Evaluating Crosswalk Safety Through Trajectory Analysis of Pedestrian Gap Acceptance and Vehicle Yielding

Anisha Tasnim[1], **Muhammad Fahad**[2], **Tianyang Xiong**[1], **Xiaowei Shi**[2], **Tian Zhao***[1]
Xiao Qin[2]

[1]Department of Computer Science, University of Wisconsin-Milwaukee, 53211
[2]Department of Civil and Environmental Engineering, University of Wisconsin-Milwaukee, 53211

Abstract

Vulnerable road-user crash data often underestimates actual risk because near-miss events, such as delayed yielding, are rarely recorded. To address this gap, we developed CrossRisk, a trajectory-based, threshold-driven framework that quantifies pedestrian-vehicle interaction risk at urban midblock crosswalks. The framework integrates panoramic 3D trajectories with site-specific safety metrics, including pedestrian gap acceptance, spatial proximity, stopping sight distance, driver behavior, and crosswalk encroachment to classify each interaction into *safe*, *risky*, or *critical* categories. CrossRisk was validated using 206 real-world interactions recorded at a midblock crosswalk in the City of Milwaukee. The framework detected 96.6 % of interaction events and achieved 98.49 % classification accuracy, 90.0 % precision, and 96.0 % recall. Timely deceleration and stopping improve yielding behavior and ensure safety. Overall, CrossRisk provides a transferable, cost-effective approach for real-time urban monitoring and enables systematic identification of high-risk interactions not captured by crash data.

Keywords: Pedestrian safety, Panoramic 3D trajectories, Risk assessment, Pedestrian gap acceptance, Stopping sight distance, Vehicle-pedestrian behavior analysis.

INTRODUCTION

Advances in sensing technologies, such as panoramic video systems, multimodal fusion, and deep-learning-based perception, have dramatically increased the capacity of cities to monitor pedestrian and vehicular movements with high precision (Lin et al. 2024; Patel et al. 2023; Teng et al. 2025; Ventura et al. 2025). Despite this technological momentum, pedestrian safety outcomes continue to deteriorate: more than 7000 pedestrian fatalities were recorded in the United States in 2023, marking the highest level in over forty years ("Pedestrian Safety" 2025).

Midblock and unsignalized crosswalks present some of the most challenging conditions for pedestrian safety because they rely entirely on real-time negotiation between pedestrians and approaching drivers. These environments require pedestrians to evaluate temporal gaps, anticipate vehicle motion, and initiate crossing under varying visibility, cognitive load, and traffic density (Liu and Li 2009; Osorio-García et al. 2023; Yue et al. 2020; Zhao et al. 2023). Drivers, in turn, must detect intent, respond rapidly, and satisfy the physical constraints imposed by perception-reaction time and stopping sight distance (SSD) (Meocci et al. 2024; Zhu et al. 2021; Zhuang and Wu 2014). Traditional surrogate safety frameworks often rely on fixed thresholds or simplified assumptions that overlook behavioral intent, lane-dependent geometry, and perception-reaction constraints. As a result, they struggle to represent real-time risk evolution at midblock crosswalks, where small timing errors can rapidly escalate into hazardous conditions. This limitation creates the need for a behaviorally grounded, context-sensitive model capable of interpreting risk as it emerges. However, few existing approaches jointly model pedestrian gap acceptance and driver stopping feasibility using panoramic trajectory data at real world midblock crosswalks.

To address the need for behaviorally grounded, high-resolution safety analytics, this study introduces CrossRisk, a dynamic trajectory-driven framework that integrates (i) panoramic 3D motion trajectory data, (ii) pedestrian gap-acceptance modeling, (iii) driver stopping feasibility, and (iv) context-aware surrogate safety indicators. The framework unifies behavioral decision processes with physical constraints and high-definition motion trajectories to capture how risk emerges and evolves at midblock crosswalks. By combining empirical behavioral determinants with SSD-based feasibility analysis and surrogate safety measures, CrossRisk offers a scalable, operationally robust system capable of supporting intelligent transportation infrastructure, proactive conflict detection, and suitable for real-time deployment.

RELATED WORKS

Early pedestrian safety research primarily relied on police-reported crashes to identify associations between roadway characteristics and injury outcomes, concluding that multilane configurations, high traffic volumes, and restricted sight distance elevate crash likelihood (Allen et al. 1978; Qiu and Xu 2011; "Safety Effects of Marked Versus Unmarked Crosswalks at Uncontrolled Locations Final Report and Recommended Guidelines, September 2005 - FHWA-HRT-04-100" n.d.; Ukkusuri et al. 2012; Yanagisawa et al. 2014; Zhang et al. 2019). While useful for macro-level planning, crash datasets provide limited insight into real-time interactions because they record only severe events and often omit the behavioral precursors that precede them. This limitation has driven the adoption of trajectory-based approaches capable of capturing near-miss events and subtle interaction dynamics that crash data alone cannot reveal.

Behavioral research has established that pedestrian crossing decisions are influenced by cognitive factors, physical abilities, attention, urgency, and social grouping (Bennett et al. 2001; Osorio-García et al. 2023; Schwebel et al. 2014). Gap-acceptance studies highlight substantial variation in accepted gaps across contexts, shaped by waiting time, walking speed, roadway width, and cultural norms (Al Bargi et al. 2023; Brewer et al. 2006; Dipietro and King 1970; Liu and Li 2009; Yannis et al. 2013; Zhao et al. 2019). These findings demonstrate the critical role of behavior in shaping pedestrian exposure but remain difficult to operate without high-resolution motion data.

In parallel, extensive research has examined driver behavior and its implications for pedestrian risk. Studies show that drivers approaching midblock crosswalks often maintain speeds inconsistent with safe stopping, yield inconsistently under ambiguous right-of-way conditions, and adjust poorly to unexpected pedestrian entry (Figliozzi and Tipagornwong 2016; Wang et al. 2016). SSMs such as TTC, PET, and DRAC have emerged to quantify near-miss severity using trajectory data (Chen et al. 2017; Patel et al. 2023; Sankaran and Vedagiri 2020; Wang et al. 2021). However, many SSM-based applications depend on fixed thresholds and do not account for the behavioral intent, perception-reaction constraints, or site-specific context necessary for realistic safety assessment. CrossRisk addresses this need by combining panoramic trajectories with behavioral and physical constraints to produce high-resolution, real-world pedestrian risk assessments.

Current surrogate safety frameworks inadequately capture the dynamic, context-sensitive characteristics of pedestrian-vehicle interactions. There is a clear need for an integrated, trajectory-based approach that unifies behavioral decision-making, physical motion constraints, and environmental variability to support proactive, high-resolution safety evaluation.

This study advances pedestrian safety analytics through three primary contributions, each addressing limitations in existing surrogate safety and trajectory-based methods:

1. Trajectory-Driven Interaction Event Extraction: A high-fidelity interaction extraction pipeline is developed using panoramic 3D trajectories from the CrossTraj dataset, generated through YOLOv9 and DeepSORT-based detection and tracking. This pipeline reconstructs pedestrian and vehicle motion with sufficient spatiotemporal precision to enable fine-grained interpretation of interaction dynamics at midblock crosswalks.
2. Site-Specific Pedestrian Gap-Acceptance Modeling: It provides context-sensitive thresholds, including critical, medium, and large temporal gaps that reflect actual pedestrian decision-making patterns at the studied midblock crosswalk.
3. Dynamic, Context-Aware Risk Classification: An adaptive risk-assessment model is formulated by integrating driver-speed profiles, stopping-sight-distance feasibility, environmental factors, and pedestrian gap-acceptance behavior. This framework classifies interactions into *safe*, *risky*, and *critical* categories with improved sensitivity to real-world variability.

METHODOLOGY

The CrossRisk framework evaluates pedestrian-vehicle interactions using a high-resolution 3D trajectories dataset, collected through a panoramic roadside perception system (Fahad et al. 2025). The methodology consists of four main components: trajectory dataset preprocessing, pedestrian gap acceptance modeling, driver stopping-feasibility assessment, and integrated surrogate safety and risk classification. Figure 1 summarizes the workflow.

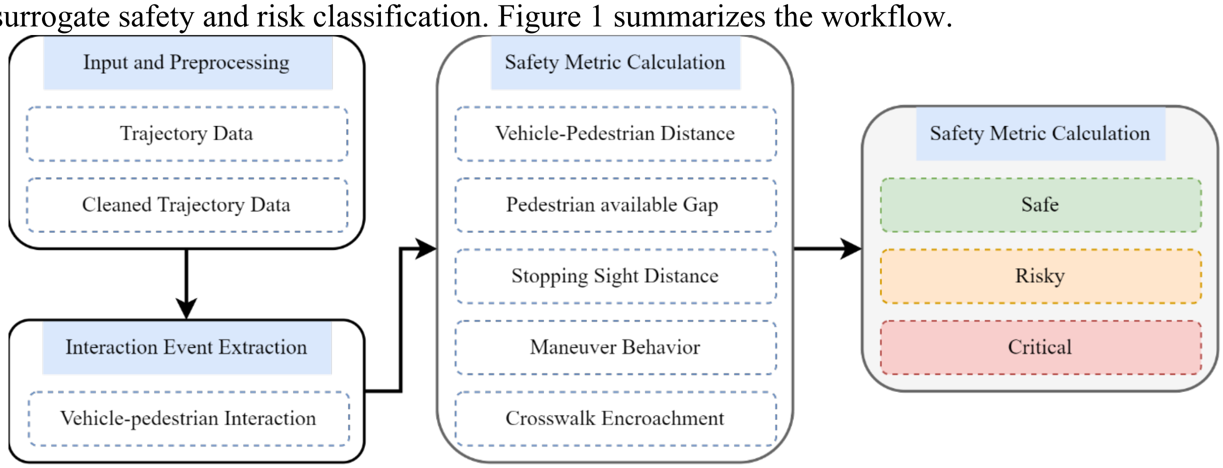


Figure 1: The proposed CrossRisk framework for evaluating crosswalk safety using trajectory data

The workflow begins with extraction and preprocessing of trajectories. Preprocessing ensures temporal continuity and produces stable motion profiles that serve as input.

Trajectory Dataset and Preprocessing

This study uses panoramic 3D trajectory data extracted from a single roadside camera system deployed at a midblock crosswalk in the City of Milwaukee (Figure 2(a)). We used CrossTraj (Fahad et al. 2025) dataset for pedestrian gap acceptance modeling and CrossSafe (Tasnim et al. 2025) to validate the framework. The dataset provides timestamps and georeferenced trajectories with latitude and longitude coordinates for pedestrians and vehicles, along with object identities, synchronized timestamps, and derived kinematic attributes such as speed and acceleration. All perception operations, including object detection, multi-object tracking, camera calibration, and image-to-world homography were completed by the sensing platform prior to data delivery, enabling analysis to begin directly from high-level trajectory data.

Preprocessing includes timestamp normalization, removal of fragmented, inconsistent tracks, and refinement of motion profiles. These steps generate stable, high-fidelity trajectories suitable for microscopic safety modeling tasks such as gap-acceptance estimation, stopping sight distance analysis, and surrogate safety measure computation.

Interaction Identification and Temporal Alignment

Following preprocessing, pedestrian-vehicle interactions were isolated by detecting time intervals where a pedestrian and at least one vehicle simultaneously occupied the influence zone surrounding the crosswalk. For each detected interaction, trajectories were temporally aligned to support synchronized evaluation of gap availability, vehicle motion, stopping feasibility, and pedestrian behavior as illustrated in Figure 2(b). Interaction events were segmented into three types: (i) pedestrian events (waiting or crossing), (ii) approach events (vehicle directions), and (iii) decision events (pedestrian accepts or rejects available gaps). A waiting event is when a pedestrian is standing at the curb and a crossing event is when the pedestrian steps into the crosswalk. These events support consistent computation of behavioral indicators and surrogate safety measures.

(a) Area of Study (b) Interaction Event Analysis

Figure 2 Area of study and interaction event analysis at the midblock crosswalk, showing the waiting, approaching, stopping, crossing, and leaving phases for pedestrian-vehicle interactions

Pedestrian Gap-Acceptance Modeling

CrossRisk incorporates a context-sensitive gap-acceptance model calibrated using the 3D trajectory dataset (CrossTraj). Using site geometry derived from geo-referenced points, the crosswalk and its two curbs were encoded as polygons and each pedestrian sample was assigned to a region through point-in-polygon classification. Waiting event is identified using a data-driven speed threshold, while crossing event is detected when a trajectory transitioned from curb to crosswalk. Vehicle trajectories that overlap with waiting or crossing events are extracted and coalesced into interaction segments. The arrival time of the conflicting vehicle at the crosswalk was estimated using its time-to-arrival (T_{tta}). Under constant acceleration, the T_{tta} is obtained from the kinematic relation in Equation 2, the smallest positive root provides the expected arrival time. The CrossRisk implementation uses a piecewise formulation to ensure stability: when the vehicle is coasting or accelerating, $T_{\mathrm{tta}} = d/v_{\mathrm{veh}}$ and under strong braking, the framework evaluates whether the vehicle can stop upstream of the crosswalk and selects the appropriate constant-deceleration solution. The available temporal gap at the pedestrian's decision time is computed using Equation 1.

$$G_p(t) = T_{tta}(t) - T_{dec} \tag{1}$$

where $G_p(t)$ represents the temporal margin between vehicle arrival and the time required for the pedestrian to decide whether to cross. Positive values of G_p indicate sufficient temporal separation, whereas negative values reflect a conflict in which the vehicle would reach the crosswalk before the pedestrian decides it.

Vehicle arrival time under constant acceleration is estimated using:

$$d = v_{veh}t + \frac{1}{2}at^2 \tag{2}$$

where d is the longitudinal distance from the vehicle to the crosswalk and t is the arrival time whose smallest positive root yields T_{tta}.

Every pedestrian decision point is either the moment of actual entry to the crosswalk (accepted gaps) or an instant during waiting (rejected gaps). Each observed decision is labeled as a binary outcome (accepted = 1, rejected = 0), producing a dataset of binary choices paired with continuous TTC-style gaps. A binary logit model is estimated via maximum likelihood to characterize the probability that a pedestrian accepts a gap of size (Equation 3). This model represents a population-level gap-acceptance function.

$$Pr(accept = 1|G) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 G)}} \tag{3}$$

where G is the temporal gap (s), β_0 is the baseline acceptance tendency, and β_1 expresses how strongly pedestrians adjust their decisions as gap size increases.

Once the model is calibrated, site-specific behavioral thresholds are obtained by inverting the logit curve to find the gap $G(p)$ at which the predicted probability of acceptance equals a chosen value p in Equation 4.

$$G(p) = \frac{ln\left(\frac{p}{1-p}\right)}{\beta_1} \tag{4}$$

where p is the desired acceptance probability.

This procedure produces model-derived temporal gap thresholds by evaluating the fitted logit function at acceptance probabilities. Specifically, the critical, medium, and large gaps correspond to $p = 0.5$, $p = 0.85$, and $p = 0.95$ respectively. This gap-acceptance formulation provides a consistent trajectory-based measure of pedestrian decision-making.

Context-Aware Risk Classification (*CrossRisk*)

CrossRisk assigns each pedestrian-vehicle interaction with a safety label of *safe*, *risky*, or *critical* using temporal, spatial, and kinematic indicators extracted from 3D trajectories. Curb-belt and crosswalk polygons are constructed, and two pedestrian events are identified: waiting and crossing. For every pedestrian event, vehicle trajectories within a spatial window (< 80 m) are considered as interacting vehicles.

For each pedestrian-vehicle pair, the framework analyzes the segment of the vehicle trajectory that is temporally aligned with the pedestrian event. Within this window, four key indicators are computed: (i) the temporal gap between vehicle arrival and the pedestrian's required crossing time, (ii) the minimum pedestrian-vehicle separation distance, (iii) the vehicle's stopping sight distance relative to its distance to the crosswalk, and (iv) crosswalk encroachment and lane-level conflict states. Proximity risk uses minimum distances with thresholds at < 3 m (critical), 3-4.5 m (risky), and > 4.5 m (safe). Dynamic feasibility evaluates whether the vehicle can safely yield using SSD in Equation 3:

$$SSD = v_{veh}t + \frac{{v_{veh}}^2}{2g\left(\frac{a}{g} \pm G\right)} \tag{3}$$

where v_{veh} is the speed of the vehicle, a is acceleration, g is the gravitational constant and G is roadway grade (+ for uphill and - for downhill) in percent/100. For calculation simplicity, we ignored G. The three dimensions are fused with lane-conflict and encroachment checks to assign a final class. Critical events occur when encroachment happens during a pedestrian episode, when stopping is physically infeasible, or when conflicts exceed thresholds. Risky events show moderate temporal or spatial deficiency. Safe events meet all temporal, spatial, and feasibility criteria.

RESULTS AND DISCUSSION

Pedestrian Gap Acceptance Modeling

We used the CrossTraj dataset, an one-hour 3D trajectory recording from the midblock crosswalk in Milwaukee, to perform pedestrian gap-acceptance modeling. The calibrated logit model was used to quantify pedestrian gap-acceptance behavior at the study site. The dataset captures detailed pedestrian and vehicle trajectories, enabling accurate estimation of crossing decisions and driver responses. Figure 3 visualizes the interaction dynamics. Table 1 report the model-driven gap acceptance thresholds and Figure 4 represents the logistic gap-acceptance curve showing the model-predicted acceptance probability as a function of gap size, with critical ($p = 0.50$), medium ($p = 0.85$), and large ($p = 0.95$) behavioral thresholds indicated.

Table 1 Pedestrian's gap acceptance threshold at the crosswalk

Gap Type	**Acceptance Probability, p**	**$G(p)$ (seconds)**
Critical	0.5	2.62
Medium	0.85	5.97
Large	0.95	8.31

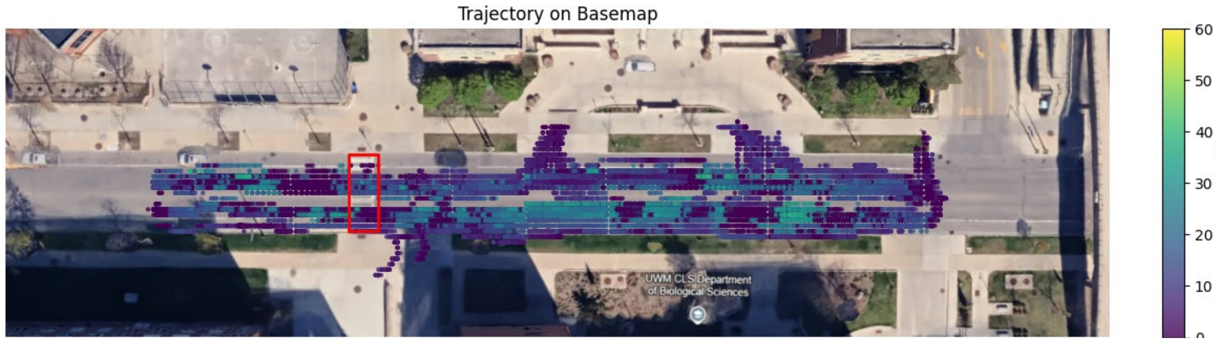


Figure 3 CrossTraj Trajectory on Basemap

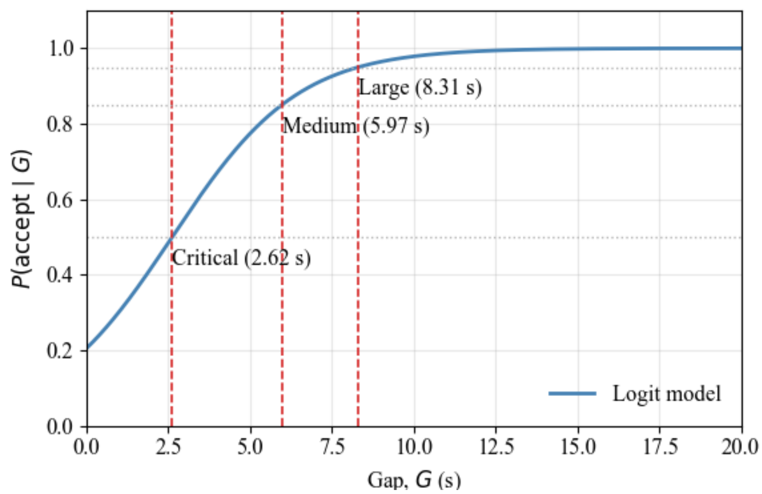


Figure 4 Model-based pedestrian gap-acceptance curve estimated using a binary logistic regression.

These thresholds reflect site-specific pedestrian behavior at the midblock crosswalk in the City of Milwaukee, and are consistent with previously reported heterogeneous traffic ranges(Al Bargi et al. 2023; Dipietro and King 1970; Zhao et al. 2019) reinforcing their external validity. The thresholds were subsequently integrated into the risk classification framework to classify pedestrian-vehicle interactions into safe, risky, and critical categories.

Test Dataset Overview

A total of 15 short video segments were collected at the university midblock crosswalk during two clear sunny days on May 5th and May 6 in 2025, each with one-hour duration, capturing a diverse range of pedestrian-vehicle interactions. From these recordings we manually selected short segments where we captured all types of events, and a total of 206 events were identified, including pure waiting scenarios, active crossing events, and mixed interactions in which pedestrians displayed both waiting and crossing behaviors within the same clip, which are listed in Table 2.

Table 2 Ground Truth Risk Classification of Events from Videos

Events	Total events	Safe	Risky	Critical
Crossing	186	171	8	7
Waiting	20	15	1	4
Total	206	186	9	11

The trajectories are extracted using Yolov9E and DeepSort algorithm(Fahad et al. 2026a; b) and are shown in Figure 5. The proposed risk classification framework was applied to each segment to generate corresponding risk classifications. These classifications were subsequently validated against the ground-truth CrossSafe dataset, which encodes interaction outcomes based on pedestrian-vehicle distances and relative positioning on the crosswalk.

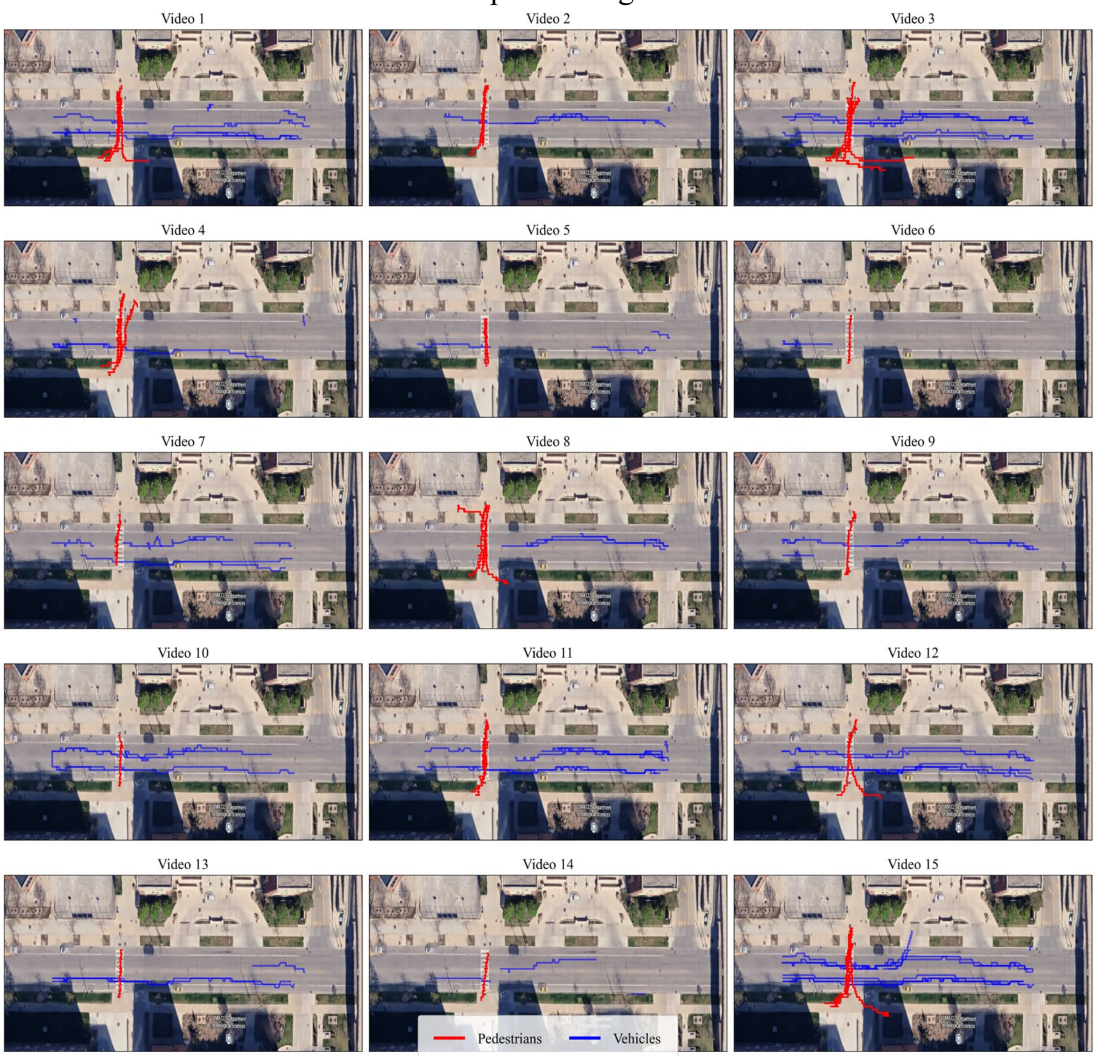
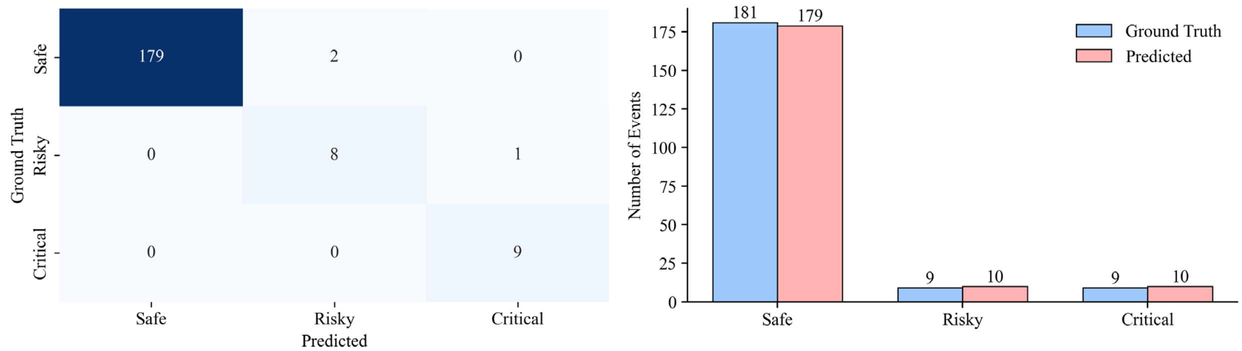


Figure 5 Trajectory Plots for 15 short video segments

Performance

Across all scenarios, the framework produced 199 predicted interactions. The evaluation of interaction detection and risk classification was based on aggregated counts and performance indicators derived and listed in Table 3 along with the definitions of each reported metric. The results demonstrate that the framework achieves event detection accuracy of 96.6% with overall classification accuracy of 98.49%, with a precision of 90.0% and a recall of 96.0%. Risk level classification is shown in Figure 5. This imbalance reflects the influence of ID switches across tracked entities, the geolocation error in the trajectory data and missed detections of pedestrian waiting events occurring outside the defined curb regions. Figure 6 visualizes these outcomes, with Figure 6(a) presenting the confusion matrix used to derive the performance metrics and Figure 6(b) comparing ground-truth and predicted event counts for each risk category.



(a) Confusion Matrix (b) GT vs Predicted Risk Levels

Figure 6 Risk Classification (Ground Truth vs Predicted by CrossRisk)

Table 3 Definitions of framework evaluation metrics and Overall Framework Performance.

Metric	Definition	Interpretation in This Study	Results
Total Ground Truth Interactions	Total annotated interactions (ground truth baseline)	Reference interaction events	206
Total Predicted Interactions	Number of interactions output by the framework.	Indicates the predicted output, including correct, incorrect, and spurious predictions.	199
Matched Interactions	Predicted interaction events matchable with ground truth	Correctness analysis.	199
False Positive	Predicted interactions without corresponding ground-truth interaction.	Spurious detection.	0
Not Detected	Ground truth interactions with no system prediction.	Missed events (false negatives).	7
Event Detection Accuracy	$\frac{\text{Number of Detected Events}}{\text{Total Ground Truth Events}}$	Interaction event coverage.	96.6 %
Risk Classification Accuracy	$\frac{\text{Correct}}{\text{Correct + Incorrect label}}$	Reliability of predicted labels once detection alignment occurs within matched interaction.	98.49 %

Precision	$\frac{Correct}{Correct + False\ Positive}$	Fraction of predicted interactions	90.0 %
Recall	$\frac{Correct}{Correct + Not\ Detected}$	Fraction of ground truth interactions captured within matched interaction.	96.0 %
f1	Harmonic mean of precision and recall.	Balances completeness (recall) and reliability (precision).	93.0 %

Error Analysis

This section examines the principal error modes of the framework that were not detected (ground-truth interactions with no prediction) and their root causes in the trajectory-to-interaction pipeline. Across 206 ground-truth events, the system produced 199 event detection and risk classifications, and 7 ground-truth events were missed (not detected). In this scenario, the pedestrians were waiting outside of the curb region. Additionally, our trajectory data only contains data for car, bus, and cargo vehicles. Whenever other vehicle types, such as small utility vehicles, appear in the scene, the current system does not consider them. These error modes highlight the importance of accurately defining waiting regions and expanding object classes within the perception pipeline, which informs the directions outlined in the conclusion.

Conclusion and Future Work

This research developed and validated a dynamic, trajectory-based framework, CrossRisk, for classifying pedestrian safety at midblock crosswalks, moving beyond retrospective crash analyses to classify real-time pedestrian-vehicle interactions with 96.6% event detection accuracy and 98.49% overall risk classification accuracy with 90% precision. By integrating pedestrian gap-acceptance thresholds, stopping sight distance for vehicles, vehicle's behavior along with lane conflict rules, this study confirmed that the most hazardous situations occur when drivers encroach on the crosswalk during pedestrian presence, whereas stopped and steady deceleration align with safer outcomes. During real-time deployment, weather conditions such as fog, snow, and rain, can be incorporated into the system via a weather API. These environmental inputs dynamically adjust pedestrian visibility, vehicle maneuvering behavior, and allowable operating speeds. Based on the detected conditions, the framework selects the appropriate gap-acceptance thresholds to enable context-aware and weather-adaptive safety classification. Current limitations include occasional missed event detections when pedestrians wait outside designated curb regions and the use of only a single integrated weather condition. Future work will focus on improving data quality, refining event-detection algorithms, incorporating multiple weather-dependent thresholds, and integrating perceptual cues such as pedestrian gaze. Additional goals include expanding the dataset across seasons and locations and advancing the system toward real-time deployment to enhance its predictive and proactive safety capabilities.

REFERENCES

Al Bargi, W. A., M. M. Rohani, B. D. Daniel, N. A. Khalifaa, M. I. M. Masirin, and J. Kironde. 2023. "Estimating of Critical Gaps at Uncontrolled Intersections under Heterogeneous

Traffic Conditions.” *Automotive Experiences*, 6 (2): 429–437. https://doi.org/10.31603/ae.9406.

Allen, B. L., B. T. Shin, and P. J. Cooper. 1978. “ANALYSIS OF TRAFFIC CONFLICTS AND COLLISIONS.” *Transportation Research Record*, (667).

Bennett, S., A. Felton, and R. Akçelik. 2001. *Pedestrian movement characteristics at signalised intersections*.

Brewer, M., K. Fitzpatrick, J. Whitacre, and D. Lord. 2006. “Exploration of Pedestrian Gap-Acceptance Behavior at Selected Locations.” *Transportation Research Record: Journal of the Transportation Research Board*, 1982: 132–140. https://doi.org/10.1177/0361198106198200117.

Chen, P., W. Zeng, G. Yu, and Y. Wang. 2017. “Surrogate Safety Analysis of Pedestrian-Vehicle Conflict at Intersections Using Unmanned Aerial Vehicle Videos.” *Journal of Advanced Transportation*, 2017: 1–12. https://doi.org/10.1155/2017/5202150.

Dipietro, C. M., and L. E. King. 1970. “PEDESTRIAN GAP-ACCEPTANCE.” *Highway Research Record*, (308).

Fahad, M., A. Tasnim, T. Xiong, A. Damaraju, T. Zhao, X. Qin, and X. Shi. 2025. “ACEMS-lab/CrossTraj-Dataset: CrossTraj, a high-resolution, bi-season vehicle-pedestrian interaction trajectory dataset captured at a midblock pedestrian crosswalk in City of Milwaukee, WI.”

Fahad, M., A. Tasnim, T. Xiong, A. Damaraju, T. Zhao, X. Qin, and X. Shi*. 2026a. “A Comprehensive Evaluation Framework for Roadside Perception Systems.” *Transportation Research Board Annual Meeting*.

Fahad, M., A. Tasnim, T. Xiong, A. Damaraju, T. Zhao, X. Qin, and X. Shi*. 2026b. “Evaluating Roadside Perception with Trajectory Data from Pedestrian Vehicle Interactions at Crosswalks.”

Figliozzi, M. A., and C. Tipagornwong. 2016. “Pedestrian Crosswalk Law: A study of traffic and trajectory factors that affect non-compliance and stopping distance.” *Accident Analysis & Prevention*, 96: 169–179. https://doi.org/10.1016/j.aap.2016.08.011.

Lin, T., Z. Jin, S. Choi, and H. Yeo. 2024. “A Real-time Evaluation Framework for Pedestrian’s Potential Risk at Non-Signalized Intersections Based on Predicted Post-Encroachment Time.” arXiv.

Liu, G., and K. Li. 2009. “Pedestrian’s Psychology on Gap Selecting when Crossing Street.” In: *Int. Conf. Transp. Eng. 2009*, 2138–2144. Southwest Jiaotong University, Chengdu, China: American Society of Civil Engineers.

Meocci, M., A. Terrosi, A. Paliotto, R. Arrighi, and I. Petrizzo. 2024. “Drivers’ performance assessment approaching pedestrian crossings through the analysis of the speed and perceptive data recorded during on-field tests.” *Heliyon*, 10 (1): e24249. https://doi.org/10.1016/j.heliyon.2024.e24249.

Osorio-García, D., G. Hernández-Pulgarín, and D. A. Escobar. 2023. “Profiles of pedestrian risk behavior while crossing the street.” *Safety Science*, 163: 106120. https://doi.org/10.1016/j.ssci.2023.106120.

Patel, D., P. Hosseini, and M. Jalayer. 2023. “A framework for proactive safety evaluation of intersection using surrogate safety measures and non-compliance behavior.” *Accident Analysis & Prevention*, 192: 107264. https://doi.org/10.1016/j.aap.2023.107264.

“Pedestrian Safety.” 2025. *National Highway Traffic Safety Administration*. Accessed August 19, 2025. https://www.nhtsa.gov/book/countermeasures-that-work/pedestrian-safety.

Qiu, D., and Q. Xu. 2011. “Traffic Safety of Pedestrian Crossing—A Case Study of Wenzhou City.” In: *ICTE 2011*, 2916–2921. Chengdu, China: American Society of Civil Engineers.

“Safety Effects of Marked Versus Unmarked Crosswalks at Uncontrolled Locations Final Report and Recommended Guidelines, September 2005 - FHWA-HRT-04-100.” n.d. Accessed November 19, 2025. https://www.fhwa.dot.gov/publications/research/safety/04100/03.cfm.

Sankaran, M., and P. Vedagiri. 2020. “PEDESTRIAN SAFETY EVALUATION OF SIGNALIZED INTERSECTIONS USING SURROGATE SAFETY MEASURES.” *Transport*, 35 (1): 48–56. https://doi.org/10.3846/transport.2020.12157.

Schwebel, D. C., B. K. Barton, J. Shen, H. L. Wells, A. Bogar, G. Heath, and D. McCullough. 2014. “Systematic Review and Meta-Analysis of Behavioral Interventions to Improve Child Pedestrian Safety.” *Journal of Pediatric Psychology*, 39 (8): 826–845. https://doi.org/10.1093/jpepsy/jsu024.

Tasnim, A., T. Zhao, M. Fahad, T. Xiong, X. Shi, and X. Qin. 2025. “anisha150213/CrossSafe.”

Teng, X., Z. Shen, L. Huang, H. Li, and W. Li. 2025. “Improving Intelligent Perception and Decision Optimization of Pedestrian Crossing Scenarios in Autonomous Driving Environments Through Large Visual Language Models.” SSRN.

Ukkusuri, S., L. F. Miranda-Moreno, G. Ramadurai, and J. Isa-Tavarez. 2012. “The role of built environment on pedestrian crash frequency.” *Safety Science*, 50 (4): 1141–1151. https://doi.org/10.1016/j.ssci.2011.09.012.

Ventura, R., S. Roussou, A. Ziakopoulos, B. Barabino, and G. Yannis. 2025. “Using computer vision and street-level videos for pedestrian-vehicle tracking and behaviour analysis.” *Transportation Research Interdisciplinary Perspectives*, 30: 101366. https://doi.org/10.1016/j.trip.2025.101366.

Wang, C., Y. Xie, H. Huang, and P. Liu. 2021. “A review of surrogate safety measures and their applications in connected and automated vehicles safety modeling.” *Accident Analysis & Prevention*, 157: 106157. https://doi.org/10.1016/j.aap.2021.106157.

Wang, T., X. Jiang, W. Wang, and Q. Cheng. 2016. “Analysis of Vehicle Speed Change at Non-signalized Crosswalks Based on Driving Behavior.” *Procedia Engineering*, 137: 547–553. https://doi.org/10.1016/j.proeng.2016.01.291.

Yanagisawa, M., E. D. Swanson, and W. G. Najm. 2014. “Target crashes and safety benefits estimation methodology for pedestrian crash avoidance/mitigation systems.” Accessed November 19, 2025. https://rosap.ntl.bts.gov.

Yannis, G., E. Papadimitriou, and A. Theofilatos. 2013. “Pedestrian gap acceptance for mid-block street crossing.” *Transportation Planning and Technology*, 36 (5): 450–462. https://doi.org/10.1080/03081060.2013.818274.

Yue, L., M. Abdel-Aty, Y. Wu, S. Hasan, and O. Zheng. 2020. “Identifying Pedestrian Crash Contributing Factors using Association Analysis and Their Implications for Development of Active Pedestrian Safety System.” *Transportation Research Record: Journal of the Transportation Research Board*, 2674 (8): 861–874. https://doi.org/10.1177/0361198120925472.

Zhang, C., F. Chen, and Y. Wei. 2019. “Evaluation of pedestrian crossing behavior and safety at uncontrolled mid-block crosswalks with different numbers of lanes in China.” *Accident Analysis & Prevention*, 123: 263–273. https://doi.org/10.1016/j.aap.2018.12.002.

Zhao, J., J. O. Malenje, Y. Tang, and Y. Han. 2019. “Gap acceptance probability model for pedestrians at unsignalized mid-block crosswalks based on logistic regression.” *Accident*

Analysis & Prevention, 129: 76–83. https://doi.org/10.1016/j.aap.2019.05.012.
Zhao, Q., X. Zhuang, T. Zhang, Y. He, and G. Ma. 2023. "Pedestrian gaze pattern before crossing road in a naturalistic traffic setting." *European Transport Research Review*, 15 (1): 31. https://doi.org/10.1186/s12544-023-00605-1.
Zhu, H., A. Almukdad, M. Iryo-Asano, W. K. M. Alhajyaseen, H. Nakamura, and X. Zhang. 2021. "A novel agent-based framework for evaluating pedestrian safety at unsignalized mid-block crosswalks." *Accident Analysis & Prevention*, 159: 106288. https://doi.org/10.1016/j.aap.2021.106288.
Zhuang, X., and C. Wu. 2014. "Pedestrian gestures increase driver yielding at uncontrolled mid-block road crossings." *Accident Analysis & Prevention*, 70: 235–244. https://doi.org/10.1016/j.aap.2013.12.015.