather, this descriptive statistic is based on only 10 instances of non-yielding in the rain *versus* 358 in non-

rain conditions. Given the small sample size, no meaningful conclusions can be drawn regarding the effect of rain on driver yielding behavior, and so we do not consider weather conditions in our estimation.

Finally, in the category of vehicle characteristics, among all observed vehicle-pedestrian interactions, SUVs were the most frequently observed vehicle type, accounting for 42.5% of cases. This was followed by sedans (38.5%), pickup trucks (11.4%), commercial vehicles (5.4%), and other vehicle types (2.2%). The data suggest that NCPC rates were higher in the case of pedestrian interactions with pick-up trucks and commercial vehicles (relative to SUVs, sedans, and other vehicle types). In contrast, non-yielding behavior was lowest among commercial vehicle drivers but highest among drivers of “other” vehicle types. However, due to the small number of observations in some vehicle categories, these results should be interpreted with caution.

Overall, the descriptive statistics offer insight into the distributional characteristics of the data and preliminary behavioral patterns across different variable categories. However, these are univariate relationships of a single exogenous variable with each of the two binary endogenous outcomes (NCPC and driver non-yielding), without controlling for the effects of other exogenous variables at the same time. To obtain the effect of each exogenous variable accurately, it is important to consider a multivariate analysis considering multiple exogenous variables simultaneously as well as potential interactions of the exogenous variables, which is the motivation for estimating a multivariate binary logit model for each of the two dependent variables of this study: non-compliant pedestrian crossing behavior (NCPC) and driver non-yielding. The estimation results of these two binary logit models are presented and discussed in the next section.

**Table 3. Sample Descriptive Statistics**

Variable	Total Number of Observations (Rel. Freq.)	Vehicle Interaction Rate (%)	Non-Compliant Pedestrian Crossing Rate (%)	Non-Yielding Rate (%)
<b>Outcome Variables</b>				
<i><b>Pedestrian Crossing Behavior</b></i>				
CPC	15847 (91.9%)	16.7%	0.0%	12.4%
NCPC	1404 (8.1%)	8.2%	100.0%	34.8%
<i><b>Driver Yielding Behavior</b></i>				
Yielding	2399 (86.7%)	100.0%	3.1%	0.0%
Non-Yielding	368 (13.3%)	100.0%	10.9%	100.0%
<b>Explanatory Variables</b>				
<b>Pedestrian Sociodemographic Variables</b>				
<i><b>Pedestrian Perceived Gender</b></i>				
Female	5672 (32.9%)	17.1%	6.2%	12.0%
Male	11579 (67.1%)	15.5%	9.1%	14.0%
<i><b>Pedestrian Perceived Age</b></i>				
Minor	39 (0.2%)	23.1%	5.1%	10.3%
Young adult	14839 (86.0%)	15.9%	8.0%	11.5%
Older	2373 (13.8%)	16.9%	9.0%	23.2%
<i><b>Pedestrian Perceived Skin Tone</b></i>				
MST 1-2 (White)	13784 (79.9%)	16.0%	8.2%	12.5%
MST 3-8 (Brown)	2222 (12.9%)	16.7%	5.8%	16.2%
MST 9-10 (Black)	1245 (7.2%)	15.2%	11.5%	16.9%
<i><b>Pedestrian Exhibiting Visual Markers of Housing Insecurity (VHI)</b></i>				
No VHI identified	16976 (98.4%)	16.0%	7.9%	12.7%
VHI identified	275 (1.6%)	21.1%	21.1%	39.7%
<b>Pedestrian Activity and Contextual Variables</b>				
<i><b>Social Context</b></i>				
Solo crossing	15453 (89.6%)	15.5%	8.4%	13.3%
Group crossing	1798 (10.4%)	20.8%	5.9%	13.1%
<i><b>Pedestrian Distraction</b></i>				
Not distracted	16948 (98.2%)	16.0%	8.1%	13.3%
Distracted	303 (1.8%)	15.1%	5.3%	13.0%
<i><b>Pedestrian Activity Type</b></i>				
Walker	16011 (92.8%)	16.4%	7.6%	13.1%
Runner	1240 (7.2%)	11.5%	15.6%	16.2%



Variable	Total Number of Observations (Rel. Freq.)	Vehicle Interaction Rate (%)	Non-Compliant Pedestrian Crossing Rate (%)	Non-Yielding Rate (%)
<b>Time-of-Day and Weather Variables</b>				
<i>Time-of-Day</i>				
Dawn (04:00-05:59)	100 (0.6%)	6.0%	22.0%	0.0%
Morning (06:00-11:59)	6335 (36.7%)	13.4%	8.7%	15.9%
Noon (12:00-13:59)	2238 (13.0%)	17.0%	6.0%	11.3%
Afternoon (14:00-17:59)	4443 (25.8%)	19.6%	5.5%	13.1%
Dusk (18:00-19:59)	2075 (12.0%)	20.0%	8.1%	9.2%
Evening (20:00-21:59)	1178 (6.8%)	16.3%	9.4%	15.1%
Night (22:00-03:59)	882 (5.1%)	6.1%	19.6%	16.7%
<i>Weather Condition</i>				
Raining	104 (0.6%)	26.0%	9.6%	37.0%
Not raining	17147 (99.4%)	16.0%	8.1%	13.1%
<b>Vehicle Characteristics</b>				
<i>Vehicle Type</i>				
SUV	1177 (42.5%)	100.0%	3.2%	11.9%
Sedan	1065 (38.5%)	100.0%	4.2%	13.6%
Pickup truck	316 (11.4%)	100.0%	5.7%	14.9%
Commercial*	150 (5.4%)	100.0%	6.0%	10.0%
Other*	59 (2.2%)	100.0%	0.0%	35.6%

\*Commercial vehicles include box-trucks, company-branded cars and vans, garbage trucks, and city buses. "Other" vehicle types include motorcycles, emergency vehicles, and any vehicles that could not be clearly identified.

#### 4.2. Model Estimation Results

The selection of explanatory variables in the binary logit models for the two outcomes followed a systematic approach that balanced theoretical relevance with statistical robustness. Since all exogenous variables were categorical variables, we examined, based on the descriptive statistics, whether there were enough observations in each category of each exogenous variable, especially whether there were adequate observations in each category corresponding to each of the two states of each binary outcome variable (for example, we did not consider weather conditions for this reason, as mentioned earlier, and also did not consider the pedestrian distraction variable). The issue of adequate observations is particularly relevant for the binary model of driver non-yielding behavior due to the limited number of observations (2,767 observations, with only 368 observations of driver non-yielding) compared to NCPC behavior (17,251 individuals with 1,404 observations exhibiting NCPC behavior). Beyond these first-level exclusions based on sample sparsity, all available exogenous variables in the dataset, and their interactions, were considered as potential explanatory variables to ensure comprehensive coverage of potentially influential

factors. The model specification process involved extensive exploration of alternative functional forms and variable combinations. For naturally discrete variables such as group size, we tested the most disaggregated dummy variable specifications and progressively combined categories based on statistical significance tests to achieve model parsimony. The binary specification distinguishing group *versus* solo pedestrians proved the most effective. For categorical variables, including age groups, skin tone, pedestrian activity type, time-of-day, and vehicle type we similarly began with the most disaggregated form and systematically combined categories based on statistical criteria. Notably, while the time-of-day variable performed efficiently in its most aggregated form for direct effects, a combined specification merging night and dawn periods into a single time period (referred to as “Nighttime”) demonstrated significance when interaction effects were considered. For NCPC behavior, only the interactions between gender and the nighttime variable, and between skin tone and the nighttime variable, achieved statistical significance and were retained in the final specification. For driver non-yielding behavior, only the gender-nighttime interaction was significant and included in the final model.

Table 4 presents the final model specifications. The first three columns, under the heading “Non-Compliant Pedestrian Crossing Model,” display results from the binary logit model estimating the likelihood of NCPC behavior. The final three columns, labeled “Driver Non-Yielding Model,” present results from the binary logit model of driver failure to yield behavior. For each model, we report the estimated coefficients, their corresponding t-statistics, and the percentage Average Treatment Effects (%ATE) of exogenous variables. For the NCPC model, we retained coefficients that were statistically significant at the 95% confidence level ( $|t\text{-statistic}| > 1.96$ ). But we used a lower confidence level of 85% ( $|t\text{-statistic}| > 1.45$ ) for the driver non-yielding model because of the smaller sample size of only 2,767 cases with pedestrian-vehicle interactions as well as the small fraction of these 2,767 cases in which the pedestrians were not yielded to (only 368 of 2,767 cases, or 13.3%).<sup>1</sup> Additionally, note that a dash (“--”) in Table 4 indicates that the corresponding variable was not statistically significant in the model, while “*n.a.*” denotes that the explanatory variable is not applicable to the given outcome variable.

In the subsequent discussion, we focus on the %ATE values, as they offer an intuitive interpretation of both the magnitude and direction of effects. While the estimated coefficients reflect the impact of exogenous variables on the underlying latent propensity (i.e.,  $y_q^*$  in Section 3.4.1), they do not directly reflect changes in the observed outcome ( $y_q$ ). In contrast, the %ATE represents the percentage change in the predicted probability (or share) of an outcome when shifting from the base category to the treatment category of a given variable. For illustration, consider a pedestrian with visible markers of housing insecurity (VHI). The %ATE of 177.8%

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<sup>1</sup>As discussed at length by the American Statistical Association (ASA) (see Wasserstein and Lazar, 2016; Wasserstein et al., 2019), analysts need to exercise context-specific judgements related to confidence levels rather than adhering strictly to a 95% confidence level as some kind of an absolute gold standard. In the current application, our focus in the driver non-yielding behavior model was on reducing the probability of Type II errors (that is, incorrectly rejecting variable effects) even if allowing for a slightly higher probability of Type I error (that is, using an 85% confidence level to retain variables). This can inform future specifications using larger and possibly more balanced samples.

indicates that the share of pedestrians with VHI displaying NCPC behavior is 177.8% higher than the share of pedestrians with no VHI displaying NCPC behavior, other factors being the same. Another way of looking at this is that a randomly selected person with VHI is 177.8% more likely to exhibit NCPC behavior than a randomly selected person without VHI; that is, if 10 out of 100 pedestrians with non-VHI exhibit NCPC behavior, approximately 27.78 (about 28) out of 100 pedestrians with VHI would be expected to do so ( $[(0.2778-0.10)/0.10]*100=177.8\%$ ). More simply, we will just say that a person with VHI is 177.8% more likely to exhibit NCPC behavior than a person without VHI. Additional nuances arise when interpreting %ATE values in the presence of interaction effects. Consider the main effects of gender and time-of-day, alongside their interaction in the NCPC model. The main model coefficient effect of gender, which is positive, indicates a higher likelihood of NCPC behavior among males compared to females during non-nighttime periods (i.e., morning, dusk, and evening), holding other variables constant. However, this gender effect is moderated (reduced) at nighttime (defined as a combination period of dawn and night) by the negative coefficient on the “Male  $\times$  Nighttime” interaction term, as presented in Table 4 under “Pedestrian Demographics and Time-of-Day Interactions.” The interpretation becomes more complex when considering additional interactions between the nighttime period and pedestrian skin tone. A technically rigorous interpretation would involve jointly evaluating combinations of gender, time-of-day, and skin tone to compute ATEs. However, for clarity and interpretability, we separate the discussion of main effects from that of interaction effects. Main effects represent sample-averaged treatment effects and are calculated while accounting for the full model specification, including interaction terms. For example, the main gender %ATE is derived by simulating a shift from female (base category) to male (treatment category) pedestrians across the entire sample, holding other covariates constant and incorporating all coefficients. Similarly, %ATEs for dawn and night periods are computed by transitioning the full sample from the noon/afternoon base category to the respective treatment period, across all gender and skin tone subgroups. Based on these computations, Table 4 shows that, on average, male pedestrians are 57.1% more likely than female pedestrians to exhibit NCPC behavior. Pedestrians crossing during dawn and night periods are 183.1% and 235.6% more likely, respectively, to exhibit NCPC behavior compared to those crossing during the noon/afternoon period. On the other hand, interaction effects capture how the marginal impact of one variable varies depending on the level of another. These %ATEs are computed by comparing specific subgroups to isolate conditional relationships. For instance, the %ATE for the “Male  $\times$  Nighttime” interaction compares female pedestrians crossing at dawn or night (base category) to male pedestrians crossing in the same period (treatment category). Given the negative sign of the interaction coefficient, the %ATE of 15.8% for the “Male  $\times$  Nighttime” interaction variable indicates that the gender effect is reduced at nighttime relative to the overall gender %ATE of 57.1% across all time periods.

The results presented in Table 4 indicate that a range of factors, spanning pedestrian sociodemographics, activity context, and time-of-day factors, significantly influence both pedestrian crossing behavior and driver yielding decisions. Overall, the %ATEs in Table 4 suggest that dawn and night period pedestrian crossings (especially for men and people of color during

these dawn and night periods) are most strongly associated with NCPC, followed by pedestrians exhibiting visible indicators of housing insecurity (VHI), evening crossings, runners, and men during non-nighttime periods. For driver non-yielding behavior, the strongest predictor is pedestrian non-compliance, followed by VHI status, older pedestrian age, and male pedestrians crossing at night. It is also important to note that the effects of exogenous variables (and the corresponding %ATEs) in the driver non-yielding behavior model represent direct effects **after** controlling for any effects of exogenous variables through the NCPC outcome. Thus, for example, the %ATE for male pedestrians in Table 4 corresponding to driver non-yielding indicates that, across all time periods, men are 21.9% less likely to be yielded to relative to women (everything else remaining the same). This effect is not because men are more likely to exhibit NCPC behavior, because NCPC behavior is controlled for as a determinant variable in the driver non-yielding model. This effect cannot be explained by a higher propensity among men to engage in NCPC behavior, as the non-yielding model explicitly includes NCPC as a covariate, thereby isolating the direct effect of gender on driver yielding behavior.

#### ***4.2.1. Pedestrian Sociodemographic Variable Effects***

##### ***Pedestrian Perceived Gender***

The model results reveal that male pedestrians are 57.1% more likely to engage in NCPC behavior compared to female pedestrians, suggesting significant gender-related differences in risk-taking behavior. This finding, which aligns with existing literature (e.g., Xie et al., 2018; Zhu et al., 2021; Rafe et al., 2025), could be a result of several psychological and sociocultural reasons. For instance, previous psychology and personality/gender studies (see Reniers et al., 2016, and Blanch and Martínez, 2025) have observed that men exhibit higher levels of sensation-seeking and impulsivity, which lead them to prioritize immediate rewards over long-term consequences, thereby increasing their likelihood of engaging in risky behaviors. Additionally, peer influence, media portrayals, and societal norms of masculinity emphasizing toughness, competition, and dominance can encourage men to adopt riskier behaviors (see Morgenroth et al., 2018, and Dellosa and Browne, 2024). Simultaneously, the probability of experiencing driver non-yielding behavior is 21.9% higher for male pedestrians than for their female counterparts, consistent with previous observational findings (e.g., Zafri et al., 2022; Almukdad et al., 2023). This behavior may also be attributed to gendered social expectations that characterize women as more vulnerable and deserving of protection, prompting more courteous behavior from drivers toward them (see Almukdad et al., 2023, and Soathong et al., 2023). Overall, the observation that male pedestrians are both more likely to engage in risky behaviors and are more vulnerable in interactions with vehicles provides a plausible explanation for their overrepresentation in pedestrian crash statistics (McGuckin et al., 2018; U.S. Department of Transportation, 2024). These findings suggest that effective safety interventions must extend beyond traditional enforcement approaches to address the behavioral and sociocultural factors underlying male risk-taking and driver perceptions. Campaigns that leverage peer influence and temper traditional masculinity norms (i.e., emphasizing responsibility and caution over bravado), as well as underscore the vulnerability of

pedestrians regardless of gender may be particularly effective in reshaping attitudes toward safer street behavior on the part of both pedestrians and motorists.

### *Pedestrian Perceived Age*

Although age did not significantly influence pedestrian crossing compliance, older pedestrians experienced an 84.7% higher probability of driver failure to yield compared to younger individuals. While this contradicts some previous studies, our findings may be explained by slower walking speeds in older individuals due to mobility limitations or a higher risk of falling (see Avineri et al., 2012, Brosseau et al., 2013, and Liu and Tung, 2014). These reduced speeds could lead to drivers losing patience when waiting for older pedestrians to cross. Addressing this issue requires design changes in areas with older populations. Design enhancements, such as extended crossing times, signalized midblock crossings, curb extensions, and tactile and auditory cues, can reduce exposure and support safer mobility. These physical changes should be paired with public awareness campaigns encouraging drivers to exercise additional caution and patience, reinforcing pedestrians' right to safe and accessible mobility.

**Table 4. Model Estimation Results**

Variable	Non-Compliant Pedestrian Crossing Model			Driver Non-Yielding Model		
	Coef.	t-stat	%ATE	Coef.	t-stat	%ATE
<b>Pedestrian Sociodemographic Variables</b>						
<i>Pedestrian Perceived Gender (Base: Female)</i>						
Male	0.489	7.18	57.1	0.238	1.99	21.9
<i>Pedestrian Perceived Age (Base: Young adult or minor)</i>						
Older (over 40 years)	--	--	--	0.760	5.76	84.7
<i>Pedestrian Perceived Skin Tone (Base: White - MST 1-2)</i>						
Brown - MST 3-8	-0.165	-1.98	-13.3	0.244	2.01	22.1
Black - MST 9-10	0.469	4.97	50.2	0.244	2.01	22.1
<i>Pedestrian Exhibiting Visual Markers of Housing Insecurity (VHI) (Base: No VHI identified)</i>						
VHI identified	1.242	8.93	177.8	0.985	3.52	112.6
<b>Pedestrian Activity and Contextual Variables</b>						
<i>Social Context (Base: Solo crossing)</i>						
Group crossing	-0.439	-4.64	-32.7	-0.300	-1.86	-21.2
<i>Pedestrian Activity Type (Base: Walker)</i>						
Runner	0.736	8.80	88.2	--	--	--
<i>Vehicle Interaction (Base: No vehicle interaction)</i>						
Vehicle interaction	-0.734	-7.74	-48.9	<i>n.a.</i>	<i>n.a.</i>	<i>n.a.</i>
<b>Time-of-Day and its Interactions</b>						
<i>Time-of-day (Base: Noon or Afternoon; 12:00-17:59)</i>						
Dawn (04:00-05:59)	1.196	5.53	183.1	--	--	--
Morning (06:00-11:59)	0.407	6.25	44.7	0.335	2.90	31.8
Dusk (18:00-19:59)	0.361	4.02	39.0	--	--	--
Evening (20:00-21:59)	0.887	6.08	119.6	--	--	--
Night (22:00-03:59)	1.413	10.03	235.6	--	--	--
<i>Pedestrian Demographics and Time-of-Day Interactions</i>						
Male × Nighttime (Dawn/Night)	-0.304	-2.08	15.8 <sup>a</sup>	0.491	2.77	82.0 <sup>a</sup>
Brown × Nighttime (Dawn/Night)	-0.849	-2.21	-57.1 <sup>b</sup>	--	--	--
Black × Nighttime (Dawn/Night)	-0.381	-1.97	7.0 <sup>b</sup>	--	--	--
<b>Vehicle Characteristics</b>						
<i>Vehicle Type (Base: SUV, sedan, pickup truck, other)</i>						
Commercial vehicle	--	--	--	-0.348	-1.49	-25.4
<b>NCPC Behavior</b>						
Pedestrian exhibiting NCPC (Base: CPC)	<i>n.a.</i>	<i>n.a.</i>	<i>n.a.</i>	1.210	5.99	150.0
<b>Constants</b>	-3.071	-42.09	<i>n.a.</i>	-2.384	-20.77	<i>n.a.</i>
<b>Goodness-of-Fit</b>						
Number of observations	17,251			2,767		
Number of parameters	16			10		
Log-likelihood at convergence $L(\beta)$	-5131.692			-1180.421		

Variable	Non-Compliant Pedestrian Crossing Model			Driver Non-Yielding Model		
	Coef.	t-stat	%ATE	Coef.	t-stat	%ATE
Log-likelihood of constant-only model L(c)	-5396.065			-1240.614		
Log-likelihood of equal shares model L(0) <sup>c</sup>	-11957.482			-1917.938		
Nested likelihood ratio test <sup>d</sup>	LR = 528.74 > $\chi^2_{(15,0.00001)} = 37.70$			LR = 123.39 > $\chi^2_{(9,0.00001)} = 39.34$		
Adjusted likelihood ratio index $\bar{\rho}_0^2$ <sup>e</sup>	0.571			0.384		
Adjusted likelihood ratio index $\bar{\rho}_c^2$ <sup>e</sup>	0.046			0.041		

<sup>a</sup> The base category for Male × Nighttime in the %ATE comparison is Female × Nighttime.

<sup>b</sup> The base category for Brown × Nighttime in the %ATE comparison is White × Nighttime. The base category for Black × Nighttime in the %ATE comparison is White × Nighttime.

<sup>c</sup>  $L(0) = [(\text{Number of parameters}) \times \ln(0.5)]$  for a binary model.

<sup>d</sup> The nested likelihood ratio test is computed with respect to the constants only model.

<sup>e</sup> The adjusted likelihood ratio indices are computed as follows:

$$\bar{\rho}_c^2 = 1 - (L(\beta) - M) / L(c) \text{ and } \bar{\rho}_0^2 = 1 - (L(\beta) / L(0)), \text{ where } M \text{ is the number of parameters excluding constants.}$$

### Pedestrian Perceived Skin Tone

Skin tone plays a significant role in shaping pedestrian crossing behavior and driver responses, revealing layered inequities in public space. While the effects are smaller than those associated with gender or time-of-day, they remain statistically significant and socially meaningful. The results show that pedestrians with darker skin tones (MST 9-10-Black) are 50.2% more likely, and those with medium skin tones (MST 3-8-Brown) are 13.3% less likely, than lighter-skinned (MST 1-2-White) individuals to partake in NCPC behavior. Although naturalistic pedestrian studies have rarely examined the effect of skin tone, as already identified in Section 2, research in behavioral science and psychology suggests that experiences of discrimination, stereotype threat, and systemic inequities may heighten risk-taking behaviors among marginalized groups, particularly Black or African American individuals (see Factor et al., 2013, Jamieson et al., 2013, and Xie et al., 2020). Disparities are also observed in driver behavior. Pedestrians with darker skin tones are 22.1% more likely to experience driver failure to yield than their lighter-skinned counterparts, echoing past research on racial bias in driver responses (see Goddard et al., 2015, Coughenour et al., 2017, Schneider et al., 2018, and Coughenour et al., 2020). These disparities may stem from implicit racial bias, a well-documented issue in the United States (see Payne and Hannay, 2021, Skinner-Dorkenoo et al., 2023, and The White House, 2024). Such bias often operates outside of conscious awareness and can shape rapid, discretionary decisions, such as whether to yield to a pedestrian (Goddard et al., 2015). In these situations, drivers may subconsciously rely on racialized stereotypes, such as perceiving phenotypically Black individuals as more unpredictable or prone to risk-taking (Wages et al. 2022), resulting in hesitation in, or reduced, yielding.

Importantly, our results highlight that under the same infrastructure, environmental, and social contexts, behavioral differences, rooted in social and institutional inequities, place racial

minorities at greater risk in public space, potentially explaining the persistent overrepresentation of Black and Brown individuals in pedestrian fatalities and injuries (e.g., Roll and McNeil, 2022; Haddad et al., 2023; Smart Growth America, 2024). For instance, institutional practices, particularly in law enforcement, provide important context for contextualizing these risks, not as isolated actions, but as risk-avoidance strategies shaped by experiences of over-policing. Black and Latino pedestrians are disproportionately targeted by jaywalking laws, comprising 92% of citations in New York City (Fitzsimmons, 2024), and 32% in Los Angeles, where Black residents make up just 9% of the population (Widera, 2024). Studies also show Black pedestrians are up to 4.5 times more likely than white pedestrians to be stopped for the same behavior (Widera, 2024). These patterns perpetuate community mistrust and may prompt further behavioral adaptations, such as avoiding marked crossings to minimize police encounters, ironically increasing exposure to unsafe conditions.

Addressing these disparities requires more than mere infrastructure improvements or generalized awareness campaigns. Meaningful progress must begin with the communities most affected. Community-led safety initiatives, such as participatory design, storytelling, and localized education, can help uncover context-specific challenges, foster trust, and empower residents to co-develop interventions that genuinely support their safety and dignity. Simultaneously, the persistence of lower yielding rates toward Black and Brown pedestrians highlights the need to address implicit bias not just among drivers but also among police officers, first responders, and transportation professionals. Increasing evidence shows that educating both children and adults about historical and systemic racial injustices, including those embedded in transportation and law enforcement, can foster empathy, reduce prejudice, and enhance awareness of structural racism (see Skinner-Dorkenoo et al., 2023). Integrating such content into public awareness campaigns, school curricula, and driver education programs can gradually shift societal attitudes and help dismantle racialized narratives that continue to shape pedestrian safety disparities. However, the effectiveness of these efforts not only depends on the message itself, but also on how it is framed and communicated. Research on social norm messaging shows that positively framed dynamic norms (e.g., “More and more drivers are giving way to pedestrians”) and injunctive norms (e.g., “Please give way to pedestrians”) are especially effective in promoting yielding behavior, outperforming static or negatively worded messages (see Liu et al., 2022). Thus, integrating structural education with behaviorally-informed messaging strategies can offer a robust and effective approach to reshaping attitudes and addressing racialized disparities in pedestrian safety.

#### *Pedestrian Exhibiting Visual Markers of Housing Insecurity (VHI)*

The results reveal a critical and underexamined relationship between visual indicators of housing instability (VHI), used as a proxy for homelessness, and pedestrian safety outcomes. Pedestrians identified as exhibiting VHI have a 177.8% higher probability of engaging in NCPC behavior, and are 112.6% more likely to experience driver failure to yield. These represent the third strongest overall effect on NCPC behavior and the most influential variable among all pedestrian characteristics. VHI is also the second strongest predictor of driver non-yielding behavior in the model. These disparities likely stem from both behavioral factors and systemic neglect. Individuals



experiencing homelessness often face health-related vulnerabilities, including physical disabilities, mental health conditions, and substance use disorders, that may influence crossing decisions (see Richards and Kuhn, 2022, and USDOT, 2024). At the same time, reduced driver yielding toward this group echoes findings from Domine et al. (2022), who documented complete driver non-compliance in crashes occurring along corridors with overlapping encampments and high crash rates. The compounding effects of increased exposure, elevated behavioral risk, and diminished driver responsiveness position individuals with VHI among the most vulnerable pedestrians and likely contribute to the disproportionately high rates of pedestrian crashes observed in areas with larger proportions of unhoused populations (see Bernhardt and Kockelman, 2021).

Despite growing awareness of traffic violence disproportionately affecting unhoused communities, housing status remains largely excluded from Vision Zero crash reporting systems, hindering efforts to track and address these disparities in a data-driven manner (see Zimmerman, 2023, and USDOT, 2024). Municipal responses have been inconsistent, oscillating between supportive and punitive measures. For example, the city of Austin’s 2016 Vision Zero strategy acknowledged housing as a safety determinant through a “Housing First” approach, but recent revisions have retreated toward infrastructure- and behavior-based solutions. Meanwhile, the city of Portland has enacted encampment bans along high-crash corridors, and other cities, including San Jose and Colorado Springs, have implemented visibility-based interventions such as neon beanies and flashing headbands for unhoused individuals (Zimmerman, 2023). Though often well-intentioned, such efforts often reduce a structural safety crisis to a question of visibility or individual behavior, ignoring the broader environmental and systemic conditions that place unhoused pedestrians at elevated risk.

Collectively, our findings call for equity-centered, cross-sector strategies that recognize housing insecurity as both a transportation and public health concern. Transportation agencies must begin by integrating housing status into crash data systems and establishing it as a standard variable within Vision Zero and other safety frameworks. Infrastructure near encampments and areas of unsheltered habitation should also be redesigned to include pedestrian-activated signals, refuge islands, enhanced lighting, and traffic calming. Collaboration with housing and public health agencies can also be beneficial for delivering mobile outreach, navigation centers, and harm-reduction services at high-risk locations.

#### ***4.2.2. Pedestrian Activity and Contextual Variable Effects***

##### ***Social Context***

The presence of additional individuals at the crossing consistently exerted a protective influence across both models. Specifically, pedestrians crossing in groups are 32.7% less likely to commit violations and experience a 21.2% increase in the likelihood of drivers yielding compared to those crossing alone. These results align with prior findings (e.g., Dileep et al., 2016; Zhu et al., 2021; Fu et al., 2022; Zhang et al., 2023; Zafri et al., 2022; Miladi et al., 2025; Rafe et al., 2025), and may be attributed to social conformity pressures, where individuals are less inclined to violate traffic rules when others are present who may implicitly discourage non-compliant behavior (see

Zhu et al., 2021). In the context of yielding, drivers may be more likely to notice groups or feel a stronger obligation, whether social or practical, to yield when multiple people are present.

These observed patterns lend further empirical support to the “safety in numbers” phenomenon, whereby group crossings are associated with improved compliance among both pedestrians and drivers, suggesting that interventions that encourage group travel or simulate its social cues can significantly enhance safety. For instance, behaviorally informed public messaging campaigns can promote compliant crossing by framing safe behaviors, such as using marked crosswalks, waiting for signals, or utilizing grade-separated infrastructure, as social responsibilities. Emphasizing that such actions set a positive example for peers, family, and the broader community may motivate individuals to adopt safer behaviors not only for self-preservation but also out of concern for others. School-based educational programs and parent-focused campaigns can further reinforce these social norms, fostering intergenerational learning and long-term behavior change.

#### *Pedestrian Activity Type*

Pedestrian activity type significantly influences crossing behavior, with runners being 88.2% more likely to engage in NCPC compared to walkers. This elevated risk likely reflects a desire to maintain workout momentum by avoiding signal delays, as well as a lower perceived risk due to higher speeds, which can make smaller traffic gaps seem acceptable during unprotected crossings. Addressing this issue requires infrastructure and safety strategies that respond to the distinct behavioral dynamics of different pedestrian activities. For example, mid-block crossings, pedestrian overpasses, or dedicated running paths positioned away from vehicle conflict zones could help reduce unsafe behaviors among runners, particularly in parks, along trails, and in areas popular with exercise groups and dog walkers, where conventional crossing infrastructure may fall short.

#### *Vehicle Interaction*

Direct interaction with a vehicle is associated with a 48.9% reduction in pedestrian violations, suggesting that pedestrians exercise greater caution when vehicles are in the immediate vicinity in conflict with the crossing. This may indicate that NCPC behaviors are calculated decisions based on perceived traffic gaps rather than purely impulsive actions. The finding also highlights the role of real-time feedback mechanisms, such as visual contact, vehicle speed, and deceleration cues, in influencing pedestrian decision-making.

### ***4.2.3. Time-of-Day and its Interaction Effects***

#### *Time-of-Day*

Compared to the noon-to-afternoon window (12:00-17:59), pedestrians are more likely to engage in NCPC at all other times. The morning (06:00-11:59) and dusk (18:00-19:59) periods, both overlapping with typical commute hours, are associated with moderate increases in NCPC probability (44.7% and 39.0%, respectively). Driver non-yielding also increases by 31.8% during the morning period. These trends likely reflect time pressures related to work, school, and

caregiving, which reduce both pedestrian patience and driver caution. Empirical studies support these findings, documenting higher rates of crossing and yielding violations during peak travel times and under time-urgent conditions (e.g., Guo et al., 2011; Zhang et al., 2016; Zhou et al., 2016; Xiong et al., 2019; Ma et al., 2020; Dhoke and Choudhary, 2023). This behavior is attributed to what is known in behavioral theory as instrumental attitudes, wherein individuals justify unsafe actions based on perceived efficiency gains. However, as noted by Zhou et al. (2016), such savings are often negligible and come at a disproportionately high safety risk. Educational campaigns should therefore target this misperception, emphasizing that the short-term convenience of jaywalking rarely justifies the heightened crash risk. Public messaging, particularly during peak commute hours, should communicate the dangers of NCPC, especially in contexts with fast-moving or unpredictable traffic. These efforts may be most effective when integrated into school curricula, commuter outreach, and workplace safety training.

Even greater increases in the likelihood on engaging in NCPC are observed during dawn (183.1%), evening (119.6%), and especially night hours (235.6%), covering the period between 20:00 and 05:59. These findings align with Rafe et al. (2025), who attribute elevated nighttime violations to lower traffic volumes and increased anxiety in poorly lit environments. Psychological research suggests that darkness and isolation can heighten discomfort, prompting impulsive behavior (see Steimer, 2002, and Hengen and Alpers, 2021). In such contexts, lighting plays a dual role, enhancing visibility and improving perceived safety. Infrastructure upgrades such as pedestrian-scale lamps, motion-activated lighting, and illuminated signage can reduce violations by fostering a sense of security and increasing driver alertness.

#### *Pedestrian Demographics and Time-of-Day Interaction Variables*

Besides main effects, time-of-day also moderates the influence of gender and race on both pedestrian and driver behaviors. A significant interaction between male gender and nighttime conditions indicates that the risk-taking behavior typically associated with male pedestrians diminishes under low-light environments, likely due to heightened risk perception, reduced visibility, or situational caution. Specifically, while across all time periods, men are 57.1% more likely than women to engage in NCPC, at nighttime (22:00-05:59), the difference decreases to 15.8%, narrowing the gender gap in NCPC violation behavior under darker conditions. In contrast, the likelihood of drivers failing to yield to male pedestrians increases substantially at night. While men face a 21.9% higher probability of non-yielding compared to women in the overall, this gap widens to 82.0% at nighttime (22:00-05:59), suggesting that gender-related disparities in driver behavior become more pronounced when visibility is limited. This pattern may reflect the amplification of implicit gender biases under low-light conditions, where drivers may underestimate male pedestrians' vulnerability or misinterpret their crossing intentions.

The interaction between pedestrian skin tone and time-of-day also reveals important behavioral differences. Although NCPC behavior generally increases at nighttime, the effect is less pronounced among Brown (MST 3-8) and Black (MST 9-10) pedestrians. For instance, overall across all time periods, Brown pedestrians are 13.3% less likely than white pedestrians to engage in NCPC, and this reduced tendency for NCPC among Brown pedestrians becomes even more

substantial at nighttime, reaching 57.1%. Similarly, Black pedestrians are 50.2% more likely than white pedestrians to engage in NCPC across all time periods, but only 7.0% more likely at nighttime. These patterns suggest that pedestrians of color exhibit greater caution under low-light conditions, possibly due to increased risk awareness, fear of enforcement, or heightened safety concerns. However, despite more cautious behavior among racial minorities and no observed increase in racial disparity in driver yielding at night, Black pedestrians remain disproportionately involved in nighttime crashes (see Sanders et al., 2022). This suggests that other factors, such as visibility differences, driver detection biases, infrastructure quality, or unequal exposure, may contribute to the persistent safety gap and warrant further investigation.

#### ***4.2.4. Vehicle Characteristic Variable Effects***

##### ***Vehicle Type***

The commercial vehicle variable exhibits a negative effect on non-yielding behavior, with a %ATE of -25.4%. This indicates that drivers of commercial vehicles, such as box-trucks, company cars or vans, garbage trucks, and city buses, are, on average, 25.4% less likely to fail to yield to pedestrians compared to drivers of passenger vehicles (e.g., sedans, SUVs, pickup trucks, and other motorized vehicles). While this finding contrasts with earlier studies suggesting lower compliance among commercial drivers (e.g., Dileep et al., 2016; Figliozzi and Tipagornwong, 2016), several plausible explanations support the current result. Commercial drivers typically undergo more rigorous training and certification, including specific instruction on pedestrian safety and right-of-way laws (Gillham et al., 2023). They are also subject to greater regulatory oversight, including the use of electronic logging devices (ELDs), GPS tracking, and frequent safety inspections, which may encourage more compliant driving behavior. Moreover, the professional and financial consequences of traffic violations, including potential job loss, insurance penalties, and company-imposed sanctions, may further incentivize adherence to the rules. Nonetheless, while commercial drivers are held to higher standards and face stricter oversight, the broader literature on driver compliance yields mixed findings. There is no definitive evidence that commercial drivers are universally more compliant with traffic laws. Compliance appears to vary by context, enforcement, and operational pressures, with some studies linking tight schedules and fatigue to reduced compliance (Chen et al., 2021). Although the current study provides empirical evidence suggesting higher yielding compliance among commercial vehicle drivers, further research is needed to explore the consistency of this pattern across different traffic contexts, geographic settings, and vehicle subtypes.

#### ***4.2.5. NCPC Effect on Driver Non-Yielding Behavior***

The results in Table 4 align with prior findings by Bella and Nobili (2020), and indicate that drivers are 150.0% more likely to fail to yield when pedestrians engage in NCPC behavior. The reduced yielding likely stems from drivers' diminished expectation of encountering pedestrians outside designated crossing areas or signal phases. When pedestrians cross outside marked crosswalks or during a prohibited signal phase, drivers have less time to recognize crossing intent and react appropriately, as also suggested by Bella and Nobili (2020). This breakdown in typical visual and

behavioral cues appears to drive the lower yielding rates observed with NCPC behavior. Of course, it is also possible that drivers view non-compliant crossings as illegal and therefore deliberately and willfully choose not to yield to NCPC pedestrians, even though Texas traffic law still obligates motorists to exercise due care to avoid colliding with pedestrians, notwithstanding any other provision (Section 552.008).

Notably, the relationship between NCPC and driver non-yielding is the strongest among all variables in the model, underscoring the seriousness of this safety issue. Transportation planners and relevant agencies must prioritize systematic data collection on NCPC behavior to identify locations where additional infrastructure may be needed. In areas where NCPC behavior is frequent, formalizing common desire paths or installing new crossings, even in unconventional locations, should be considered. Emerging tools such as video analytics, trajectory tracking, and pedestrian heat maps can help pinpoint areas where NCPC is prevalent and assess whether current infrastructure or signal timing unintentionally contributes to non-compliance. In parallel, both drivers and pedestrians should be made more aware of the safety implications of NCPC behavior. Driver education campaigns should emphasize the unpredictability of pedestrian actions and the importance of yielding regardless of pedestrian compliance. At the same time, pedestrian outreach efforts should highlight the increased risks associated with NCPC behavior and promote safer, designated crossing practices.

#### ***4.2.6. Constants and Goodness-of-Fit***

The constant terms in both models represent the overall effects for the base demographic group as determined by the combination of the base categories across all exogenous variables (this is so because all exogenous variables in both the binary models are in discrete categories). In the NCPC model, the reference scenario corresponds to a female pedestrian who is a minor or young adult, has a skin tone classified as MST 1-2, shows no VHI, is walking alone during noon or afternoon hours, and is not in proximity to any vehicles. In the non-yielding model, the reference pedestrian has the same characteristics but is walking/running during any time period other than morning hours (06:00-11:59), and is interacting with a non-commercial vehicle. The constant coefficients correspond to predicted probabilities of 4.4% NCPC behavior and 8.4% driver non-yielding for these base demographic groups.

The goodness-of-fit statistics, presented at the bottom of Table 4, indicate that both the NCPC and non-yielding models provide a substantial and statistically significant improvement in explanatory power compared to their respective null models (i.e., models corresponding to predictions of equal shares and sample shares for the dependent outcomes). The nested likelihood ratio (LR) test with respect to the constants-only (that is, sample shares) model confirms that the inclusion of explanatory variables significantly enhances model fit, with test statistics exceeding the critical Chi-squared values at the 99.99999% confidence level. This provides strong statistical evidence that the included predictors are meaningfully associated with the outcome variables, and that the observed improvement in fit is unlikely due to random chance.

## 5. CONCLUSIONS AND FUTURE DIRECTIONS

This study advances our understanding of pedestrian safety disparities by examining how sociodemographic, activity, contextual, and time-of-day/weather factors influence pedestrian crossing compliance and driver yielding behavior in real-world settings. Through systematic analysis of over 17,251 pedestrian crossings and 2,767 pedestrian-vehicle interactions, our findings reveal complex patterns of risk that extend beyond individual behavioral choices to reflect broader structural and social dynamics. Non-compliant pedestrian crossings (NCPC) emerged as most prevalent during low-visibility periods (night, dawn, and evening), among individuals with visible housing insecurity indicators (VHI), male pedestrians, runners, and Black pedestrians. Conversely, group crossings and active vehicle interactions demonstrated protective effects. Driver yielding patterns revealed concerning disparities, with the lowest yielding compliance observed toward those engaging in NCPC, individuals exhibiting VHI, older adults, males (particularly during nighttime hours), morning crossings, pedestrians encountered by drivers of non-commercial vehicles, Black or Brown pedestrians, and individuals crossing alone. The observed trends, specifically the convergence of reduced driver yielding and increased NCPC among certain demographic groups, suggest that disparities in pedestrian safety are shaped by a combination of individual behaviors and broader systemic forces, including structural disadvantage, unequal exposure, and context-specific risks. As such, there is a need to shift away from framing pedestrian risk in terms of individual blame and toward developing comprehensive solutions that recognize and respond to the full context of pedestrian vulnerability. Effective pedestrian safety strategies must reflect the lived realities of marginalized groups, adapt to shifting risk profiles over time and across different contexts, and actively confront the systemic biases embedded in both infrastructure and enforcement practices.

In this context, it is also widely recognized that behaviors such as jaywalking are persistent and unlikely to be entirely eliminated (see Fitzsimmons, 2024, and Raoniar et al., 2024). Expecting full compliance with traffic rules is unrealistic, especially for those navigating exclusionary or unsafe environments. This reinforces the need for infrastructure that is inherently forgiving of human error. Rather than relying solely on enforcement, the focus should be on minimizing the consequences of unsafe actions through safer street design, such as reduced vehicle speeds, clearer crossings, and protected pedestrian spaces, while also ensuring that both drivers and pedestrians are educated about the risks and consequences of their behaviors.

While this research presented new insights into pedestrian and driver behaviors, several opportunities remain for future investigation. Some aspects of data collection, such as the subjectivity in coding pedestrian age and skin tone, could benefit from refinement to reduce observational bias. The study's geographic scope was also limited to two intersections with similar designs, including one on a university campus where drivers may be more attuned to pedestrian presence. This context likely influenced both yielding behavior and the demographic composition of observed pedestrians, particularly skewing the sample toward young adults. Additionally, data were collected exclusively in late spring and early summer, when high temperatures in Texas may influence pedestrian volumes and behavior, introducing potential seasonal effects. Future research could expand the geographic and temporal scope to capture a wider range of environmental,

demographic, and behavioral conditions. Incorporating additional variables, such as driver demographics, pedestrian gestures, walking speed, and vehicle acceleration or deceleration, would also provide a more comprehensive understanding of vehicle-pedestrian interactions. Lastly, complementary qualitative methods, including surveys, focus groups, or virtual reality simulations, could further illuminate the decision-making processes of both pedestrians and drivers.

## ACKNOWLEDGMENTS

This research was partially supported by the UT Good Systems Grand Challenge through the Good Systems Core Research Project entitled “Designing AI to Advance Racial Equity,” and by the U.S. Department of Transportation (USDOT) under Grant 69A3552348327 for the Center for Automated Vehicles Research with Multimodal AssurEd Navigation (CARMEN+) University Transportation Center. The authors thank Kenneth A. Perrine and Jan C. Rubio for their assistance in designing and implementing the video data collection system, and Dr. Katherine Asmussen and Carol Anne Starks for their contributions to data labeling. The authors are grateful to Lisa Macias for her help in formatting this document.

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