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16. Abstract

Pedestrian safety remains a critical challenge in urban environments, where rising fatalities coincide with increasingly complex operating conditions for connected and automated vehicles. Ensuring reliable positioning, navigation, and timing (PNT) under these conditions requires a deeper understanding of the pre-crash behaviors that create conflicts at intersections. 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. By embedding these empirically derived behavioral patterns into scenario templates and design guidance, the study informs the targeted deployment of roadside sensing, the design and testing of cooperative perception and vehicle-to-infrastructure/pedestrian (V2I/V2P) communication strategies, and the development of rigorous standards and validation protocols for cyber-resilient PNT systems. In doing so, this research moves beyond post-crash analysis to provide a data-driven foundation for proactive, infrastructure-supported safety in the next generation of connected and automated transportation systems.

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CARMEN+

Center for Automated Vehicles Research with Multimodal Assured Navigation

USDOT University Transportation Centers Program

Final Report: Using Infrastructure to Boost Safety in a PNT World: Balancing Reliability, Overreliance, Malfunction Risks, and Cybersecurity to Improve Intersection Safety

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Abstract

Pedestrian safety remains a critical challenge in urban environments, where rising fatalities coincide with increasingly complex operating conditions for connected and automated vehicles. Ensuring reliable positioning, navigation, and timing (PNT) under these conditions requires a deeper understanding of the pre-crash behaviors that create conflicts at intersections. 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. By embedding these empirically derived behavioral patterns into scenario templates and design guidance, the study informs the targeted deployment of roadside sensing, the design and testing of cooperative perception and vehicle-to-infrastructure/pedestrian (V2I/V2P) communication strategies, and the development of rigorous standards and validation protocols for cyber-resilient PNT systems. In doing so, this research moves beyond post-crash analysis to provide a data-driven foundation for proactive, infrastructure-supported safety in the next generation of connected and automated transportation systems.

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Executive Summary

Pedestrian safety remains a critical challenge in urban environments, where rising fatalities coincide with increasingly complex operating conditions for connected and automated vehicles. Ensuring reliable positioning, navigation, and timing (PNT) under these conditions requires a deeper understanding of the pre-crash behaviors that create conflicts at intersections. 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. By embedding these empirically derived behavioral patterns into scenario templates and design guidance, the study informs the targeted deployment of roadside sensing, the design and testing of cooperative perception and vehicle-to-infrastructure/pedestrian (V2I/V2P) communication strategies, and the development of rigorous standards and validation protocols for cyber-resilient PNT systems. In doing so, this research moves beyond post-crash analysis to provide a data-driven foundation for proactive, infrastructure-supported safety in the next generation of connected and automated transportation systems.

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Introduction

Motivation

Pedestrian safety remains a pressing concern in transportation research and practice, driven by persistently high and rising rates of injuries and fatalities, and the unbalanced distribution of these risks across communities. Despite advances in roadway design and vehicle technology, 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). 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).

These figures highlight the limitations of existing safety frameworks in explaining crash causes and dynamics, as they rely predominantly on post-crash analyses rather than the proactive identification of pre-crash behaviors and interactions. In recognition of these limitations, the U.S. Department of Transportation (USDOT) has emphasized the Safe System approach in its RDandT Strategic Plan (2022-2026), which prioritizes eliminating roadway fatalities through proactive, system-level interventions. To advance this vision, the plan outlines several key priorities, including: improving the understanding of attitudes and behaviors that shape transportation safety outcomes; deepening knowledge of how human interactions with technology influence safety in order to guide the design and deployment of safer systems; developing new methods and tools for the collection, management, analysis, and evaluation of safety data; and advancing transportation safety by rigorously assessing existing technologies while ensuring the safe integration of emerging innovations.

While this Safe System approach provides a foundation for proactive, system-level safety, its successful implementation in an era of connected and automated transportation requires assured Positioning, Navigation, and Timing (PNT). Yet PNT-dependent systems face well-documented vulnerabilities: Global Navigation Satellite System (GNSS) signals degrade under multipath interference and urban canyons, onboard perception is disrupted by occlusion and adverse visibility, and both can be compromised by malicious attacks such as spoofing or jamming. These vulnerabilities are particularly acute at intersections, where multimodal flows, signal phasing, and unpredictable pedestrian-driver interactions combine to create complex operating conditions. In such settings, even minor lapses in perception or localization can escalate into serious conflicts. Compounding these technical limitations are the behavioral uncertainties introduced by pedestrians who cross against signals, drivers who fail to yield, or vehicles that obstruct sightlines. Such behaviors create dynamic, real-world stress scenarios that vehicle-only systems are often ill-equipped to handle reliably. Accordingly, infrastructure-supported sensing that leverages roadside cameras, radar, and LiDAR integrated with connected vehicle technologies can offer a critical redundancy layer. By cross-validating vehicle-based PNT streams, detecting anomalies, and capturing behaviors that onboard systems may miss, infrastructure-based sensing has the potential to enhance resilience and prevent conflicts before they result in harm.

Research Contributions and Objectives

This research project advances the effort to strengthen PNT resilience in complex intersection environments by leveraging large-scale observational video data from urban intersections, treating fixed vantage points as proxies for infrastructure-based sensing systems. Using logistic regression models, we estimate the likelihood of two critical outcomes, namely non-compliant pedestrian crossings (NCPC) and driver non-yielding, under varying temporal, environmental, and situational conditions. These outcomes define critical safety scenarios reflecting recurring situations that systematically elevate conflict risk at intersections. Importantly, such scenarios also constitute PNT-relevant stress conditions, because they occur precisely in contexts where GNSS and onboard perception are most vulnerable. For example, jaywalking introduces unpredictable pedestrian trajectories that challenge automated prediction, non-yielding drivers create conflicts requiring rapid localization and response, and occlusion from buses or trucks prevents onboard sensors from detecting pedestrians in time. By systematically identifying these scenarios, this research makes three primary contributions presented in Table 1.

Table 1 Contributions and Alignment with CARMEN+ Objectives

Contribution	Description	Alignment with CARMEN+ Objectives
1. Labeled dataset of pedestrian-driver interactions	Creation of a labeled dataset of pedestrian and driver interactions at urban intersections, providing a ground-truth resource for training and validating infrastructure-based object detection and prediction algorithms.	**Objective 1:** Systematize existing knowledge and identify gaps. **Objective 2:** Generate and analyze realistic PNT threat scenarios.
2. Identification of critical safety scenarios as PNT-relevant stress conditions	Identification of critical safety scenarios, including jaywalking, non-yielding, occlusion from large vehicles, and nighttime operations, that also represent PNT-relevant stress conditions where onboard GNSS and perception systems are most vulnerable.	**Objective 2:** Generate and analyze realistic PNT threat scenarios. **Objective 3:** Develop risk mitigation strategies for HATS.
3. Scenario templates and empirical guidance	Development of scenario templates and empirical guidance that inform (i) the targeted deployment of roadside sensing to enhance resilience, (ii) the design and testing of cooperative perception and V2I/V2P communication strategies, and (iii) the advancement of standards for cyber-resilient PNT systems.	**Objective 3:** Develop risk mitigation strategies for HATS. **Objective 4:** Craft standards and guidelines for cyber-resilient PNT systems.

The preceding discussion highlights the broader significance of the study in advancing PNT resilience and infrastructure-supported safety. At a more specific level, the research was guided by two objectives: (1) to identify the temporal, environmental, and situational conditions that increase the likelihood of non-compliant pedestrian crossings, and (2) to determine the factors that influence driver yielding behavior at intersections. To accomplish these objectives, we analyzed over 1,000 hours of video footage from two urban intersections in Austin, Texas, yielding 20,995 coded pedestrian crossings and 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 provides a rigorous statistical basis for characterizing intersection-level safety risks. Additionally, by situating these behaviors within the framework of critical safety scenarios, the study not only advances understanding of pedestrian-driver dynamics but also generates empirically grounded inputs for infrastructure-supported sensing strategies and the design of resilient PNT systems.

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 characterizing variability in safety outcomes; however, there is still a need to uncover, at a fine-grained behavioral level, the mechanisms that drive these outcomes. 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 the objectives of this research, our synthesis of the literature focuses specifically on naturalistic observational research that examines pedestrian and driver behaviors at intersections. This scope emphasizes the behavioral and contextual precursors of conflict, rather than built-environment or traffic flow characteristics. Accordingly, we review studies of pedestrian and driver behaviors as a function of (a) pedestrian and driver characteristics, (b) pedestrian activity and interaction context, (c) time-of-day and weather conditions, and (d) vehicle attributes. This focus reflects our interest in identifying the critical safety scenarios that emerge directly from human behavior and operational conditions. These scenarios are also highly relevant for assessing the limits of vehicle-only sensing and PNT-dependent navigation. Tables 2 and 3 provide a structured synthesis of recent naturalistic observational studies. Table 2 summarizes pedestrian crossing studies conducted over the past decade, including details on study location, data collection duration, observation sites, sample size, behavioral outcomes, and explanatory variables. Table 3 presents a similar synthesis for driver yielding behaviors, with an additional column describing data collection methods to reflect the diverse approaches used in this domain, including controlled field experiments that isolate key behavioral determinants of yielding. Together, these tables highlight common methodological practices, the range of variables considered, and the contexts most frequently studied.

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 2.

Pedestrian Sociodemographics

Gender is one of the most commonly studied factors in pedestrian behavior (see Table 2), 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 2).

Pedestrian Activity and Context

Social context (first column under “pedestrian activity and context” in Table 2) 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 2) 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.

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.

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., Figliozzi 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 3, 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.

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 3 reporting no significant effect of pedestrian gender on yielding (Dileep et al., 2016; Schneider et al., 2018). In contrast, while many studies in Table 3 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.

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).

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 differences 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 (Figliozzi 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.

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).

Vehicle Characteristics

Coughenour et al. (2020) observed that drivers in expensive, high-status vehicles 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 Figliozzi 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 2 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 and 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 and Context" corresponds to changes in pedestrian speed (change from walking to running) and use of mobility devices such as wheelchairs and scooters.

Table 3 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 and 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			×											
Figliozzi 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.

The Current Research in Context

Having outlined the project's contributions and objectives, we now situate the current paper within the broader literature, showing how our large-scale, U.S.-based naturalistic dataset advances the identification of critical safety scenarios that are directly relevant for resilient, PNT-enabled transportation systems.

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 combined influence of pedestrian characteristics, activity type, temporal and weather conditions, and vehicle attributes on these behaviors. This study addresses several of these gaps and advances empirical understanding in six key ways.

First, as observed in Table 2, 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 research 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 2 and the fourth column of Table 3). 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 age, gender, and group size have received substantial attention in past research (see Tables 2 and 3), the combined influence of pedestrian characteristics and contextual conditions on crossing compliance and driver yielding remains underexplored. Existing studies in this area often rely on staged crossings with small sample sizes or limited variation in observed conditions, constraining the scope and generalizability of their findings. In contrast, our large-scale naturalistic observational study provides a richer empirical basis for examining how pedestrian characteristics interact with situational factors, such as group dynamics, traffic conditions, and environmental variability, to shape non-compliant crossings (NCPC) and driver yielding behavior. By capturing this range of behaviors under real-world conditions, our study identifies critical safety scenarios that can inform the design of infrastructure-supported sensing strategies, cooperative perception systems, and validation protocols for resilient PNT-enabled transportation networks.

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 2 and 3) 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 2 and the fifth column of Table 3). 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.

Data Collection and Analysis Methods

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 **Error! Reference source not found.**. The intersection is signalized and features l eft-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).

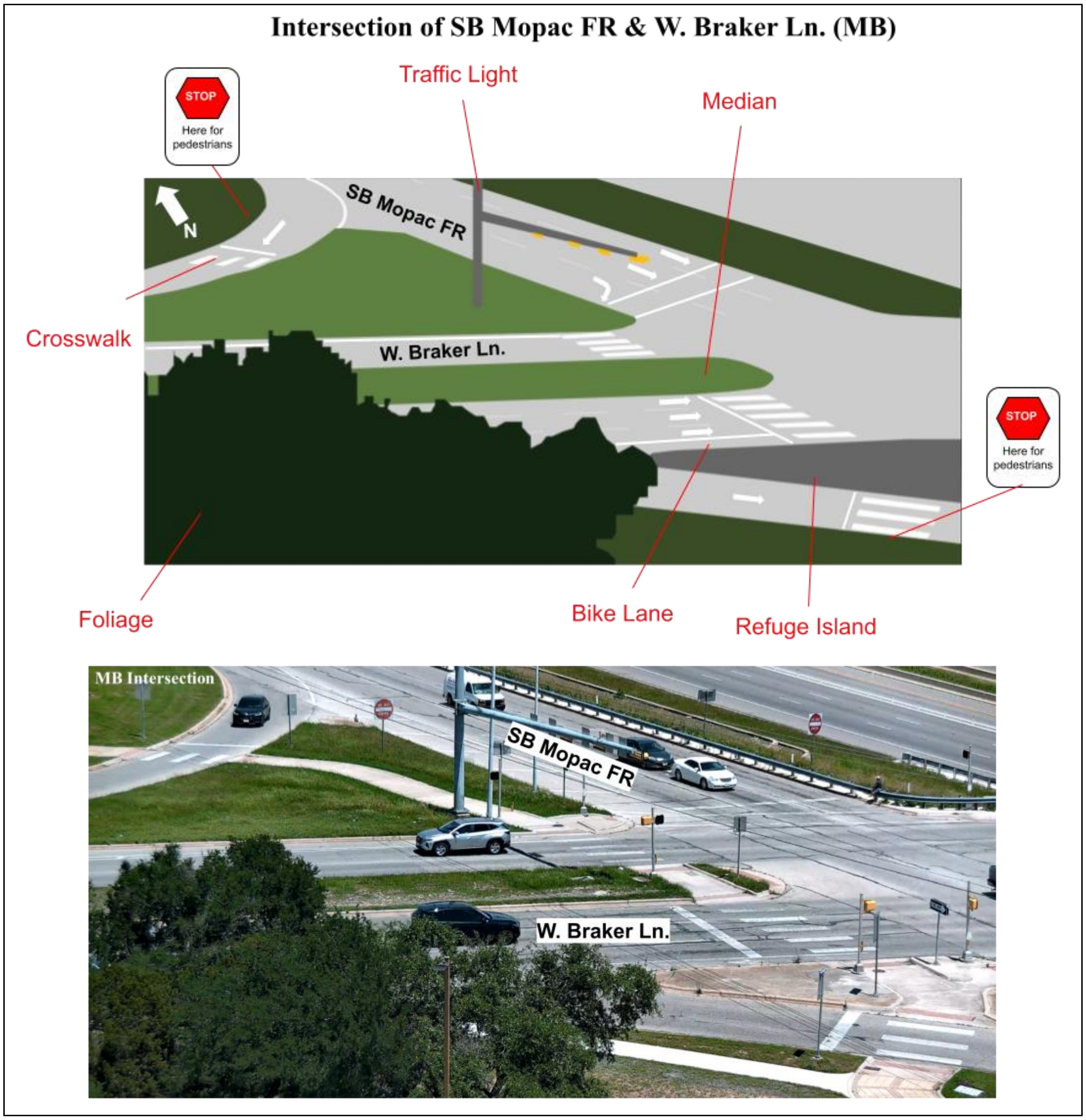

Figure 1 MB Intersection Layout

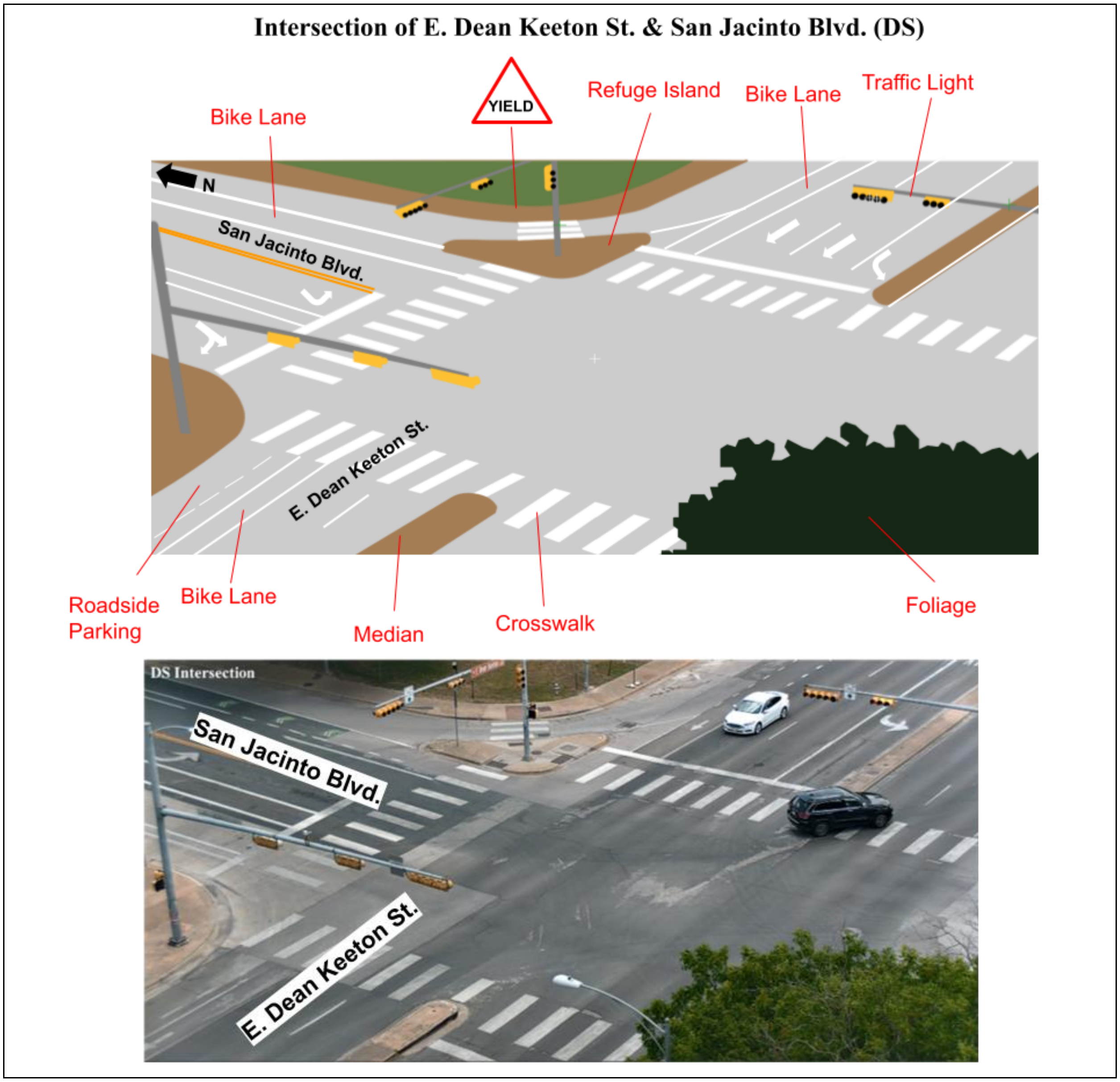

Figure 2 DS Intersection Layout

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 (**Error! Reference source not found.**), the c amera captured the eastbound crosswalk on Braker Lane and both crosswalks on the southbound Mopac Frontage Road. At the DS intersection (**Error! Reference source not found.**), all crosswalks were within t he 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.

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.

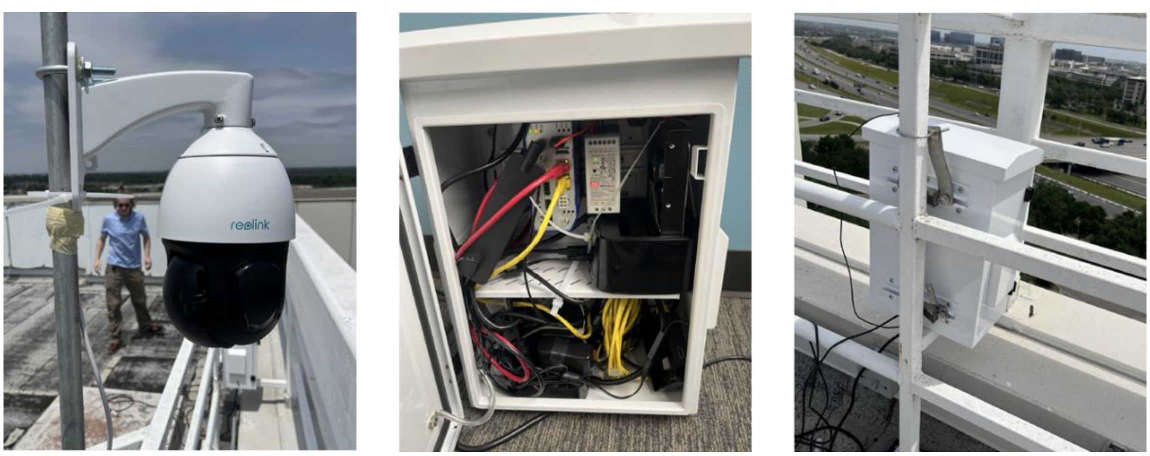

Figure 3 Video Recording Setup

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 consists of ten skin tone categories (Monk, 2022), each represented by a standardized color swatch serving 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.

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).

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 study, 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:

$$y_q^* = \beta' x_q + \varepsilon_q \tag{1}$$

where x_q is a (K×1) vector of observed exogenous variables (including a constant term), β is a corresponding (K×1) vector of coefficients to be estimated, and ε_q is a random error term representing unobserved factors affecting the propensity. We assume that ε_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:

$$P\left(y_q = 1 \mid x_q\right) = \frac{\mathrm{e}^{(\beta' x_q)}}{1 + \mathrm{e}^{(\beta' x_q)}}, \text{ and } P\left(y_q = 0 \mid x_q\right) = 1 - P\left(y_q = 1 \mid x_q\right) \tag{2}$$

The parameters β 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 later sections.

Empirical Results Analysis

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 4 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 4) 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 4 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 differences 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 4 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 4 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 4 Sample Descriptive Statistics

Variable	Total Number of Observations (Rel. Freq.)	Vehicle Interaction Rate (%)	Non-Compliant Pedestrian Crossing Rate (%)	Non-Yielding Rate (%)
Outcome Variables				
Pedestrian Crossing Behavior				
CPC	15847 (91.9%)	16.7%	0.0%	12.4%
NCPC	1404 (8.1%)	8.2%	100.0%	34.8%
Driver Yielding Behavior				
Yielding	2399 (86.7%)	100.0%	3.1%	0.0%
Non-Yielding	368 (13.3%)	100.0%	10.9%	100.0%
Explanatory Variables				
Pedestrian Sociodemographic Variables				
Pedestrian Perceived Gender				
Female	5672 (32.9%)	17.1%	6.2%	12.0%
Male	11579 (67.1%)	15.5%	9.1%	14.0%
Pedestrian Perceived Age				
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%
Pedestrian Perceived Skin Tone				
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%
Pedestrian Exhibiting Visual Markers of Housing Insecurity (VHI)				
No VHI identified	16976 (98.4%)	16.0%	7.9%	12.7%
VHI identified	275 (1.6%)	21.1%	21.1%	39.7%
Pedestrian Activity and Contextual Variables				
Social Context				
Solo crossing	15453 (89.6%)	15.5%	8.4%	13.3%
Group crossing	1798 (10.4%)	20.8%	5.9%	13.1%
Pedestrian Distraction				
Not distracted	16948 (98.2%)	16.0%	8.1%	13.3%
Distracted	303 (1.8%)	15.1%	5.3%	13.0%

Variable	Total Number of Observations (Rel. Freq.)	Vehicle Interaction Rate (%)	Non-Compliant Pedestrian Crossing Rate (%)	Non-Yielding Rate (%)
Pedestrian Activity Type				
Walker	16011 (92.8%)	16.4%	7.6%	13.1%
Runner	1240 (7.2%)	11.5%	15.6%	16.2%
Time-of-Day and Weather Variables				
Time-of-Day				
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%
Weather Condition				
Raining	104 (0.6%)	26.0%	9.6%	37.0%
Not raining	17147 (99.4%)	16.0%	8.1%	13.1%
Vehicle Characteristics				
Vehicle Type				
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.

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 5 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-statistic| > 1.96). But we used a lower confidence level of 85% (|t-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%).[1] Additionally, note that a dash ("--") in Table 5 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 the "Analytical Approach" section), 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

[1]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 1 error (that is, using an 85% confidence level to retain variables). This can inform future specifications using larger and possibly more balanced samples.

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% 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 <u>during non-nighttime periods</u> (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 × Nighttime" interaction term, as presented in Table 5 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 5 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 × 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 × 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 5 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 5 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 <u>after</u> controlling for any effects of exogenous variables through the NCPC outcome. Thus, for example, the %ATE for male pedestrians in Table 5 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.

Table 5 Model Estimation Results

Variable	Non-Compliant Pedestrian Crossing Model			Driver Non-Yielding Model		
	Coef.	**t-stat**	**%ATE**	**Coef.**	**t-stat**	**%ATE**
Pedestrian Sociodemographic Variables						
Pedestrian Perceived Gender (Base: Female)						
Male	0.489	7.18	57.1	0.238	1.99	21.9
Pedestrian Perceived Age (Base: Young adult or minor)						
Older (over 40 years)	--	--	--	0.760	5.76	84.7
Pedestrian Perceived Skin Tone (Base: White - MST 1-2)						
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
Pedestrian Exhibiting Visual Markers of Housing Insecurity (VHI) (Base: No VHI identified)						
VHI identified	1.242	8.93	177.8	0.985	3.52	112.6
Pedestrian Activity and Contextual Variables						
Social Context (Base: Solo crossing)						
Group crossing	-0.439	-4.64	-32.7	-0.300	-1.86	-21.2
Pedestrian Activity Type (Base: Walker)						
Runner	0.736	8.80	88.2	--	--	--
Vehicle Interaction (Base: No vehicle interaction)						
Vehicle interaction	-0.734	-7.74	-48.9	*n.a.*	*n.a.*	*n.a.*
Time-of-Day and its Interactions						
Time-of-day (Base: Noon or Afternoon; 12:00-17:59)						
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	--	--	--
Pedestrian Demographics and Time-of-Day Interactions						

Variable	Non-Compliant Pedestrian Crossing Model			Driver Non-Yielding Model		
	Coef.	t-stat	%ATE	Coef.	t-stat	%ATE
Male × Nighttime (Dawn/Night)	-0.304	-2.08	15.8[a]	0.491	2.77	82.0[a]
Brown × Nighttime (Dawn/Night)	-0.849	-2.21	-57.1[b]	--	--	--
Black × Nighttime (Dawn/Night)	-0.381	-1.97	7.0[b]	--	--	--
Vehicle Characteristics						
Vehicle Type (*Base: SUV, sedan, pickup truck, other*)						
Commercial vehicle	--	--	--	-0.348	-1.49	-25.4
NCPC Behavior						
Pedestrian exhibiting NCPC *(Base: CPC)*	*n.a.*	*n.a.*	*n.a.*	1.210	5.99	150.0
Constants	-3.071	-42.09	*n.a.*	-2.384	-20.77	*n.a.*
Goodness-of-Fit						
Number of observations	17,251			2,767		
Number of parameters	16			10		
Log-likelihood at convergence L(β)	-5131.692			-1180.421		
Log-likelihood of constant-only model L(c)	-5396.065			-1240.614		
Log-likelihood of equal shares model L(0)[c]	-11957.482			-1917.938		
Nested likelihood ratio test[d]	LR = 528.74 > $\chi^2_{(15,0.00001)} = 37.70$			LR = 123.39 > $\chi^2_{(9,0.00001)} = 39.34$		
Adjusted likelihood ratio index $\bar{\rho}_0^2$ [e]	0.571			0.384		
Adjusted likelihood ratio index $\bar{\rho}_c^2$ [e]	0.046			0.041		

[a] The base category for Male × Nighttime in the %ATE comparison is Female × Nighttime.

[b] 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.

[c] L(0) = [(Number of parameters)×ln(0.5)] for a binary model.

[d] The nested likelihood ratio test is computed with respect to the constants only model.

[e] The adjusted likelihood ratio indices are computed as follows: $\bar{\rho}_c^2 = 1 - \left(\mathrm{L}(\beta) - \mathrm{M}\right) / \mathrm{L}(\mathrm{c})$ and $\bar{\rho}_0^2 = 1 - \left(\mathrm{L}(\beta) / \mathrm{L}(0)\right)$, where M is the number of parameters excluding constants.

Pedestrian Sociodemographic Variable Effects

<u>*Pedestrian Perceived Gender*</u>

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).

From a systems perspective, these findings highlight that male pedestrians' higher propensity for non-compliance and elevated exposure to driver non-yielding create recurring critical safety scenarios characterized by sudden, unpredictable crossings. These scenarios are particularly challenging for onboard perception and intent prediction systems, which rely on assumptions of compliant pedestrian behavior. Infrastructure-supported sensing can help mitigate this risk by detecting atypical trajectories earlier, cross-validating vehicle-based perception, and relaying alerts through cooperative perception frameworks, thereby enhancing PNT resilience at intersections.

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.

The elevated risk of non-yielding toward older pedestrians illustrates a scenario where longer crossing times and reduced mobility create potential conflicts. These dynamics stress PNT-dependent systems because they extend the period during which vehicles must maintain accurate localization and intent prediction under variable conditions. Infrastructure-supported sensing can enhance resilience by providing continuous monitoring of crossing progress and alerting drivers or automated systems when vulnerable users remain in the conflict zone longer than expected.

Pedestrian Perceived Skin Tone

Skin tone plays a significant role in shaping pedestrian crossing behavior and driver responses. While the effects are smaller than those associated with gender or time-of-day, they remain statistically significant. 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, these findings align with broader behavioral science and psychology research (see Factor et al., 2013, Jamieson et al., 2013, and Xie et al., 2020). Differences 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 findings (see Goddard et al., 2015, Coughenour et al., 2017, Schneider et al., 2018, and Coughenour et al., 2020).

The variation in compliance and yielding across skin tone categories further demonstrates that pedestrian and driver behaviors are not uniform, generating behavioral heterogeneity that complicates prediction models. For PNT-dependent automated systems, this variability translates into uncertainty about when pedestrians will cross and whether drivers will yield, both of which are critical for safe navigation. Recognizing these variations as stress scenarios underscores the value of roadside sensors and cooperative perception to capture and anticipate behavioral deviations, ensuring robust system performance across diverse contexts.

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).

The strong association between VHI and both pedestrian non-compliance and driver non-yielding indicates another high-risk behavioral scenario where unpredictable pedestrian actions intersect with reduced driver responsiveness. Such compounded variability creates severe stress conditions for onboard systems, which may struggle to distinguish intent or allocate sufficient reaction time. Infrastructure-supported sensing can provide critical redundancy by detecting non-compliant entries into the roadway earlier. At the same time, scenario templates based on these findings can inform AV testing and standards for operating safely in environments with elevated unpredictability.

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.

For PNT resilience, this also supports the benefits of infrastructure sensors that are capable of detecting not only pedestrian presence but also social context (solo vs. group), thereby improving trajectory forecasting and enabling safer cooperative perception interventions.

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.

The elevated NCPC likelihood among runners characterizes a high-velocity, short-horizon critical safety scenario. Specifically, entry speeds compress time-to-collision and reduce the window for onboard intent prediction. These conditions stress vehicle-only perception and planning, particularly under low light or partial occlusion. Infrastructure-supported sensing (fixed-vantage cameras/radar) can detect rapid approach vectors earlier, stabilize trajectory estimation, and cross-validate vehicle PNT streams. Practically, these cases should populate scenario libraries for AV/HAV validation (e.g., sudden speed-up to gap-accept) and trigger V2I/V2P advisories when edge analytics detect atypical approach speeds toward the crosswalk.

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. In contrast, this suggests elevated NCPC likelihood in the absence of a visible. When no vehicle is in sight, pedestrians are more likely to cross illegally, even if an unseen vehicle is approaching from around a corner or hidden by occlusion.

These are precisely the critical safety scenarios where both the pedestrian and the driver lack mutual visibility, leaving little margin for reaction. Infrastructure-supported sensing positioned at vantage points that cover blind spots and approach lanes can bridge this visibility gap by detecting pedestrians before drivers or onboard sensors can and relaying warnings via cooperative perception. Such deployments can prevent hidden-conflict scenarios from escalating into collisions, directly enhancing PNT resilience in complex intersection environments.

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.

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).

These results illustrate how temporal stressors combine with reduced visibility to generate high-risk scenarios. These are precisely the contexts where GNSS accuracy (due to multipath or signal degradation in urban environments) and onboard perception (due to low light) are simultaneously stressed. Infrastructure-supported sensing provides an essential redundancy layer in these conditions by ensuring reliable detection and augmenting vehicle-based systems, making nighttime and dawn scenarios priority candidates for resilient PNT interventions.

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 differences in driver behavior become more pronounced when visibility is limited.

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.

The asymmetries introduced by these interactions create additional nighttime critical safety scenarios in which intent prediction and detection are simultaneously stressed: pedestrians adjust behavior under low light, yet driver yielding becomes less reliable, and both parties often have reduced visibility. For automated systems, these dynamics mean that priors learned in daytime conditions may miscalibrate nighttime risk, undermining vehicle-only perception and planning. Infrastructure-supported sensing should therefore be time-conditioned and optimized for low-light operations (e.g., high-mount cameras with improved illumination coverage, thermal or radar augmentation, and approach-leg views that see past occluders). As a result, scenario libraries and validation protocols should explicitly include nighttime variants of these interactions (e.g., narrowed NCPC differentials with elevated non-yielding risk) so that PNT-dependent stacks are tested and tuned for the full range of temporal contexts. Additionally, heterogeneous nighttime adjustments observed across skin-tone categories indicate that behavioral priors should be time-aware and context-driven, reinforcing the need to train detection/prediction models on diverse nocturnal conditions rather than assuming daytime patterns generalize.

Vehicle Characteristic Variable Effects

<u>*Vehicle Type*</u>

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.

NCPC Effect on Driver Non-Yielding Behavior

The results in Table 5 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. It also defines a compound critical safety scenario in which intent prediction and localization must be both rapid and robust. These episodes are precisely where onboard systems are most vulnerable to late detection or misclassification. Infrastructure-supported sensing can flag NCPC early, cross-check vehicle PNT/perception, and issue time-critical V2I alerts (e.g., SPaT/MAP-aligned warnings) to extend reaction time.

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 5, 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.

Discussion

The results of the logit models presented above revealed several patterns of pedestrian and driver behavior that represent not merely behavioral anomalies but empirically recurring, high-risk conditions. Each of these conditions coincides with well-documented PNT stressors such as GNSS multipath and signal blockage, low-light perception loss, sensor occlusion, or prediction miscalibration. The intersection of these behavioral and technical vulnerabilities defines critical safety scenarios that are critical not only for understanding pedestrian safety but also for advancing Positioning, Navigation, and Timing (PNT) resilience in highly automated transportation systems (HATS).

Nighttime non-compliant crossing provides a clear illustration. The probability of NCPC increases more than twofold between 20:00 and 05:59, while driver yielding simultaneously decreases. These temporal patterns translate directly into PNT stress conditions. At night and dawn, cameras face degraded performance, GNSS signals suffer greater multipath interference in urban environments, and both pedestrian and driver visibility are reduced. As a result, the time available for detection and response is compressed precisely when human behavior is least predictable. This makes nighttime NCPC and dawn or morning non-yielding prime scenarios for testing and validating cyber-resilient PNT systems.

Other critical factors include occlusion and visibility-related conflicts, which our models show are significantly coupled to crossing decisions. Our findings indicate that pedestrians are more likely to cross illegally when they perceive the approach to be clear, even if a vehicle is hidden around a corner or behind a large occluder such as a bus or truck. Such hidden-approach conditions generate mutual invisibility: pedestrians cannot see the vehicle, and onboard sensors cannot see the pedestrian until the moment of conflict. From a PNT perspective, these situations are among the most challenging, as neither GNSS positioning nor vehicle-mounted cameras or LiDAR can compensate for line-of-sight loss without support from infrastructure-based sensors.

Other behavioral patterns identified in the models further enrich this landscape of critical scenarios. Runners are more likely to engage in NCPC than walkers, a difference that decreases the available prediction horizon and raises the likelihood of late or missed detection, especially in low light. Solo pedestrians are both more likely to commit violations and less likely to elicit driver yielding than those in groups, presenting reduced visual salience and fewer social cues, complicating both human and automated intent estimation. Older adults have a higher likelihood of driver non-yielding, which extends the time they remain in the conflict zone and requires longer and more stable tracking by automated systems. As a result, factors including high entry speed, low social visibility, and extended dwell time, combine to create short-horizon or long-duration conflicts that are especially demanding for PNT-dependent perception and decision modules.

The model results also reveal systematic variation in crossing and yielding behavior across pedestrian characteristics that adds further complexity to these safety scenarios. For instance, male pedestrians display a higher tendency for non-compliant crossings and experience more frequent driver non-yielding, with these patterns shifting further at night. Differences also emerge by skin tone, with darker- and medium-toned pedestrians showing distinct crossing and yielding tendencies, and by social context, as pedestrians exhibiting visual markers of housing insecurity are especially prone to both non-compliance and reduced driver yielding. These combinations of unpredictable movement and reduced driver responsiveness define the most severe risk profiles observed in the data. For automated vehicles, these population-linked differences mean that intent prediction and trajectory modeling cannot safely assume uniform pedestrian behavior. For PNT systems, they represent domain shifts that can degrade the performance of learning-based perception if not explicitly incorporated into scenario design and training data.

Overall, these empirically grounded scenarios can be translated into actionable templates for infrastructure deployment and cooperative perception. They also form a foundation for standards and validation of cyber-resilient PNT systems. Each scenario can serve as a required test case in the certification of automated and connected vehicle stacks, ensuring robust performance under empirically documented, high-stress conditions. Key evaluation metrics include time-to-first detection, added warning time, and false-negative rates. By embedding these scenarios and metrics in national and industry standards, transportation agencies and technology developers can move beyond post-crash analysis toward proactive, infrastructure-supported safety systems that remain dependable even when GNSS is degraded, onboard perception is challenged, or human behavior departs from expected patterns.

Table 6 summarizes the empirically derived critical safety scenarios, each combining observed behavioral risk factors with documented PNT vulnerabilities, and highlights their associated stress mechanisms, recommended infrastructure and cooperative-perception strategies, and key applications for standards and validation of cyber-resilient PNT systems.

Table 6 Critical Safety Scenarios, PNT Stressors, and Design Guidance

Scenario	Key Triggers / Behavioral Context	Primary PNT Stressors	Infrastructure and Cooperative Perception Guidance	Standards / Validation Uses
Nighttime Non-Compliant Crossing (NCPC)	Sharp increase in NCPC and driver non-yielding during dawn, dusk, and night hours	Low-light camera degradation; GNSS multipath and signal noise; prediction miscalibration	Deploy thermal/infrared cameras and short-range radar; time-aware detection algorithms; low-latency V2I pedestrian-entry alerts	Required nighttime scenarios in AV/HAV testing; metrics: time-to-first-detection (TTFD), added warning time, false-negative rate
Hidden-Approach Conflict	Pedestrians cross when no vehicle is visible but one is occluded (e.g., behind buses, trucks, or at slip lanes)	Mutual invisibility; occlusion blind spots for cameras/LiDAR; delayed localization	Elevated corner-mounted cameras and radar; cooperative perception messages (CPM) revealing hidden approach; occlusion-aware analytics	Occlusion-breach detection benchmarks; test V2I/V2P latency for conflict warnings
Runner High-Speed Entry	Runners accelerate to accept small gaps, compressing time for prediction and braking	Short reaction-time horizon; trajectory estimation error; low-light detection lag	High-sampling edge analytics for approach velocity; early V2I alerts for high-speed pedestrian approach	Mandatory sudden-speed-up test case; metrics: prediction horizon extension, emergency braking success rate
Solo Crossing Variability	Solo pedestrians exhibit lower compliance and elicit less driver yielding	Reduced visual salience; weaker intent cues; higher intent-classification error	Group-size detection with roadside sensors; risk-scored cooperative alerts; priority V2I/V2P messaging for solo detections	False-negative detection rate for solo pedestrians; yielding compliance improvement after V2I cue
Extended-Duration Crossing (Older Pedestrians)	Slower walking speeds prolong conflict zone exposure and increase driver impatience	Longer localization and tracking windows; higher risk of GNSS drift	Full-crosswalk tracking using multi-sensor fusion; continuous crossing-status updates to approaching vehicles	Tracking persistence, safe re-acceleration inhibition rate metrics
Morning-Peak Non-Yielding	Time pressure elevates both NCPC and driver non-yielding during commute hours	Dense traffic interferes with GNSS and onboard perception; reduced reaction margins	Peak-period adaptive thresholds in roadside sensing; time-aware conflict detection algorithms	Validation of peak-hour risk prediction and warning time
Dual Deviation: NCPC + Non-Yielding	Drivers fail to yield when pedestrians cross illegally, combining the strongest risk factors	Compound intent ambiguity; minimal behavioral redundancy; high collision probability	Highest-priority V2I alerts; cross-validated vehicle and infrastructure PNT data	Core combined-violation test case; evaluation of emergency-response and fail-safe behaviors

Scenario	Key Triggers / Behavioral Context	Primary PNT Stressors	Infrastructure and Cooperative Perception Guidance	Standards / Validation Uses
Appearance / Context-Linked Variability	Crossing and yielding vary with pedestrian appearance (e.g., clothing contrast, VHI markers) and social context	Domain-shift risk for machine-learning perception; confidence-calibration errors	Use diverse-condition training datasets; confidence-aware cooperative alerts; context-aware detection	Robustness and confidence calibration tests across appearance/context conditions

Conclusions

This research advances the understanding of how pedestrian and driver behaviors generate critical safety scenarios that also serve as PNT-relevant stress conditions at urban intersections. Using more than 20,000 observed pedestrian crossings and over 3,000 pedestrian vehicle interactions captured in 1,000 hours of video, we quantified how factors such as time of day, social context, pedestrian activity, and individual characteristics (e.g., gender, appearance-linked traits, and visible indicators of housing insecurity) shape the likelihood of non-compliant pedestrian crossings and driver non-yielding. These empirically grounded patterns were used to define recurring operating conditions where GNSS degradation, low-light perception loss, and sensor occlusion can jointly undermine vehicle-only positioning and prediction.

By framing these behaviors as scenario templates for PNT resilience, the study provided actionable guidance for targeted roadside sensing, cooperative perception (V2I/V2P) design, and standards for cyber-resilient PNT systems. The findings showed how infrastructure-based sensing and cross-validated PNT data can detect unpredictable movements earlier, issue low-latency warnings, and maintain localization integrity when onboard perception is stressed.

Several opportunities remain for future work. Expanding the geographic and temporal scope beyond the two studied intersections would help test the generality of these scenarios across different built environments and seasonal conditions. Incorporating additional explanatory variables, such as driver demographics, pedestrian gestures, walking speed, or vehicle acceleration patterns, could further refine scenario definitions and enrich cooperative perception models. Complementary qualitative or simulation-based methods, including surveys and virtual-reality experiments, could also study pedestrian and driver decision-making in ways that strengthen predictive modeling.

Lastly, by moving beyond post-crash analysis to identify and systematize behaviorally grounded, PNT-relevant stress conditions, this research delivers the data, analytical framework, and scenario templates needed to inform the next generation of infrastructure-supported, cyber-resilient transportation systems that anticipate and prevent conflicts rather than merely documenting their aftermath.

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