Comparative Risk Assessment of VRUs and AVs Across Urban Intersections

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***Abstract*—In heterogeneous traffic environments involving Autonomous Vehicles (AVs), ensuring the safety of Vulnerable Road Users (VRUs)—such as pedestrians and cyclists—remains a critical challenge. This paper proposes a unified risk evaluation framework for various urban intersection types, including Highways, Roundabouts, T-Intersections, and 4-Way Intersections. The framework integrates real-world and synthetic data through temporal alignment of two diverse datasets: PIE (2D pedestrian intention) and RADIATE (3D radar-lidar-vision AV sensor data). Conflict scenarios are modeled using histogram-based probabilistic profiling and Monte Carlo-based binomial risk validation. Key risk factors—VRU decisiveness, AV driving style, channel quality,road surface, and weather—are incorporated to compute intersection-specific conflict probabilities and risk scores. Results reveal distinct risk variations across intersection types, with roundabouts exhibiting the highest combined risk and highways the lowest. The findings support the development of adaptive, context-aware safety strategies for cooperative intelligent transportation systems (C-ITS), enabling improved spectrum reuse and informed urban planning for autonomous mobility. Temporal alignment is achieved by timestamp synchronization and frame level association between PIE pedestrian intention annotations and corresponding RADIATE sensor frames under matched environmental conditions.**

***Index Terms*—Autonomous Vehicles (AVs), Vulnerable Road Users (VRUs), Conflict Probability, Intersection Safety, Cooperative Intelligent Transportation Systems (C-ITS), Risk Modeling, Spectrum Reuse, Urban Mobility**

I. Introduction

The evolution of intelligent transportation systems (ITS) has enabled significant advancements in vehicular automation and infrastructure-based communication. However, the safety of Vulnerable Road Users (VRUs)—including pedestrians, cyclists, and other non-motorized participants—remains a persistent concern, particularly at urban intersections where traffic dynamics are highly complex and unpredictable. As Autonomous Vehicles (AVs) become increasingly integrated into these environments, it is imperative to understand how intersection geometry, environmental conditions, and behavioral interactions contribute to conflict scenarios between AVs and VRUs. Traditional traffic safety models often simplify or overlook the dynamic interactions between automated agents and human behavior, especially in heterogeneous traffic conditions. To address this limitation, the present study focuses on evaluating conflict probability and combined risk across four representative intersection types: Highways, Roundabouts, T-Intersections, and 4-Way Intersections. These configurations embody a spectrum of control mechanisms and geometric complexities, each exerting a unique influence on AV–VRU interaction patterns. This research adopts a data-driven methodology that integrates real-world perception data from two complementary sources: the PIE dataset [1], which captures 2D pedestrian intention cues, and the RADIATE dataset [2], which provides 3D sensor data from AVs across varying weather and traffic conditions. By temporally aligning and enriching these datasets with simulated attributes such as weather, channel quality, VRU decisiveness, and AV driving style, we construct a comprehensive framework for modeling risk. Our objective is to compute conflict probabilities, analyze the influence of environmental and behavioral variables, and rank intersection safety using a unified risk metric. The proposed framework contributes to the development of adaptive safety mechanisms within cooperative intelligent transportation systems (C-ITS) [3], supporting context-aware decision-making in cooperative intelligent transportation systems (C-ITS) in autonomous urban mobility.

II. Literature Survey

Ensuring safety in mixed traffic environments has been an active research area in intelligent transportation systems (ITS). Key challenges include modeling pedestrian behavior, estimating conflict probabilities, optimizing communication strategies, and coordinating intersection decisions.

Pedestrian intention modeling plays a vital role in proactive safety. The PIE dataset offers detailed annotations of pedestrian behaviors, enabling analysis of cues like decisiveness and trajectory. Similarly, the RADIATE dataset provides multimodal automotive sensor data under diverse weather and traffic conditions, supporting AV perception modeling.

For conflict estimation, Zhang et al. [4] proposed a probabilistic framework based on road geometry and vehicle dynamics, while Deo and Trivedi [5] developed a behavior forecasting model to help AVs determine pedestrian crossing intent. These works highlight the role of both motion prediction and risk modeling in reducing accidents.

Cooperative communication has been emphasized in several works. Yang et al. [6] developed a V2X protocol to enhance pedestrian safety at intersections. Elhenawy et al. [7] presented a safety evaluation framework using Cooperative Awareness Messages (CAMs) in C-ITS. Spectrum usage was critically analyzed by Basaure et al. [8], contrasting local licensing with shared reuse strategies. Jiang et al. [9] proposed a joint spectrum sharing and power allocation scheme for D2D communication in 5G vehicular networks, supporting efficient spectrum reuse.

Clustering-based communication frameworks are widely studied for VANETs. Barve and Patheja [10] assessed clustering techniques for dynamic vehicular networks. Saha et al. [11] introduced a cluster-based protocol for prioritized message communication, improving VANET performance under dense traffic.

For intersection control and decision-making, Gholamhosseinian and Seitz [12] proposed CAI2M2, a centralized intersection management system for heterogeneous connected vehicles. Wang et al. [13] developed an RSU-based coordination strategy to optimize safety and throughput at intersections using real-time traffic states.

Building on these contributions, our study combines perception-aware modeling, joint AV–VRU risk profiling, and spectrum-aware communication into a unified risk evaluation framework. It compares intersection types under identical simulation conditions and supports context-aware decision-making in cooperative ITS. We are considering an urban traffic scenario involving Automated Vehicles (AVs) and Vulnerable Road Users (VRUs) in the common wireless spectrum. Uncoordinated communication will increase latency and interference and poor reaction performance due to the limited spectrum resources and large VRU density near the urban road geometry. The solution is to create a spectrum-conscious cooperative communication system that reduces latency and maximizes throughputs of AV-VRU interaction with changing road geometries and allows spectrum reuse.

III. Methodology

A. Multi-Factor Risk Profiling Using Histograms

To evaluate the influence of environmental and behavioral factors on intersection safety, we generated frequency-based risk distributions using a unified dataset derived from PIE and RADIATE. The PIE dataset provides 2D pedestrian intention annotations from monocular video, while the RADIATE dataset contains time-synchronized 3D radar–lidar–camera sensor frames. Since the datasets were collected independently, temporal alignment was performed at the scenario level by synchronizing timestamps and matching environmental conditions such as weather and road type. Pedestrian intention labels were associated with the nearest corresponding AV sensor frames in time, assuming local consistency of intent over short temporal windows.

Each VRU and AV data point was categorized using a 4-factor tuple:

- **For VRUs:** Channel Quality — Weather — Road Condition — Decisiveness
- **For AVs:** Channel Quality — Weather — Road Condition — Driving Style

Color-coded histograms were generated to visualize the frequency and severity of each condition combination. Low-risk scenarios (e.g., good channel and decisive behavior) were marked in green, moderate-risk in yellow, and high-risk (e.g., poor channel with rash driving or indecisiveness) in red.

Risk categories were defined using percentile-based thresholds derived from the empirical distribution of observed condition combinations. Low-risk scenarios (green) correspond to lower-percentile conflict-prone combinations, moderate-risk scenarios (yellow) represent mid-range frequencies, and high-risk scenarios (red) reflect upper-percentile combinations associated with increased conflict likelihood.

As shown in Fig. 1 and Fig. 2, these histograms highlight common condition combinations and their associated risk levels for AVs and VRUs, respectively.

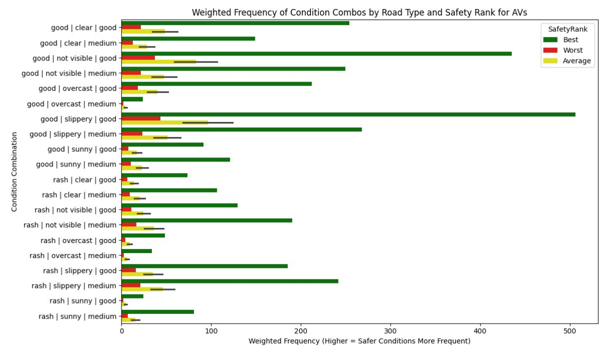

Fig. 1. AV histogram showing risk distribution based on environmental and behavioral conditions.

B. Conflict Probability and Combined Risk Metric

Intersection layouts were analyzed using two main factors:

- **VRU Entry Points (VEP):** A fixed value indicating the number of likely conflict zones at each intersection type:

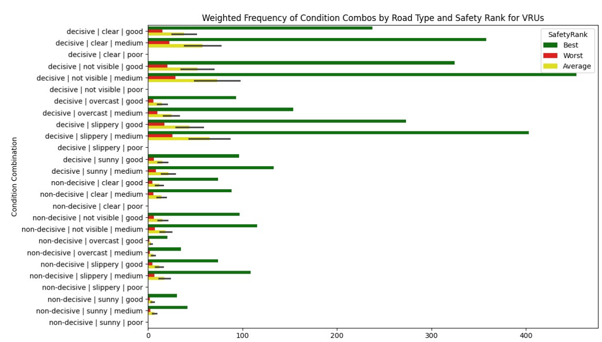

Fig. 2. VRU histogram showing risk distribution based on decisiveness and environmental conditions.

  - Highway: 2
  - Roundabout: 12
  - T-Intersection: 5
  - 4-Way Intersection: 8
- **Conflict Probability (CP):** The average number of observed conflicts per intersection.

We computed a unified metric:

$$\text{Combined Risk} = \text{VEP} \times \text{CP}$$

VRU Entry Point (VEP) values were assigned based on the geometric structure of each intersection type and the number of distinct pedestrian entry and crossing points present in the layout. Each entry point represents a potential AV–VRU interaction zone, capturing relative exposure rather than measured traffic flow. This geometry-driven assignment ensures consistent comparison of intersection types under identical behavioral and environmental conditions.

A conflict is defined as a safety-critical interaction in which an autonomous vehicle and a vulnerable road user enter a predefined proximity threshold within the pedestrian response time window. Based on established pedestrian behavior studies, a VRU response time of approximately 4 seconds was assumed, leading to a conservative distance threshold of about 70 meters for conflict identification. Conflict Probability (CP) was computed as the average number of detected conflict events per intersection type across all evaluated scenarios. To avoid bias due to repeated interactions, conflicts were evaluated using a round-robin strategy, sequentially assessing AV-VRU pairs within each intersection scenario.

As shown in Fig. 3 and Fig. 4, these values help quantify how intersection complexity and risky behavior contribute to overall safety.

	RoadType	CP	VEP	CombinedRisk	SafetyRank
0	Highway	0.510	2	1.020	Best
1	Standard Intersection	0.942	8	7.536	Average
2	T Intersection	0.832	5	4.160	Average
3	Roundabout	0.986	12	11.832	Worst

Fig. 3. Conflict probability for AVs across different intersection types.

	RoadType	CP	VEP	CombinedRisk	SafetyRank
0	Highway	0.360	2	0.720	Best
1	Standard Intersection	0.832	8	6.656	Average
2	T Intersection	0.672	5	3.360	Average
3	Roundabout	0.931	12	11.172	Worst

Fig. 4. Conflict probability for VRUs across different intersection types.

C. Binomial Model Validation via Monte Carlo Simulation

To validate the combined risk rankings, we performed a Monte Carlo simulation using a binomial model. For each intersection:

- Fixed the number of VRU entry points (VEP) represented by n.
- The number of conflicts is denoted by k.
- Assigned conflict probabilities per entry point (p_{VRU}, p_{AV}).
- Repeated simulations to compute the likelihood of at least one conflict occurring.

$$P(X = k) = (nCk)\, p^k (1-p)^{n-k} \tag{1}$$

The pseudocode below outlines the procedures that were involved in estimating the Combined Risk measure and Safety Rank of the various types of road geometries according to VRU access points and conflict statistically significant rates.

1. Start
2. Define the type of road geometry or intersection as I.
3. Assign VRU Entry Points (VEP) for each I.
4. From the observed data, estimate Conflict Probability (CP) for each I.
5. For each I, compute Combined Risk as follows:

$$\text{Combined Risk}(I) = \text{VRU}(I) \times \text{CP}(I)$$

6. Rank the geometries in ascending order of Combined Risk.
7. Assign Safety Rank: best to lowest risk and worst to highest risk.
8. End

IV. Key Observations

A. Joint-Probability Histograms

We generated joint-probability histograms across all 4-factor combinations: channel quality, weather, road condition, and behavior (VRU decisiveness or AV driving style). Each unique condition tuple was mapped to its empirical frequency within the dataset.

Peaks in these histograms indicated the most common real-world situations, such as “good channel — clear weather — four-way intersection — decisive VRU.” Conversely, the long tail exposed rare yet high-risk conditions that warrant targeted safety strategies.

B. Combined Risk Rankings

Using the defined Combined Risk metric: Combined Risk = Mean Conflict Count × VRU Entry Points (VEP), we separately ranked intersection types for AVs and VRUs.

- For VRUs, roundabouts posed the highest risk due to numerous entry points combined with moderate conflict rates.
- For AVs, risk levels varied based on driving style and channel quality, causing a different ranking order than VRUs.

Each intersection type was categorized as ”Best,” ”Average,” or ”Worst” based on its overall safety impact. These labels provide clear guidance for urban planners and C-ITS designers.

A qualitative sensitivity analysis indicates that while absolute conflict probabilities vary with changes in VRU decisiveness and AV driving style, the relative ranking of intersection types remains stable. This suggests that intersection geometry exerts a dominant influence on combined risk outcomes, even under behavioral variability.

V. Results

This study introduces a comprehensive intersection safety framework that advances the field in the following key ways:

1) **Joint Multi-Factor Risk Modeling:** Unlike traditional approaches that assess risk based on one or two isolated variables, our framework jointly analyzes four critical factors—channel quality, weather, road condition, and

behavioral traits (e.g., AV driving style or VRU decisiveness). This enables the identification of hidden high-risk combinations that marginal analyses often overlook.

2) **Unified Comparison of AV and VRU Behavior:** Most prior studies evaluate AVs and VRUs separately. We apply the same multi-dimensional analysis pipeline to both, enabling direct comparison under identical environmental and geometric conditions. This unified analysis supports more equitable and inclusive intersection design.
3) **Combined Risk Metric Integrating Exposure and Probability:** We introduce a novel Combined Risk metric that fuses the number of conflict-prone entry points with the probability of a conflict occurring. This creates a single interpretable value for ranking intersection safety, aiding decision-makers in prioritizing improvements.
4) **Validation via Monte Carlo-Based Binomial Modeling:** We validate our empirical findings using a simulated binomial model of conflict occurrence, strengthening the credibility and repeatability of the risk rankings.
5) **Actionable Focus on Medium-Risk, High-Frequency Scenarios:** While rare high-risk events attract attention, our histograms reveal that medium-risk combinations occur far more frequently. Targeting these common yet moderate-risk scenarios offers higher potential for safety gains in real-world deployments.

The final combined risk rankings for all intersection types are summarized in Fig. 5, showing agreement between histogram-based and simulation-based analysis.

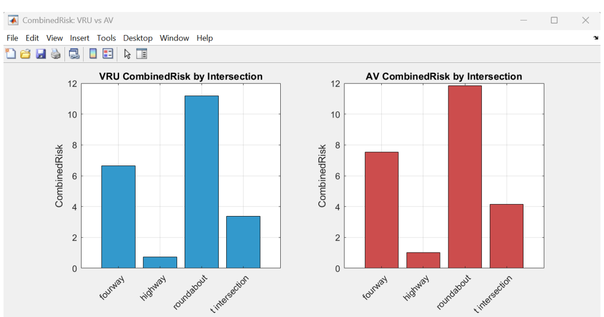

Fig. 5. Final combined risk rankings across all intersection types for AVs and VRUs.

	RoadType	CP	VEP	CombinedRisk	SafetyRank
0	Highway	0.1836	2	0.3672	Best
1	Standard Intersection	0.7837	8	6.2696	Average
2	T Intersection	0.5591	5	2.7955	Average
3	Roundabout	0.9179	12	11.0148	Worst

Fig. 6. Monte Carlo simulation of conflict probabilities using binomial distribution.

The resulting probabilities, shown in Fig. 6, confirm that higher VEP values and risk-inducing behaviors significantly increase the likelihood of conflict.

VI. Conclusion and Future Work

This paper presents a comprehensive risk evaluation framework for urban intersections by integrating real-world and synthetic data sources, probabilistic modeling, and behavior-aware analysis. By aligning and fusing the PIE and RADIATE datasets, we constructed a unified simulation platform that accounts for channel conditions, weather, road surface, AV driving style, and VRU decisiveness.

Our findings confirm that intersection geometry significantly affects safety outcomes. Roundabouts demonstrated the highest combined risk due to a high number of entry points and moderate conflict probability, while highways showed the lowest risk. Importantly, the application of a Combined Risk metric, validated through Monte Carlo-based binomial modeling, offers a scalable method for ranking and comparing intersection safety under real-world complexity.

Moreover, evaluating AV and VRU behavior under identical conditions enabled generation of joint risk profiles that support safer routing decisions in cooperative intelligent transportation systems (C-ITS).

A. Future Work

Future enhancements to this framework include:

- **Real-Time Communication Simulation:** Integrate real-time interactions between Roadside Units (RSUs), VRU devices, and AVs to evaluate message delays, packet loss, and malicious interference under spectrum reuse scenarios.
- **Deep Learning-Based Intention Prediction:** Incorporate video-based pose estimation and temporal modeling to enhance VRU behavior classification and dynamic risk prediction.
- **Multi-Agent Risk Modeling:** Extend the current single-agent framework to group scenarios such as VRU clusters and vehicle platoons to study collective behavior and its impact on intersection throughput.
- **Adaptive Spectrum Allocation:** Simulate intelligent spectrum reuse using reinforcement learning or RSMA/FNOMA-based strategies to reflect communication challenges under varying traffic densities.

These extensions aim to improve both the realism and applicability of the proposed model for future smart city deployments.

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