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Quantifying Safety Impacts of V2X-Enabled Traffic Systems (Phase 2)

November 2026

Executive Summary

Vehicle-to-Everything (V2X) communication technologies have the potential to enhance traffic safety by enabling real-time exchange of information between vehicles and infrastructure. Despite this potential, V2X technologies remain in an early deployment phase, and traditional cost-benefit approaches that require large quantities of deployment data are therefore insufficient. To address this gap, probabilistic risk assessment approaches used by the nuclear, aerospace/aviation, and automated vehicle (AV) industries are applied to credibly quantify V2X safety benefits. This study presents Phase 2 of Quantifying Safety Impacts of V2X-Enabled Traffic Systems, which extends the probabilistic risk assessment (PRA) framework developed in Phase 1[1] to two infrastructure-dependent V2X applications: Red-Light Violation Warning (RLVW), based on signal phase and timing (SPaT) and basic safety messages (BSM), and Pedestrian Collision Warning (PED-CP), based on Sensor Data Sharing Messages (SDSM) enabled by cooperative perception.

Both applications are modeled using event sequence diagrams, fault trees, and Bayesian networks calibrated against crash records (FARS/CRSS), literature-derived component reliability estimates, and vehicle kinematics, evaluated across SAE Level 0 (unassisted human driver), Level 2 (partial automation, including automated emergency braking functions as an independent safety mechanism), and Level 4 (automated driving system-equipped) automation. Each scenario is further evaluated across a range of connected infrastructure deployment (V2I) levels and connected vehicle (CV) market penetration rates, then translated into area-level safety and economic impact estimates.

Applied to a 92-intersection reference deployment in Downtown Los Angeles, the results suggest that both applications produce positive safety and economic benefit, with RLVW addressing a larger volume of crashes while PED-CP delivers a higher economic return per crash avoided due to the greater severity of pedestrian-vehicle conflicts. CV% sets how large the benefit is at each equipped location; V2I% sets how many geographical locations receive infrastructure-enabled benefit. Between 25% and 100% CV, the per-encounter crash probability for human drivers (L0) falls by 29–85% for RLVW and by 33–82% (midblock crossings) and 35–66% (intersections) for PED-CP. The example figures below (**Figure A, Figure B**) show the overall crash reduction trend as a percentage of the L0 no-V2X baseline, by CV penetration and V2I deployment, for L0, L2, and L4, for

[1] Correa-Jullian, C., Mosleh, A., Zhu, D., & Ma, J. (2025). Quantifying Safety Impacts of V2X-Enabled Traffic Systems (Phase 1). *UCLA: Mobility Center of Excellence*. http://dx.doi.org/10.82903/B2CC78 Retrieved from https://escholarship.org/uc/item/6tz6n000

the PED-CP scenarios. The analysis results indicate that the absolute benefit is largest for vehicles with a human driver (L0, L2), and the relative benefit is largest when either the driver or partial automation can respond (L2). This suggests that **V2X combined with partial automation is the strongest pairing to improve safety.**

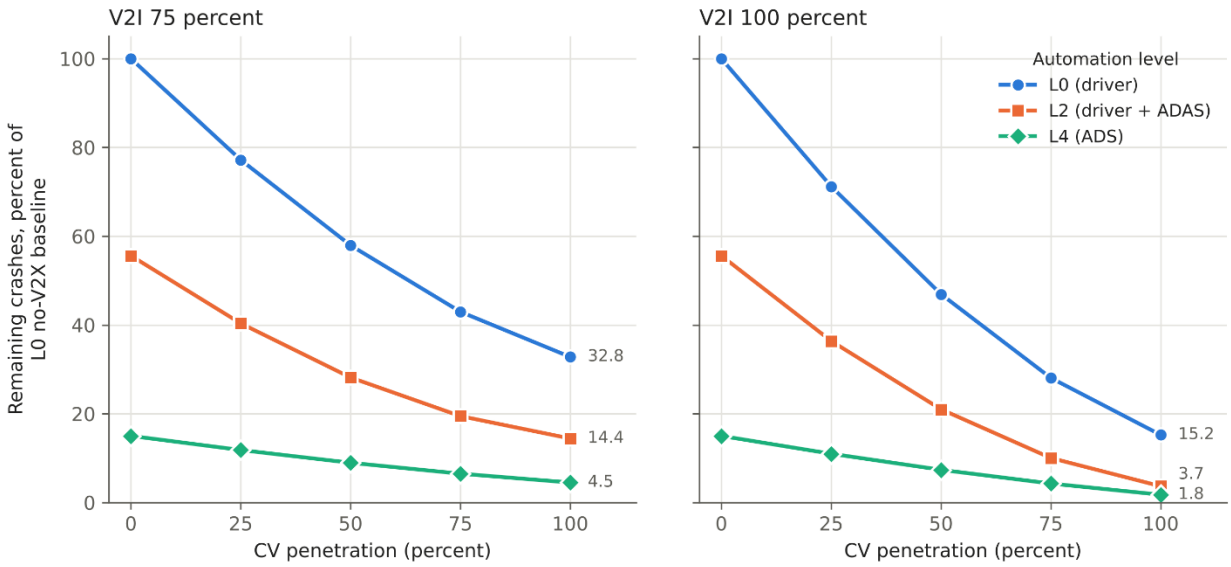

Figure A: RLVW: Study Area crashes as a percentage of the L0 no-V2X baseline, by CV penetration and V2I deployment (75%-100%), for L0, L2, and L4.

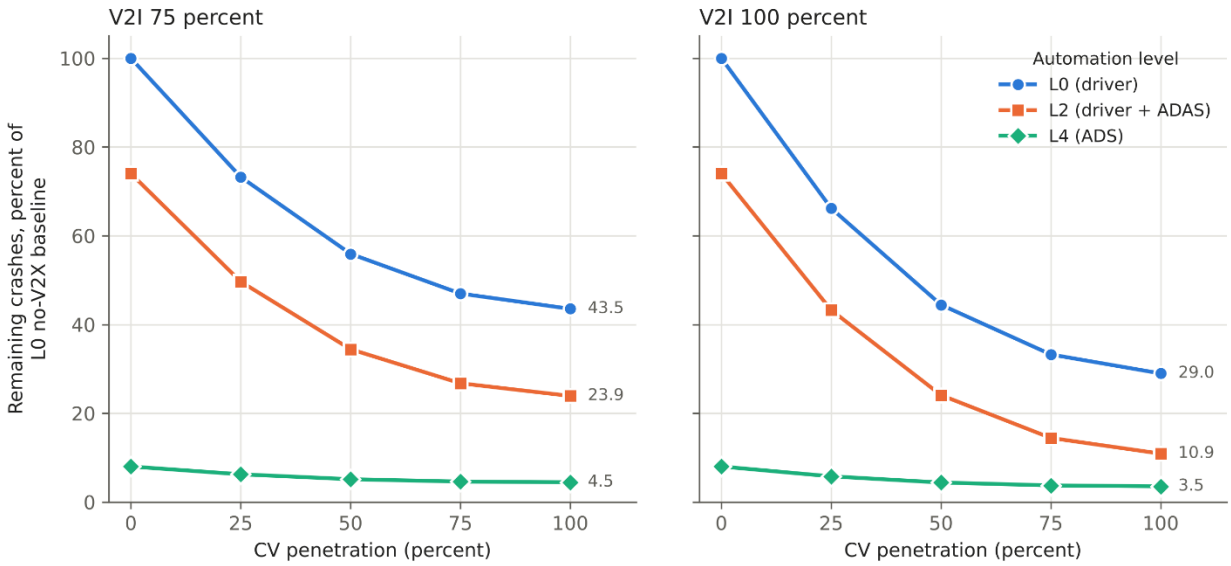

Figure B: PED-CP: Study Area crashes as a percentage of the L0 no-V2X baseline, by CV penetration and V2I deployment (75%-100%), for L0, L2, and L4. Intersection and midblock crossings are combined in the Study Area results.

Safety benefits are comparatively modest at Level 4 in absolute terms, because low L4 baseline crash rates (based on today's limited L4 crash data) leave less room for further reduction. Even so, the L4 *relative* benefit remains substantial: V2X removes an estimated additional 88% of RLVW related crashes and 56–61% for pedestrian crashes at full deployment (V2I 100%, CV 100%), and 27–29% already at CV 25% (V2I 100%).

At full deployment (V2I and CV), the estimated safety improvement for human drivers (L0) is 85% for RLVW and 71–74% for PED-CP, and it is largest when partial automation can also respond (L2: 93% and 85%). Low CV penetration rates provide the largest relative gain per percentage point of penetration: CV 25% delivers about 27%–35% (RLVW) and 28%–42% (PED-CP). This relative gain corresponds to about 30%-37% (RLVW) and 48%-50% (PED-CP) of the crash reduction benefit at full-penetration (**Table A**). Expressed as crash modification factors (CMF), CV 25% corresponds to CMFs of 0.65-0.73 for RLVW and 0.58-0.72 for PED-CP. CV 100% corresponds to CMFs of 0.07-0.15 and 0.15-0.44, respectively, depending on the level of automation[2]. In terms of crash costs, 25% CV market penetration rate could achieve 30–37% and 45–47% of the safety benefits of 100% market penetration rate for RLVW and PED-CP, respectively (**Table B**). Beyond 25%, the benefits begin to plateau with increasing CV% across RLVW and PED-CP scenarios.

Importance-measure analysis (Risk Reduction Worth and Risk Achievement Worth) identifies which model components most influence these results and where additional field data would improve the estimates. For RLVW, V2X message reception reliability and the underlying red-light-running rates are the model inputs that most impact these estimated risk results, while stopping and yield behavior show the highest sensitivity to failure, with AEB performance dominating at L2. For PED-CP, pedestrian detection performance (driver, L2, or ADS) under occlusion dominates at midblock crossings, while warned stopping performance and PAEB (L2) dominates at intersections. SDSM reception reliability ranks among the top three contributors at every automation level and crossing geometry. This study also documents modeling limitations tied to the current state of V2X field deployment: communication reliability estimates are not yet calibrated against site-specific field measurements, SPaT data integrity and false-positive warning effects are not represented, and standardized real-world Automated Driving System (ADS) incident data remains limited in the literature. These limitations bound the precision

[2] A crash modification factor (CMF) is the ratio of the crashes expected with a countermeasure to the crashes expected without it; values below 1.0 indicate a reduction. The crash reduction factor (CRF) expresses the same effect as a percentage decrease: $CRF = 100 \times (1 - CMF)$. In this report, the CMF compares crashes at the equipped locations with V2X at a given CV penetration to crashes at the same locations without V2X, for the same automation level. It therefore varies with CV%. It covers crash frequency only, at a fixed severity mix, and does not include effects of V2X on crash severity.

of the current estimates without undermining their overall direction and relative magnitude and are discussed alongside the specific data collection priorities.

Table A: Crashes averted per year and crash modification factors (CMF/CRF) at CV=25% compared to CV=100% across (V2I 100%). Shares (crashes averted at CV25%/CV100%) vary by less than 1.5 points across V2I levels. CMF and CRF are relative to each automation level's own no-V2X baseline

Scenario	Level	Baseline No-V2X crashes/ yr	Crashes Averted, CV 25%	Crashes Averted, CV 100%	CMF (CRF), CV 25%	CMF (CRF), CV 100%	Benefit Share CV25/ CV100
RLVW (Enhanced)	L0	116.57	33.56	98.81	0.71 (28.8)	0.15 (84.8)	34%
	L2	64.81	22.41	60.53	0.65 (34.6)	0.07 (93.4)	37%
	L4	17.49	4.68	15.44	0.73 (26.8)	0.12 (88.3)	30%
PED-CP	L0	55.77	18.85	39.61	0.66 (33.8)	0.29 (71.0)	48%
	L2	41.27	17.15	35.19	0.58 (41.6)	0.15 (85.3)	49%
	L4	4.46	1.23	2.49	0.72 (27.7)	0.44 (55.7)	50%

Table B: Crash costs avoided per year at CV=25% and CV=100% at V2I 100%. Shares (savings at CV25%/CV100%) vary by less than 1.5 points across V2I levels. Crash cost reduction is relative to each automation level's own no-V2X crash cost

Scenario	Level	Baseline No-V2X crash cost ($M/yr)	Savings, CV 25% ($M)	Savings, CV 100% ($M)	Cost reduction, CV 25%	Cost reduction, CV 100%	Benefit Share CV25/ CV100
RLVW (Enhanced)	L0	16.84	4.85	14.28	28.8%	84.8%	34%
	L2	9.36	3.24	8.75	34.5%	93.4%	37%
	L4	2.53	0.68	2.23	26.8%	88.3%	30%
PED-CP	L0	79.09	26.47	58.73	33.5%	74.3%	45%
	L2	58.53	22.90	49.61	39.1%	84.8%	46%
	L4	6.33	1.81	3.84	28.6%	60.7%	47%

Based on these findings, RLVW has great potential cost-benefit given its large addressable crash population, while PED-CP deployment at selected high-severity, high-exposure locations presents the strongest economic case in terms of crash costs avoided. Analysis suggests the **greatest short-term safety return-on-investment may come from equipping high-crash locations first and instrumenting 25% of the human-driven vehicles that use them with V2X.** At equipped locations, CV 25% captures about 34% for RLVW to 48% for PED-CP of the full-penetration benefit.

These priority applications align with stakeholder engagement conducted for this project: public agencies participating in the Accelerating V2X Cohort Meeting rated RLVW and PED-CP as their highest-interest use cases and identified benefit-cost justification as a primary intended use for a safety benefit estimation tool. To support these deployment

decisions, this project also developed the V2XPRA tool, a GIS-based decision support dashboard that translates the underlying risk models into road-link-level estimates of crashes avoided and equivalent economic savings as a function of automation level, infrastructure deployment, and market penetration.

Quantifying Safety Impacts of V2X-Enabled Traffic Systems (Phase 2)

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List of Acronyms

Acronym	Full Term
AADT	Annual Average Daily Traffic
ADAS	Advanced Driver Assistance Systems
ADS	Automated Driving System
AEB	Automatic Emergency Braking
BBN	Bayesian (Belief) Network
BSM	Basic Safety Message
CDA	Cooperative Driving Automation
CP	Cooperative Perception
CRSS	Crash Report Sampling System
CST	Critical Stopping Time
CV	Connected Vehicle
C-V2X	Cellular Vehicle-to-Everything
DSRC	Dedicated Short-Range Communications
DTLA	Downtown Los Angeles
ESD	Event Sequence Diagram
EV	Encountering Vehicle
FARS	Fatality Analysis Reporting System
FCW	Forward Collision Warning
FHWA	Federal Highway Administration
FT	Fault Tree
GIS	Geographic Information System
HMI	Human-Machine Interface
HV	Host Vehicle
IIHS	Insurance Institute for Highway Safety
IOO	Infrastructure Owner-Operator
L0 / L2 / L4	SAE Automation Level 0 / Level 2 / Level 4
LOS / NLOS	Line-of-Sight / Non-Line-of-Sight
MAP	MapData (intersection geometry message)
MoPRA	Mobility PRA (Phase 1 web tool)
NHTSA	National Highway Traffic Safety Administration
ODD	Operational Design Domain
PAEB	Pedestrian Automatic Emergency Braking
PDO	Property Damage Only
PDR	Packet Delivery Rate

Acronym	Full Term
PED-CP	Pedestrian Collision Warning (via Cooperative Perception)
PRA	Probabilistic Risk Assessment
PRT	Perception-Reaction Time
RAW	Risk Achievement Worth
RLVW	Red-Light Violation Warning
RRW	Risk Reduction Worth
RSU	Roadside Unit
SAE	Society of Automotive Engineers
SDSM	Sensor Data Sharing Message
SPaT	Signal Phase and Timing
TTC	Time-to-Collision
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
V2XPRA	V2X Probabilistic Risk Assessment (Phase 2 dashboard tool)
VRU	Vulnerable Road User

1. Introduction

As new technologies emerge that may improve the safety, efficiency, and mobility aspects in transportation, there is a critical need for systematic tools to evaluate and quantify their safety impacts under real-world conditions. Many of these technologies operate at the vehicle or infrastructure level but with anticipated benefits at scale, which complicates safety assessment and may present a barrier to broader adoption. Advancements in Vehicle-to-Everything (V2X) communication paradigms have the potential to accelerate safety and efficiency improvements, enabling vehicles, infrastructure, and other road users to share timely information about their location and surroundings. This addresses the limitations of single-vehicle perception and decision-making capabilities across different Levels of Driving Automation (SAE J3016[3], SAE J3216[4]), while also supporting drivers through real-time driving condition updates. However, local and state agencies require explainable and clear cost-benefit to invest in these infrastructure improvements that represent a key element of V2X successful impact on overall traffic safety.

When analyzing the potential safety benefits of V2X technologies, it is important to recognize that the intended impacts will differ depending not only on the type of message, but also the targeted level of driving automation. Up to Level 2, the purpose of enabling V2X communication technologies is to increase the information and time available for drivers or ADAS algorithms to support human driver decision-making in dynamic road conditions. V2X applications have the potential to increase the reliability of the driver warnings and vehicle's automated responses – in the case the triggering conditions have not been detected by its own sensors – as well as to improve the vehicle's perception by receiving messages from infrastructure (Vehicle-to-Infrastructure, V2I), other vehicles (Vehicle-to-Vehicle, V2V), and other road users. In addition, as higher-level driving automation features and systems (Levels 3-5) are incorporated into the vehicle fleet, the potential of cooperative driving automation (CDA) to support traffic safety and efficiency improvements increases.

In recent years, several pilot projects and public-private partnerships have sought to quantify the safety benefits of different V2X technologies, providing the first estimations

[3] SAE On-Road Automated Vehicle Standards Committee. "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles." SAE Standard J3016_202104. 400 Commonwealth Drive, Warrendale, PA, United States: SAE International, April 2021. https://doi.org/10.4271/J3016_202104.

[4] SAE Cooperative Driving Automation (CDA) Committee. "Taxonomy and Definitions for Terms Related to Cooperative Driving Automation for On-Road Motor Vehicles." SAE Standard J3206_202107. 400 Commonwealth Drive, Warrendale, PA, United States: SAE International, June 25, 2022. https://doi.org/10.4271/J3216_202107.

of real road safety improvement[5,6]. At the federal level, the USDOT Connected Vehicle Pilot Deployment Program has provided many insights through the testing conducted at three sites[7]: New York City (NYCDOT)[8], Tampa-Hillsborough Expressway Authority (THEA)[9], and Wyoming DOT (WYDOT)[10]. These studies have mostly focused on V2X-enabled driver warnings that provide basic traffic, weather, and safety information (as defined in SAE J2735). These applications consider the use of messages such as Basic Safety Messages (BSM) detailing the state of the vehicle and Road Weather Messages (RWM) or Road Side Alerts (RSA) providing relevant information about road conditions. In the context of ADAS, these messages are then displayed through a combination of visual, audio, or haptic signals, alerting drivers to evolving road conditions ahead of time.

However, low penetration rates of V2X-connected vehicles and other technical limitations made it difficult to apply conventional longitudinal safety studies due to insufficient data. These studies addressed limited sample size and reproducibility concerns by supplementing field observations with simulated data. While providing useful information on driver behavior, the applicability of these results is limited, especially given the transition from DSRC to C-V2X[11]. Further, models built on DSRC measurements (e.g. time-to-collision, packet loss, message latency distributions) might systematically under- or over-estimate safety benefits if applied to C-V2X deployments.

Under the USDOT Saving Lives with Connectivity: Accelerating V2X Deployment program[12], three new grants were awarded in late 2024 to further accelerate the study and deployment of different V2X applications. These sites and applications include:

- Arizona: The Maricopa DOT will connect 750 physical roadside units and virtual roadside units to an estimated 400 vehicle onboard units targeting transit,

[5] Florida Department of Transportation, CAV Deployments. https://www.fdot.gov/traffic/teo-divisions.shtm/cav-ml-stamp/cv

[6] Georgia Department of Transportation, Connected Vehicle Program https://cvprogram-gdot.hub.arcgis.com/

[7] "Advancing Interoperable Connectivity Deployment: Connected Vehicle Pilot Deployment Results and Findings", 2023

[8] "Connected Vehicle Pilot Deployment Program Phase 3, Understanding and Enabling Cooperative Driving for Advanced Connected Vehicles in New York City – New York City Department of Transportation (NYCDOT)", 2021

[9] Kamrani, M., S. Concas, A. Kourtellis, M. Rabbani, V. C. Kummetha, and O. Dokur. Drivers' Reactions to Connected Vehicle Forward Collision Warnings: Leveraging Real-World Data from the THEA CV Pilot. Transportation Research Part F: Traffic Psychology and Behaviour, Vol. 92, 2023, pp. 108–120. https://doi.org/10.1016/J.TRF.2022.10.011.

[10] "Connected Vehicle Pilot Final System Performance Measurement and Evaluation – WYDOT CV Pilot", 2022

[11] R, Dhinesh Kumar, and Rammohan A. "Revolutionizing Intelligent Transportation Systems with Cellular Vehicle-to-Everything (C-V2X) Technology: Current Trends, Use Cases, Emerging Technologies, Standardization Bodies, Industry Analytics and Future Directions." Vehicular Communications 43 (October 1, 2023): 100638. https://doi.org/10.1016/J.VEHCOM.2023.100638.

[12] U.S. DOT FHWA Office of Operations, Connected/Automated Vehicles and Emerging Technologies. Available [online] at: https://ops.fhwa.dot.gov/program_areas/ops-cavet.htm

emergency and freight fleets. The target V2X applications of this site are Emergency Vehicle Preemption, Vulnerable Road User detection, Transit Signal Priority, and Freight Signal Priority

- Texas: Texas A&M Transportation Institute will deploy V2X technology in two metropolitan cities (Greater Houston, College Station) and the corridors connecting them. Multiple applications will be deployed, including Flood Warning, Signal Phase and Timing (SPaT) Enabled-Intersections, Right Turn on Red Warning, Red Light Violation Warning, Wrong Way Driving Detection, Emergency Vehicle Response Time and Safety, Traffic Signal Preemption and Priority, Enhanced Highway Construction Worker Safety, as well as Hurricane Evacuation and Planned Special Events/Construction.
- Utah: The Utah DOT will develop deployment sites in Utah, Colorado, and Wyoming, including Connected Intersection Preferential Treatment (CIPT), Spot Weather Impact (SWIW), Curve Speed Warning messages (CSW), Traveler Information Alerts, Vulnerable Road User (VRU) Safety System, Disabled Vehicle Alerts, and Vehicle-based Safety Applications.

As more real-world driving condition data is collected, a systematic cost-benefit approach is needed to incorporate new evidence and fairly assess the effect of these technologies on driver behavior and road safety. As these technologies target a wide range of applications, there is a need for systematic methods and approaches to quantify the traffic and safety impacts of V2X technologies, including key aspects of hardware, software, and human reliability; and improved methods to assess traffic and safety impacts. The impact of connectivity, such as latency and network stability, on safety outcomes also needs to be systematically quantified. Similarly, as new mobility technologies become available in the vehicle market – such as highly automated driving features – it is important to design research and assessment tools that can evaluate the fundamental differences between them and their implications for V2X infrastructure deployment.

Developing robust V2X cost-benefit analysis tools is key to support different stakeholders' decision to deploy infrastructure-side technologies at scale. Model-based probabilistic risk analysis can play a significant role in assessing the safety of emerging technologies when limited operational data is available[13,14].

Phase 1 of the project, Quantifying Safety Impacts of V2X-Enabled Traffic Systems, provided a model-based approach to estimate safety impacts of V2X in crash avoidance

[13] Aven, T., & Zio, E. (2011). Some considerations on the treatment of uncertainties in risk assessment for practical decision making. Reliability Engineering & System Safety, 96(1), 64-74.

[14] US Nuclear Regulatory Commission (NRC) (2016). NUREG-1855: Guidance on the Treatment of Uncertainties Associated with PRA in Risk-Informed Decision Making.

scenarios and develop the initial version of the Mobility PRA web tool. Phase 2 aims to advance, extend, and communicate a structured, context-sensitive framework for quantifying and visualizing the safety impacts of V2X-enabled traffic systems. Building upon previous work, we refine and expand the safety impact assessment framework and develop a deployment visualization tool to support state and local infrastructure investment decisions.

The main contributions of this work are described below:

- **V2X Reliability and Deployment**: Since V2X technologies have not been deployed at scale, compiling performance or safety data is a challenging task. While many V2X studies focus on observable driver behavior changes, such as speed reduction, or performance metrics like packet loss rates and average latency to evaluate communication quality, translating these metrics into tangible traffic-level safety benefits remains challenging due to the high human behavior and environmental variability. In Phase 1, we extracted information from the FARS[15] and the CRSS[16] databases to estimate base crash probabilities and partially validate the models based on recent reports detailing the crash reduction factors of ADAS applications[17]. However, phase 1 did not include extensive performance or safety related information about the V2X systems, relying on academic sources to justify model parameters. Therefore, phase 2 improves and expands the V2V and V2I communication models (e.g., considering the impact of weather or traffic density on connectivity quality), and identifies the most important sources of uncertainty when estimating V2X safety benefits.
- **V2X Applications:** Phase 1 focused on crash avoidance scenarios, specifically focusing on rear-end crashes between two vehicles, in which the host vehicle is equipped with V2X technologies (receiving BSM) and is expected to receive messages either from the lead vehicle (using V2V) or from supporting infrastructure (using V2I). Analyzing this scenario from a driver behavior perspective, we investigated the role of V2X as a redundant source of BSM and its interaction with FCW and AEB. In Phase 2, we evaluate the cost-benefit of infrastructure-dependent V2X applications, such as Red-Light Violation Warning

[15] Fatality Analysis Reporting System (FARS) - National Highway Traffic Safety Administration, part of the U.S. Department of Transportation. Available [online] at https://www.nhtsa.gov/research-data/fatality-analysis-reporting-system-fars

[16] Crash Report Sampling System (CRSS) - National Highway Traffic Safety Administration, part of the U.S. Department of Transportation. Available [online] at https://www.nhtsa.gov/crash-data-systems/crash-report-sampling-system

[17] Aukema, Amy, Kate Berman, Travis Gaydos, Ted Sienknecht, Chou-Lin Chen, Chris Wiacek, Tim Czapp, and Schuyler St Lawrence. “Real-World Effectiveness of Model Year 2015–2020 Advanced Driver Assistance Systems,” 2023.

(RLVW) based on SPaT/BSM and Pedestrian Detection based on Sensor Data Sharing Message (SDSM) enabled by Cooperative Perception (CP).

- **V2X Impact and Metrics:** In Phase 1, we provided tools to estimate the sensitivity of the crash avoidance impact results based on weather conditions, the state of the driver and some high-level road type descriptions. Traffic-level effects of V2X were not directly incorporated in this calculation as it focused on vehicle-to-vehicle interactions. In addition, V2X availability was only subject to weather conditions, but did not consider the impact of V2V market penetration or V2I deployment rate. Phase 2 provides a more robust scaling of crash reduction factors and other safety-related performance metrics by incorporating more realistic traffic-level impacts in the form of conflict exposure and traffic density (as an indicator of incident likelihood) and the availability of V2X technologies (as a function of the deployment of V2I-supporting infrastructure and V2V market penetration).
- **Explainable Decision-Support Tool**: Phase 1 highlighted the need for an integrated, user-friendly tool to communicate V2X safety impacts to both technical and non-technical audiences in state and local agencies. While the initial web tool Mobility PRA (MoPRA) allowed users to explore how factors like weather or driver state affected crash scenarios, outputs were limited to end-state probabilities, requiring offline processing to estimate safety benefits. It also lacked the ability to assess broader deployment variables such as automation levels, RSU availability, or V2X market penetration. Phase 2 translates the estimated safety benefits from vehicle-to-vehicle interactions into traffic-level dynamics, and provides an explainable, user-friendly interface to addressing the cost-benefit evaluation challenges that state and local agencies face in the short-to-medium term regarding V2X deployment goals. The result is an interactive decision-support tool that integrates risk model outputs into a GIS-based interface, visualizes safety impacts at the road-link level, and evaluates the influence of deployment parameters such as vehicle automation levels, V2X infrastructure availability, and connected vehicle market penetration. This tool presents actionable insights by estimating crashes avoided per severity and equivalent economic costs avoided.

By promoting harmonized risk assessment principles and enabling transparent evaluation of assumptions, our work provides a critical foundation for supporting evidence-based decision-making when traditional large-scale statistical deployment studies are not available. These model-based methods can isolate, track, and assess the safety contributions of V2X technologies relative to the vehicle ADAS/ADS functions, and can incorporate partial information, adapt to new field data, and model causal relationships between information sources, human or automated driver or system responses, and safety outcomes.

The remainder of this report is organized as follows:

- **Section 2** describes how the use cases were selected and includes a detailed description of the modeling logic for the selected use cases.
- **Section 3** provides the scenario library for Red-Light Violation Warning (RLVW) based on SPaT/BSM and Pedestrian Detection and Collision Warning based on SDSM (referred to as PED-CP).
- **Section 4** summarizes the estimated safety benefits per application as a function of V2I availability and CV market penetration for the sample area in downtown Los Angeles, California. This section also includes an importance-measure analysis of the model components that drive these estimates, used to indicate priorities for future data collection efforts.
- **Section 5** reports the stakeholder engagement activities, as well as analysis of collected stakeholder feedback.
- **Section 6** provides concluding remarks.

In addition, this report comprehensively includes six appendices:

- Appendix A provides an overview of the V2X applications considered.
- Appendix B contains the V2XPRA tool user guide.
- Appendix C provides the technical modeling details (complementing Section 3) and the description of the data preparation for crash-type data used for model calibration.
- Appendix D contains the detailed crash and cost estimates and the tabulated importance measures complementing those presented in Section 4.
- Appendix E contains details on the stakeholder engagement activities discussed in Section 5.
- Appendix F contains the V2XPRA tool specifications and technology transfer market analysis.

2. V2X Safety Benefit Modeling

The Hybrid Causal Logic (HCL) framework serves as the analytical core of the decision-support dashboard. This includes two major components: (1) generalizing the risk assessment framework to cover additional V2X use cases (Sections 2-3), and (2) using the resulting models to identify data collection priorities to support ongoing model development and validation; and derive system design requirements (Sections 4.3-4.4.3).

- **Technology models refinement**: Improve vehicle-side and infrastructure-side models, emphasizing the impact of communication degradation (latency, packet loss, handover delays) and variability as a function of network, traffic, and weather conditions.
- **Expand human-system integration models**: Embed more detailed driver behavior, human-machine-interaction, and automated driving response models to quantify the impact of V2X messages under varying levels of driving automation.
- **Introduce traffic-level impacts**: Extend risk modeling from individual interactions to fleet-level and corridor-scale analyses to assess safety outcomes under different market penetration scenarios, traffic conditions, and dynamics between multiple connected and automated vehicles.

2.1. Risk Modeling Background

The HCL framework consists of a model-based approach to system analysis, containing a multi-layer structure: (1) Event Sequence Diagrams (ESDs) to capture the dynamic sequence of system events and scenario outcomes; (2) Fault Trees (FTs) to represent the causal structure of hardware and software failures contributing to critical events; and (3) Bayesian Belief Networks (BBNs) to encode uncertainty and soft dependencies, such as human behavior, environmental factors, and organizational conditions. These modeling approaches, employed in both research and industry, have provided a basis for many industry standards[18]. More details about the HCL implementation and functionality

[18] International Organization for Standardization. ISO 26262:2018, Road Vehicles — Functional Safety.

can be found in Phase 1 report[19]. Phase 2 implements the model development logic established in Phase 1, grounded in the Information, Decision, and Action (IDA) cognitive model and supported by data-driven or expert-derived parameters[20] This approach categorizes failures and errors stemming from three different stages: data collection and initial interpretation (Information Phase), reasoning and decision-making (Decision Phase), and action implementation (Action Phase).

Figure 2.1 presents a high-level diagram of the I-D-A tasks associated with each decision-making agent in the system, i.e., the driver and the vehicle, depending on the level of driving automation. As depicted in the figure, V2X has the potential to provide redundancy, either to complement the driver's or the single-vehicle's real-time perception functions (I-Stage) and better inform both agents' decision-making processes (D-Stage).

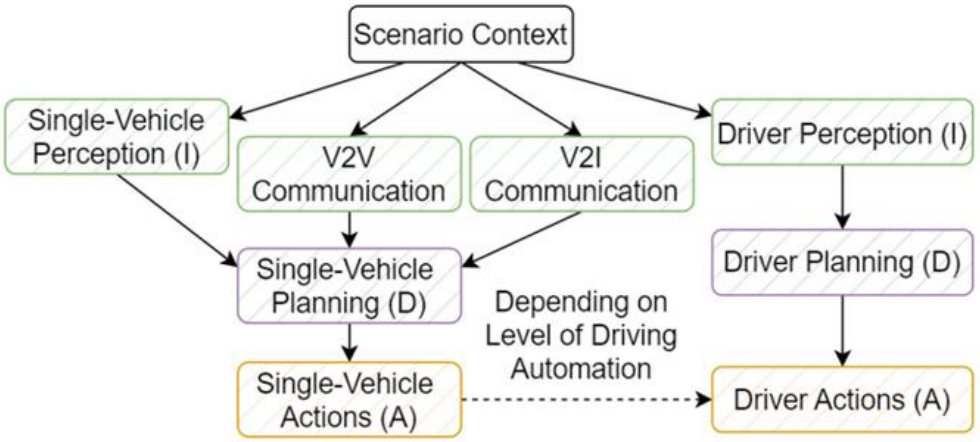

Figure 2.1: IDA functional flow chart.

2.1.1. Event Sequence Diagrams

Event sequence diagrams, a widely used tool in PRAs, represent system state evolution following an initiating event. Traditional ESDs trace binary success/failure branches through a series of events with associated probabilities and end-state consequences, providing a clear and traceable framework for modeling relatively static systems. **Figure 2.2** illustrates a typical ESD structure.

[19] Correa-Jullian, C., Mosleh, A., Zhu, D., & Ma, J. (2025). Quantifying Safety Impacts of V2X-Enabled Traffic Systems (Phase 1). UCLA: Mobility Center of Excellence. http://dx.doi.org/10.82903/B2CC78 Retrieved from https://escholarship.org/uc/item/6tz6n000

[20] Chang, Y. H. J., and A. Mosleh. Cognitive Modeling and Dynamic Probabilistic Simulation of Operating Crew Response to Complex System Accidents. Part 1: Overview of the IDAC Model. *Reliability Engineering and System Safety*, Vol. 92, No. 8, 2007, pp. 997–1013. https://doi.org/10.1016/j.ress.2006.05.014.

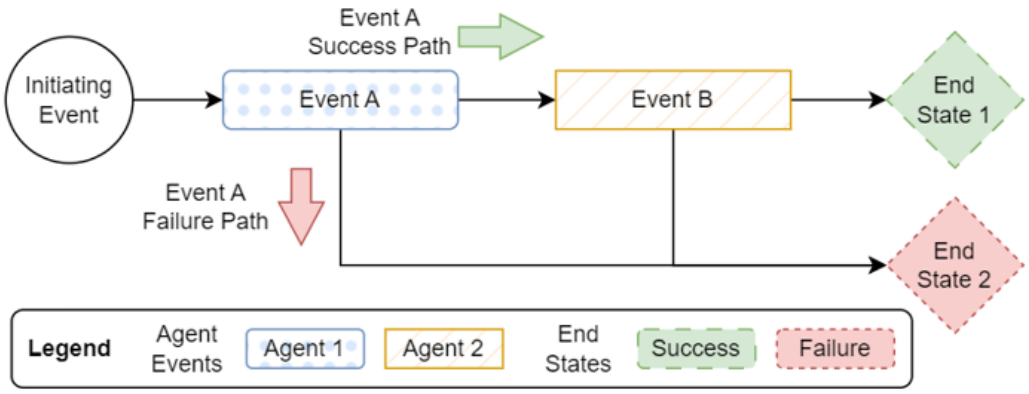

Figure 2.2: A sample of a traditional ESD model.

2.1.2. Fault Trees

Within HCL, Fault Trees (FTs) complement ESDs by enabling causal decomposition of critical events. While ESDs describe scenario temporal flow and decision logic, FTs model the contributing technical, human, or organizational failure modes using Boolean logic (e.g., AND/OR) as depicted in **Figure 2.3**. Linking ESD nodes to corresponding FTs bridges time-sequenced scenario modeling with causal failure analysis, allowing for a more traceable and structured risk representation. In Phases 1-2, FTs were used to primarily address individual driver and vehicle failures, including hardware, software, and environmental factors, with basic event probabilities derived from known distributions or supporting models such as BBNs.

2.1.3. Bayesian Networks

Within HCL, Bayesian Belief Networks (BBNs) are used to model uncertainty, particularly contextual factors, e.g., weather and traffic situations, as well as human behavior variability. Conditional probability tables (CPTs) were used to define how these states impact exposure to crash conditions under various contexts, such as attention levels and road speeds. **Figure 2.4** presents a typical BBN structure, where Performance Shaping Factors (PSFs) represent the impact of different contextual conditions over scenario factors, and the overall task success.

In combination, these models within the HCL software provide analysts with the ability to construct system models where the success or failure of any event can be represented by probabilistic models. The output of the HCL models are end-state probabilities, which are then transformed into equivalent crash rates and economic values.

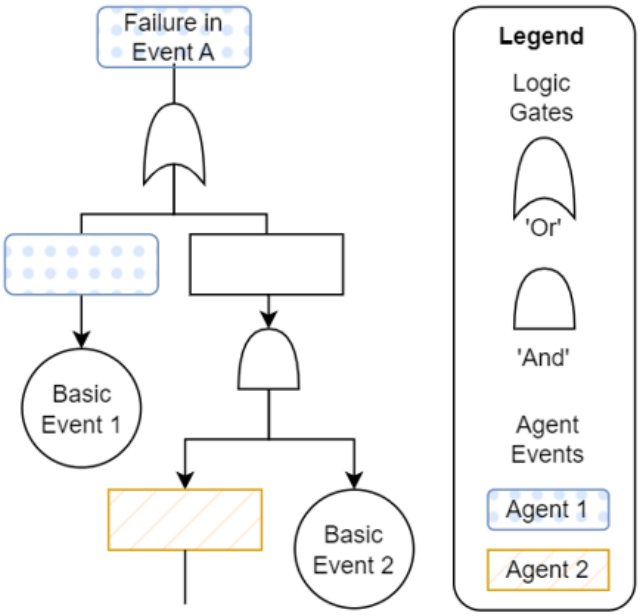

Figure 2.3: A sample of a traditional FT model.

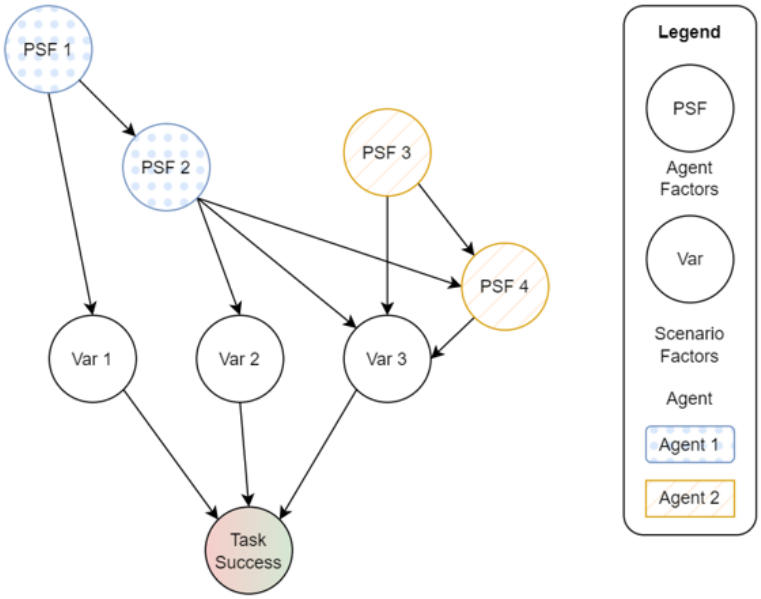

Figure 2.4: A sample of a traditional BBN model.

2.1.4. Rank Importance Measures

Rank importance measures are implemented in HCL to rank system components with respect to their influence on the overall system reliability. This ranking may be used to find the top contributors to system failure, relax reliability requirements for the lowest contributors to system failures, and perform sensitivity analysis for model parameters.

These measures are dependent on the system's logic, structure, and reliability values. Some relevant measures to identify critical components are:

- Risk Achievement Worth (RAW): Quantifies the relative increase in the system failure probability given that a specific component has failed. Values close to 1 imply that the failure of the component has a negligible effect on system risk.
- Risk Reduction Worth (RRW): Quantifies the relative decrease in the system failure probability given that a specific component is functioning. Values close to 1 imply that further improving the component's reliability offers little risk reduction.

These measures are used to indicate the relative impact of selected failure modes over the overall scenario development (Section 4.3).

2.2. V2XPRA Tool Development

2.2.1. Selected V2X Applications

A structured review of V2X applications was conducted to identify the use cases most suitable for safety impact modeling within the Phase 2 framework. Applications were first catalogued and organized by message type (e.g., signal priority, safety warnings, probe data sharing) and target user (human-driven vehicles, ADS, transit authority, infrastructure), resulting in a comprehensive inventory of over 25 applications currently deployed or under active development. A full summary of this inventory is provided in **Appendix A**.

From this inventory, the following selection criteria were applied to identify priority applications for modeling:

- Safety impact potential: Applications targeting crash-imminent or crash-contributing conditions with quantifiable risk reduction.
- RSU centrality: Preference for applications where the RSU plays an essential communication or sensing role, consistent with the tool's goal of guiding infrastructure deployment decisions.
- Applicability across driver types: Relevance to both human-driven vehicles and ADS, enabling the framework to support a range of automation levels.
- Alignment with active deployments: Priority given to applications featured in the V2X Accelerator Sites (Arizona, Texas, Utah).

Selection was further modulated by ongoing engagement with FHWA, which helped identify applications of highest relevance to current infrastructure investment priorities. Using these criteria, applications were organized into three tiers (**Table 2.1-Table 2.2**):

Table 2.1: V2X Application Tier Definition.

Tier	Description
A	Highest safety benefit potential; RSU-essential; applicable across vehicle types
B	High safety benefit potential in specialized locations or under specific conditions
C	Specialized locations or conditions; secondary safety benefit

Table 2.2: V2X Application Tiers.

Tier	Application	Type	Pros	Cons
A	Emergency Electronic Brake Lights (EEBL)	V2V; Optional V2I (communication-only)	High safety impact potential	Primarily V2V; V2I serves only as backup. Performance degrades significantly in curve geometries.
	Queue Warning (Q-WARN)	V2V; Optional V2I	Effective use case at low CV market penetration rates	Sensing RSU required to maximize impact
	Work Zone / Active Construction (WZW / ACM)	V2V; V2I (communication-only)	Key V2I use case	Requires portable V2I equipment.
	Intersection Crash Warning / Red-Light Violation Warning (ICW/RLVW)	V2V; V2I (communication-only)	Key V2I use case	Modeling complexity introduced by multiple V2V/V2I message routes.
	Active Emergency Vehicle Warning	V2V; Optional V2I (communication-only)	Key V2I use case when paired with EVP	Direct safety benefit is secondary.
	Forward-Collision Warning / AEB augmentation (V2V)	V2V; Optional V2I	Base case scenario already developed in Phase 1	Sensing RSU required to maximize impact

Tier	Application	Type	Pros	Cons
B	School Bus Warning	V2V; Optional V2I	V2V main mechanism	Limited exposure
	Wrong-Way Detection (WWD)	Essential V2I	High safety impact potential	Requires sensing RSUs
	Pedestrian Crash Warning	Essential V2I	High safety impact potential	Requires sensing RSUs
	Incident / Congestion Alert (INC / CAL)	V2I/V2V	Moderate safety benefit	Primarily planning-related; limited crash-imminent application
C	Curve Speed Warning (CSW)	V2I	Key V2I use case	Location-specific; requires sensing RSU
	Do-Not-Pass Warning (DNPW)	V2I	Key V2I use case	Location-specific; requires sensing RSU
	Unsafe Lane Change Warning	V2V; V2I (communication-only)	Moderate safety benefit	Primarily V2V; largely covered by existing onboard sensors.
	Transit/Freight Priority / Emergency Response Vehicle (ERV) Preemption	V2I	Key V2I use case	Safety benefit is secondary; ERV Preemption offers the most direct safety application.

2.2.2. Modeling Approach

The modeling approach in Phase 2 builds on the HCL framework described in **Section 2.1**, extending it to cover a broader set of V2X use cases through a set of generalizable modeling blocks. The underlying modeling logic is failure-oriented, addressing three core questions:

- What factors contribute to failure paths in event sequences?
- What probability is there to arrive at a certain end-state?
- How do we represent failure modes and mechanisms?

To guide model development, scenarios are abstracted into components defined by four characteristics illustrated in **Figure 2.5.**

1) RSU role and capability (communication-only vs. sensing);

2) Target risk (vehicle, VRU, road, or emergency vehicle related incidents);
3) Road type (intersection, segment, or specialized location);
4) Intended maneuver or action (deceleration, lane change, or signal timing);

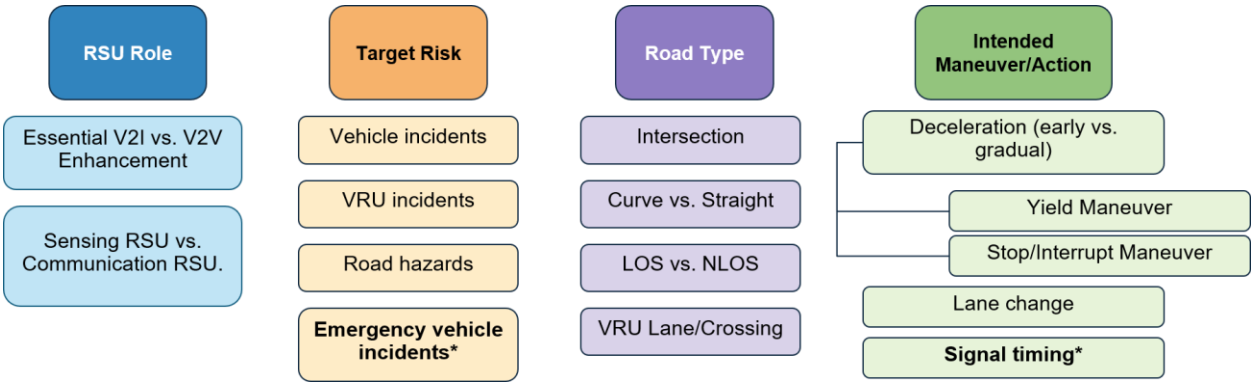

Figure 2.5: Candidate Applications Classification.

An important modulating element of the intended maneuver is timing relative to conflict (crash-imminent vs. early advisory) as well as the distinction between human-driven and ADS-equipped vehicles. For human-driven vehicles, failure modes are dominated by driver reliability factors (e.g., attention, compliance, and response latency) modeled through BBN-based performance shaping factors. For ADS-equipped vehicles, failures shift toward system reliability factors: message integrity, localization accuracy, and processing latency. **Table 2.3** summarizes the key modeling implications of this distinction.

Three properties of V2X messaging further modulate how these building blocks are parameterized across scenarios:

- Redundancy: The degree to which V2X supplements or replaces onboard perception, particularly in NLOS conditions.
- Latency: The end-to-end time budget available for the driver or ADS to act, shaped by communication pipeline delays and warning lead time.
- Compliance: The probability that a correctly received warning results in the intended behavioral or system response, which varies with warning timing, driver state, and automation level.

These properties are in turn shaped by the communication characteristics of the V2X link itself. Reliable packet delivery is bounded by range (the maximum physical distance at which a 90% packet delivery rate (PDR) can be sustained (see **Figure 2.6-Figure 2.7**)

and by message frequency. Together, these factors define the effective time budget available for the driver, ADAS, or ADS to implement a response.

Table 2.3: Vehicle Automation Modeling Implications.

Aspect	Human-Driven Vehicle	ADS Vehicle
Information Pathway	Message → Perception (I) → Decision (D) → Manual Control (A)	Message → ADS Controller → Planning/Control Module → Automated Action
Reaction Time	1–2 s typical*	< 0.2 s (estimated)
Reliance	Human attention, compliance, visibility	Communication integrity, localization accuracy, sensor fusion
Failure Modes	Driver inattentive, misinterpretation, delayed response	Message loss, timing error, localization/map mismatch
Modeling Implication	Human reliability and PSFs dominate	System reliability and latency dominate

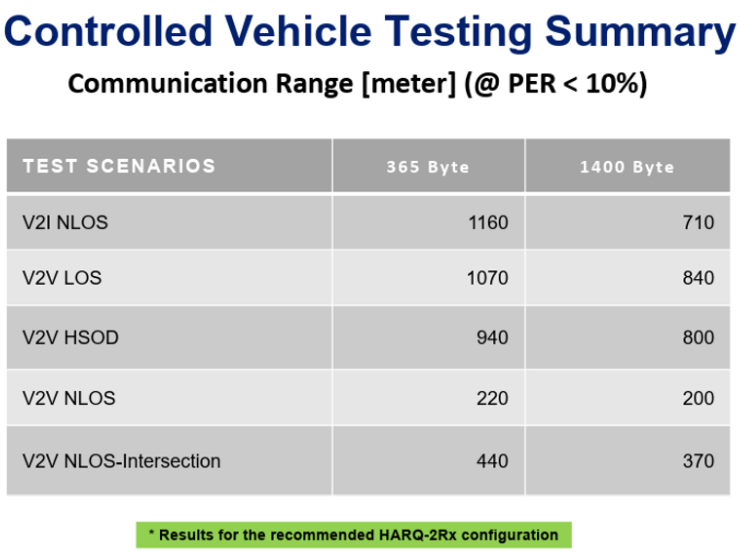

Figure 2.6: Camp LLC C-V2X Performance Assessment Project 2019.

For instance, when warning lead time is high, V2X acts as the primary perception source, particularly in NLOS conditions where onboard sensors or driver perception alone is insufficient. In this regime, communication reliability is lower due to longer transmission distances, compliance is harder to quantify, and messages may be filtered (either automatically as stale, or by the driver). Conversely, when available time is low, V2X

functions as a complement to local perception to trigger an immediate response. Reliability is higher at shorter ranges, and compliance tends to be higher, though the challenge shifts to harmonizing V2X information with onboard sensor inputs without introducing additional response latency.

See the following table (*Range comparison between DSRC and C-V2X for at 11 dBm effective transmit power* from Section 8.6 of [1]).

Test procedure	Range in (m) at 90% reliability	
	DSRC	C-V2X
Line-of-sight (LOS) range	925	>1350**
Non-line-of sight (NLOS) blocker (5GAA)	425	625*/725
Non-line-of-sight (NLOS) intersection	90*/400	600*/800
Co-existence with Wi-Fi 80 MHz bandwidth in UNII-3	550	950
Co-existence of V2X with adjacent DSRC carrier	100*/325	950

* First drop below 90% packet reception rate (PRR)

** C-V2X range >1350 m since we reached the end of the track

Figure 2.7: 5GAA P-190033, "V2X Functional and Performance Test Report; Test Procedures and Results", 5GAA April 2019 - as reported by Qualcomm: C-V2X Technical Performance (October 2019).

Based on the selection criteria in **Section 2.2.1** and the modeling block structure described above, two applications were selected for full scenario development in Phase 2: Red Light Violation Warning (RLVW), based on SPaT/BSM messaging, and Pedestrian crash Warning via Cooperative Perception (PED-CP), based on SDSM (Table 2.4). These applications represent complementary modeling challenges: RLVW emphasizes driver behavior and signal-phase timing under a well-defined conflict geometry, while PED-CP introduces sensing RSU reliability and VRU detection uncertainty as primary failure drivers. Both are described in detail in **Section 3**.

Table 2.4: V2X Use Cases Selected.

Application	RSU Role	RSU Capability	Target Risk	Road Type / Context	Intended Maneuver / Action
Red-Light Violation Warning (RLVW)	RSU generates warnings (based on BSM, SPaT, MAP)	Communication	Drivers (L0, L2), ADS (L4)	Vehicle Crashes	Intersections

Application	RSU Role	RSU Capability	Target Risk	Road Type / Context	Intended Maneuver / Action
Pedestrian Collision Warning (CP)	RSU broadcasts SDSM	Sensing + Communication	Drivers (L0, L2), ADS (L4)	VRU Crashes	Intersections and Mid-block Crossings

2.2.3. Tool Requirements

The V2XPRA decision-support tool is designed to provide state and local agencies with accessible, model-based estimates of V2X safety and operational benefits under varying deployment assumptions. Core intended uses include:

- Provide an explainable and user-friendly interface that communicates expected safety benefits from avoided vehicle crashes and mitigated traffic congestion consequences as a function of CV market penetration and V2I availability;
- Showcasing selected V2X use cases through mid-fidelity scenario representations that account for local contexts incorporating traffic-level context such as roadway type, traffic volume and historical incident patterns to inform baseline risk conditions; and
- Promoting the underlying probabilistic risk assessment framework as a risk-informed intervention tool compatible with commercial safety analytics platforms.

Key functional capabilities include a geospatial interface for road-link level visualization, scenario configuration controls for automation level and deployment parameters, and output reporting in terms of avoided crashes and equivalent economic costs. The tool operates under a set of constraints appropriate for a prototype demonstration: single-user operation over a predefined 1 sq. mile study area, with safety benefits aggregated independently across segments using annual average traffic and weather inputs. A full specification of functional, performance, data, and verification requirements is provided in the companion report for Task 3[21].

2.2.3.1. Tool Design

The tool is organized into three interconnected subsystems, as illustrated in **Figure 2.8**:

[21] 693JJ325P000037 V2X Phase II Tool Design & Market Analysis Report, December, 2025.

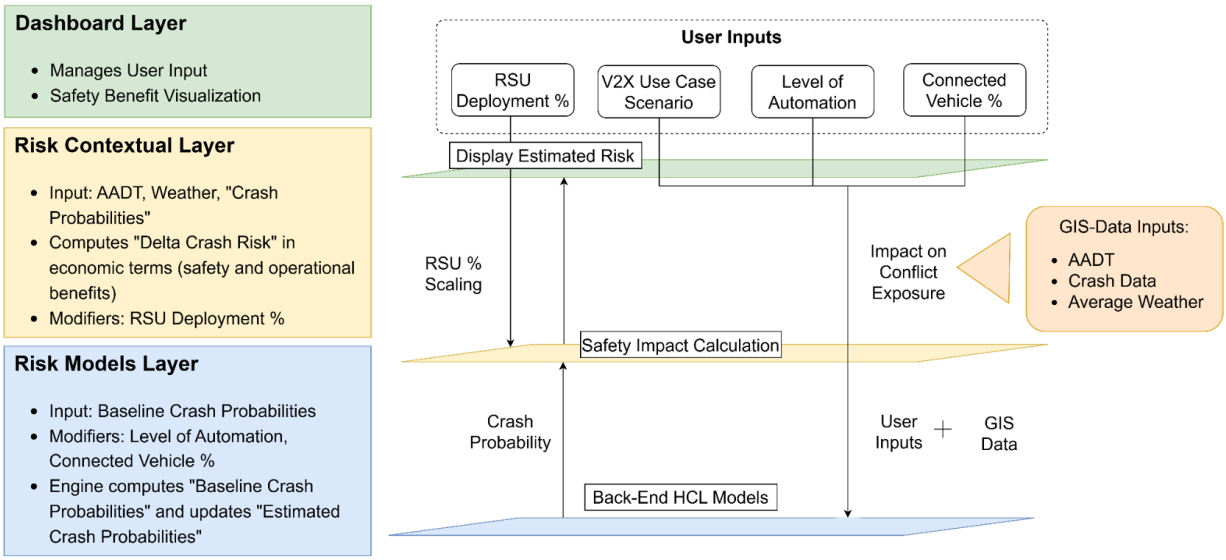

Figure 2.8: V2XPRA Architecture.

- **Subsystem 1 – User-Facing Dashboard Layer (Upper Level):** This layer provides an interactive environment through which users configure V2X intervention scenarios and visualize resulting safety impacts at the road-link level. Users can toggle between V2X use cases and adjust deployment parameters including automation level, CV market penetration rate, and RSU deployment rate (proxy for V2I availability). Results are presented as geospatial visualizations for eligible road segments (e.g., heatmaps, color scales, and tooltips) alongside summary estimates of avoided crashes, congestion, and equivalent economic benefits.
- **Subsystem 2 – Traffic and Contextual Layer (Intermediate Level):** This layer serves as the intermediary between user inputs and the risk modeling engine. It retrieves segment-specific GIS data and maps it into HCL-ready model parameters and converts end-state probabilities into expected crash counts and monetized consequences through a consequence-mapping table linking end-state categories to crash severity and associated economic values.
- **Subsystem 3 – Core HCL Risk Modeling Layer (Lower Level):** This layer instantiates the HCL model for each road segment using static contextual inputs and use-case-specific ESD, FT, and BBN structures. It computes baseline probabilities under no V2X intervention and updates them dynamically as users adjust deployment parameters. Segment-level results are then aggregated into area-level safety benefit summaries for display in Subsystem 1. Model blueprints are use-case specific but draw on the generalizable modeling blocks, with backend data managed by the system administrator.

- The developed models focus on scenarios derived from technology, communication, and human failure modes. CV market penetration and Level of Automation impact basic event probabilities of vehicles reacting to shared messages. RSU Deployment % is used as a proxy for V2I availability, but this method can be extended to network V2X analysis. A simplified workflow of the tool is presented in **Figure 2.9**.

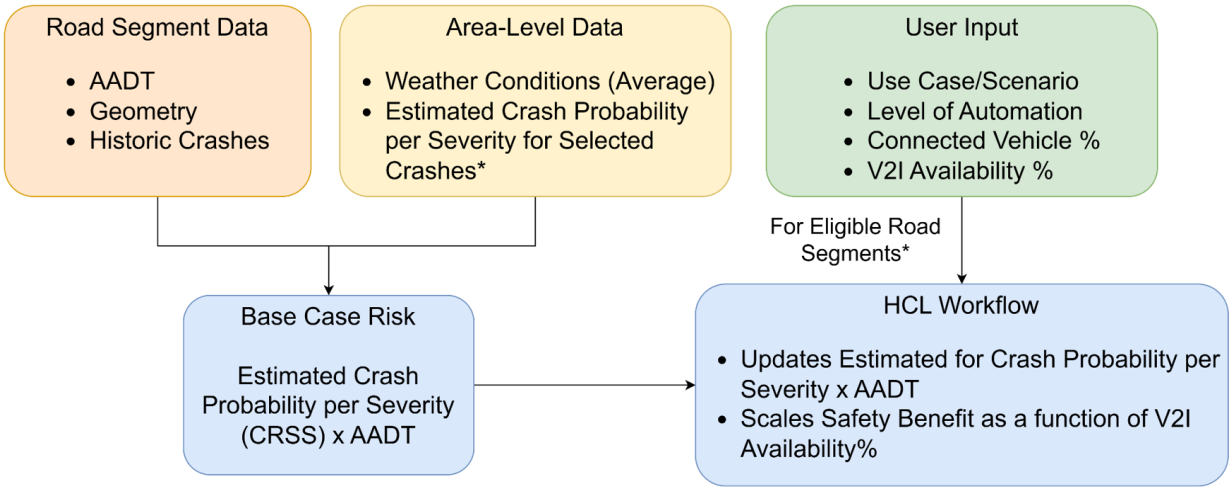

Figure 2.9: Simplified V2XPRA Workflow Diagram.

2.2.3.2. Market Analysis and Tech Transfer Strategies

The V2XPRA tool is designed with technology transfer in mind. Three primary platform categories represent near-term integration opportunities:

- Commercial safety analytics and mobility data platforms (e.g., INRIX, StreetLight, Rekor, Miovision) that fuse probe data, crashes, and other feeds to highlight high-risk locations.
- Public-sector safety management tools (e.g., AASHTOWare Safety Analyst, RITIS Probe Data Analytics) that support performance management using archived data for Highway Safety Manual (HSM) and Highway Safety Improvement Program (HSIP) programs.
- Research and simulation environments for AV/CAV safety (e.g., TeraSim, OpenCDA, and related digital twins) that target AV/ADS safety evaluation via scenario generation and simulation-based metrics.

The HCL risk engine can be packaged as a self-contained module or exposed as an API service, enabling integration across these platform types, and providing CMF-like static inputs to safety management tools, expanding the analytical capabilities of probe data

suites, or consuming simulation outputs as statistical inputs for model parameterization. A full market analysis and technology transfer strategy is provided in the companion report (**Appendix F**).

2.2.4. V2XPRA Dashboard Overview

This section briefly describes the tool and its dashboard; the full user guide is provided in **Appendix B**. V2XPRA quantifies the expected safety impact of a V2X deployment at specific locations before large-scale rollout, translating modeled crash probabilities into annual crashes avoided, and equivalent economic value. The underlying models are grounded in NHTSA CRSS/FARS crash data, V2X pilot deployment performance, reliability standards (IEC 61508, ISO 26262), CAMP requirements, and the human factors and ADAS/ADS literature. The dashboard visualizes crash risk as a heatmap across every signalized intersection in the study area, overlaying historical crash data with model-based risk estimates (**Figure 2.10**).



Figure 2.10: V2XPRA dashboard overview.

Area-specific weather, road type, and traffic exposure are built into the causal models that drive these estimates. The current build covers 92 signalized intersections and 245 road segments within a 1 mi² pilot area in Downtown Los Angeles (DTLA).V2XPRA is designed to enable users to select a specific V2X scenario and adjust deployment levers such as automation level (Level 0, Level 2, or Level 4), V2I coverage rate, and connected vehicle (CV) market penetration. Each adjustment recalculates crash counts and economic savings in real time (**Figure 2.11**, **Figure 2.12**). Outputs are calibrated to

historical crash data and reported as annual crashes avoided by severity (property-damage-only, injury, and fatality) for the base case versus the V2X deployment case, along with the corresponding economic savings using comprehensive crash costs ($15.4M per fatality, $343K per injury, $9.7K per PDO crash)[22].



Figure 2.11: V2XPRA dashboard scenario and visualization options.

Results can be generated for individual corridors/intersections (**Figure 2.12**), or for the entire area of study (**Figure 2.13** crash-count reductions, **Figure 2.14** equivalent economic impacts). Impacts are decomposed by crash severity, displaying the estimated crashes equivalent to the area of study under base (no V2X) and intervention (V2X) cases, with point estimates and the 5th-95th uncertainty bounds.

These outputs are underpinned by the causal chain modeled beneath the dashboard, which links RSU/technology performance through driver or ADS response to crash outcome using the HCL framework described in this report. Each scenario's narrative, technology specifications, performance, and limitations are grounded in standards, literature, and industry reports, and the resulting end-state (crash severity) probabilities per encounter are translated into annual, area-level crashes avoided and economic savings, with uncertainty bounds carried through from each underlying assumption to the final estimate (**Figure 2.15**).

[22] U.S. Department of Transportation, Office of the Secretary "Benefit-Cost Analysis Guidance for Discretionary Grant Programs", December 2025 Available [online]: https://www.transportation.gov/mission/office-secretary/office-policy/transportation-policy/benefit-cost-analysis-guidance

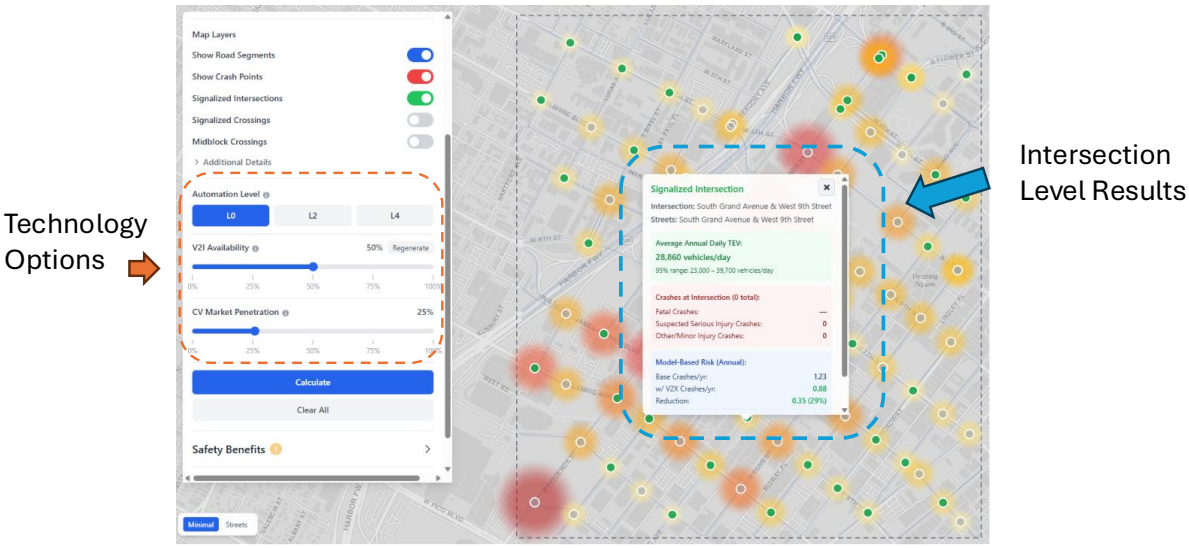

Figure 2.12: V2XPRA dashboard technology options and intersection-level results.

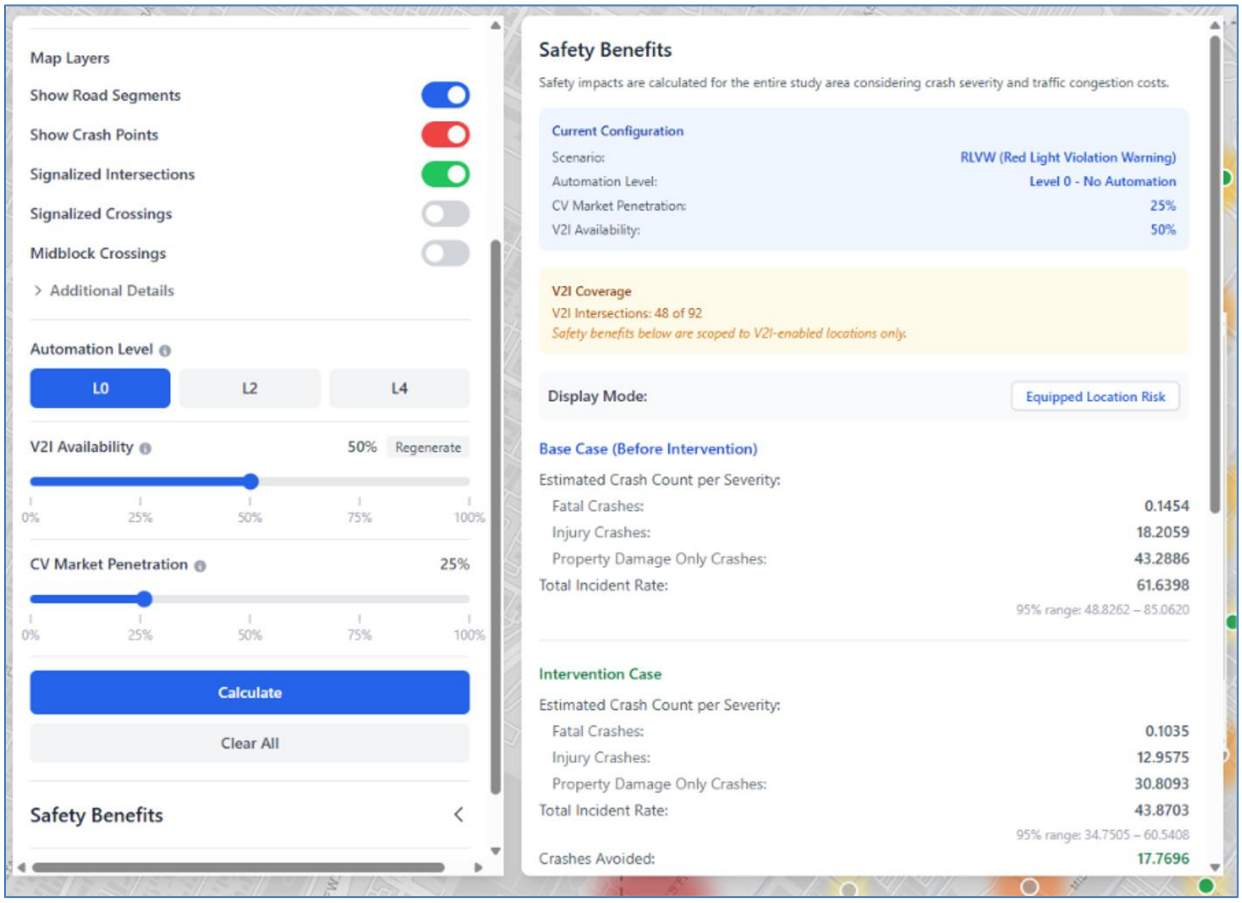

Figure 2.13: V2XPRA dashboard area-level results (safety impacts).

V2XPRA currently supports two use cases, Red-Light Violation Warning (RLVW) or Pedestrian Collision Warning (PED-CP) modeled separately for each automation level because failure behaviors and mitigations differ by level: RLVW, which follows the RSU (SPaT/BSM) to V2I communication link to driver or ADS response path at signalized intersections for human drivers with no automation (L0) and those supported by ADAS (L2), as well as Level 4 ADS (L4); and PED-CP, which follows combined infrastructure-mounted sensor system and RSU (SDSM) to share information regarding vulnerable road users at intersections and crossings for human drivers (L0), ADAS (L2), and ADS (L4).

The current implementation is a prototype interactive GIS dashboard, calibrated on national and local crash history with economic values aligned to current U.S. DOT benefit-cost analysis guidance, and built to be extensible to additional corridors and deployment configurations.

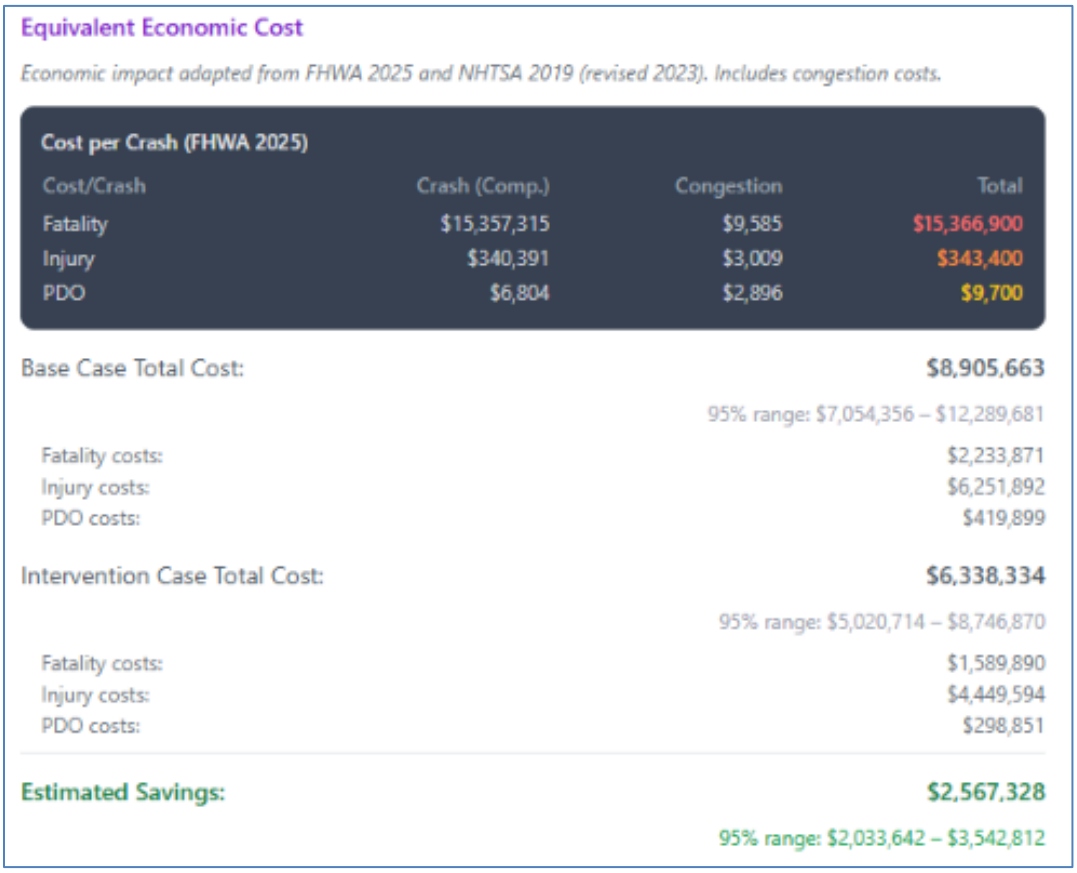

Figure 2.14: V2XPRA dashboard area-level results (equivalent economic impacts).

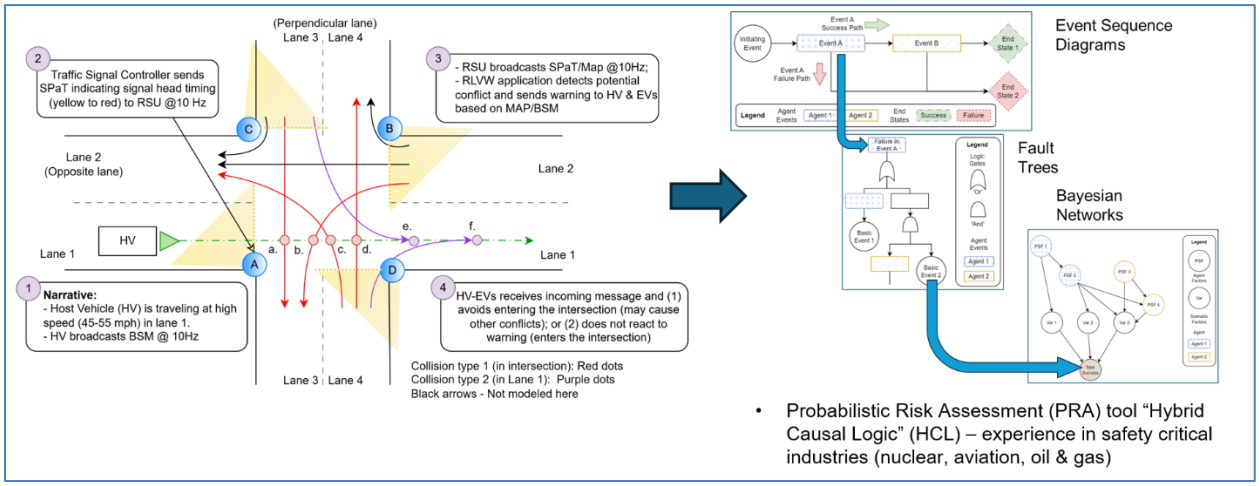

Figure 2.15: V2XPRA scenario modeling logic example.

3. Scenario Library

This section describes in detail the assumption, modeling choices, and available data that anchors the safety impact analysis. Technical details are available in Appendix Appendix C. and results for both implementation scenarios are discussed in **Section 4**.

3.1. Scenario A: RLVW

3.1.1. Scenario Summary

In this scenario, we have modeled a conflict stemming from a host vehicle (HV) running a red light at an intersection. Traditional RLVW (red-light violation warning) relies on the infrastructure-mounted roadside unit (RSU) broadcasting SPaT/MAP (signal phase and timing; road geometry) data to all oncoming vehicles. The messages are received by vehicles, whose onboard units (OBU) determine (i) whether there is a risk of the vehicle running the red light (based on vehicle position, speed, etc.), and (ii) whether a warning should be delivered. The exact modality and timing of the warning depends on the vehicle's warning mechanism. If generated, this warning will only impact the host vehicle driver's decision to continue or not through the intersection. An alternative mechanism for RLVW introduces edge devices on the infrastructure, which can generate warnings based on oncoming vehicle's basic safety messages (BSM) combined with the SPaT/MAP. This 'enhanced' RLVW allows warnings to be broadcast to all oncoming vehicles, prompting the onboard systems from all oncoming vehicles to determine if the warning should be communicated to the driver. This allows multiple drivers to be alerted simultaneously, including encountering vehicles that may be on the host vehicle's path. This scenario assumes communication devices installed at the intersection (RSUs) that receive information from the traffic cabinet (signal telemetry) and from an edge device capable of generating the RLVWs.

Differences across automation levels: At level 0 automation (L0; no automation), the warning response depends on the driver. Factors such as timing, warning compliance, and braking feasibility have been incorporated into the driver's response (of both the host vehicle and the encountering vehicles). At level 2 automation (L2; partial automation), we have assumed the automation and/or the driver can intervene based on the warning and the response's baseline is grounded on reported AEB performance (intersection-conflict specific automated emergency braking), which acts as a backup system, independent of the warning. At level 4 automation (L4; highly automated vehicle), we have assumed that the automation directly acts in response to the warning. When automation is engaged

(L2, L4), timing and braking feasibility have been considered. Factors affecting all automation levels and connectivity performance include weather, light conditions, road/intersection type, and line-of-sight effects.

3.1.2. Modeling Overview

Red light running is a persistent and disproportionately severe contributor to intersection crashes. According to FHWA, fatalities from red light running in the United States increased by over 30% between 2017 and 2021, while each year, roughly one-quarter of traffic fatalities and approximately one-half of all traffic injuries in the United States are attributed to intersections[23]. The Insurance Institute for Highway Safety (IIHS) reported 1,149 deaths and approximately 107,000 injuries resulting from red light running crashes in 2022 alone[24]. Crashes resulting from red light running (typically broadside or T-bone crashes) are disproportionately deadly: nearly 30% of fatal crashes at signalized intersections involve a driver running a red light[25].

Red light running arises from a complex set of driver behaviors and engineering conditions[26,27]. Intentional violations are associated with drivers' perception of low crash or enforcement risk, congestion-related factors, and queue-following behavior[28]. Unintentional violations occur due to signal inattention, distraction, or the inability to stop in time due to high approach speed, adverse weather, or poor signal visibility. Engineering factors also play a role, such as inadequate traffic signal control design impacting dilemma zone navigation[29].

The RLVW application was designed to address this risk by alerting drivers at a signalized intersection when a potential red-light violation is detected based on vehicle trajectory

[23] Federal Highway Administration (FHWA). (2024). About Intersection Safety. U.S. Department of Transportation. https://highways.dot.gov/safety/intersection-safety/about

[24] Insurance Institute for Highway Safety (IIHS). (2023). Red Light Running. https://www.iihs.org/research-areas/red-light-running

[25] AAA Foundation for Traffic Safety. (2019). Red Light Running Deaths Hit 10-Year High. https://newsroom.aaa.com/2019/08/red-light-running-deaths-hit-10-year-high. Tables available [online].

[26] M. R. Hossain, M.-W. Kang, S. Wu, M. R. Hossain, M.-W. Kang, and S. Wu, “Engineering Countermeasures for Red-Light Running: A State-of-the-Art Review,” J. Transp. Technol., vol. 15, no. 2, pp. 275–311, Apr. 2025, doi: 10.4236/JTTS.2025.152014.

[27] A. Jahangiri, H. Rakha, and T. A. Dingus, “Red-light running violation prediction using observational and simulator data,” Accid. Anal. Prev., vol. 96, pp. 316–328, Nov. 2016, doi: 10.1016/J.AAP.2016.06.009.

[28] H. A. Mohammed, M. Ghodrat Abadi, and D. S. Hurwitz, “Red-light running violation during car following at high-speed signalized intersections,” Transp. Eng., vol. 8, p. 100110, Jun. 2022, doi: 10.1016/J.TRENG.2022.100110.

[29] D. S. Hurwitz, M. A. Knodler, and B. Nyquist, “Evaluation of Driver Behavior in Type II Dilemma Zones at High-Speed Signalized Intersections,” J. Transp. Eng., vol. 137, no. 4, pp. 277–286, Sep. 2010, doi: 10.1061/(ASCE)TE.1943-5436.0000219.

and speed. The application mainly relies on two SAE J2735 messages broadcast from the Roadside Unit (RSU) as shown in **Table 3.1**[30].

Table 3.1: RSU messages involved in RLVW (SAE J2735).

Message	Full Name	Purpose
SPaT	Signal Phase and Timing	Conveys dynamic signal state (red/yellow/green), phase timing, and interval end-time information to approaching vehicles.
MAP	MapData (Intersection Geometry)	Provides a static geometric description of the intersection — lane geometry, approach vectors, stop lines, and allowed maneuvers.

These messages traditionally enable on-board vehicle algorithms to determine whether the host vehicle (HV) is on a trajectory to run the red light. This model additionally considers infrastructure-side warnings: using SPaT/MAP inputs alongside BSM data from approaching vehicles, the RSU independently makes this same determination and, upon detection, broadcasts RLVW alerts to all vehicles in range alongside the traditional SPaT/MAP. This broadcast simultaneously warns the HV of the impending violation and alerts encountering vehicles (EVs) on the crossing phase of the conflict. The onboard warning experience for the HV driver is equivalent regardless of whether the alert originated from the infrastructure or the vehicle's own OBU. This overall narrative is highlighted in **Figure 3.1**.

3.1.2.1. V2X Failure Behavior

RLVW-related failures fall into two categories, both detailed further in **Appendix C.1**. RSU message generation failure concerns the accuracy of the SPaT/MAP data broadcast by the RSU and, for enhanced RLVW applications where the infrastructure directly emits the warning to oncoming vehicles, the accuracy of the BSM transmitted by the red-light-running vehicle (**C.1.5.1, RSU-RLVW Generation and Transmission Failure**). Message transmission failure concerns whether that message successfully reaches the vehicle, governed by V2X link performance, weather, and line-of-sight (LOS/NLOS) conditions between the vehicle and the infrastructure-mounted RSU.

The analysis focuses on the worst-case scenario within each time bracket: the probability that a warning fails to reach the driver is $P(fail) = 1 - p$, where p is the per-packet

[30] Connected Vehicle Pooled Fund Study (February 2022), Signal Phase and Timing (SPaT) Message Connected Intersections Program Brief University of Virginia School of Engineering

delivery probability under the operating conditions. Under nominal baseline conditions, $p \approx 0.97$, further modified by weather and line-of-sight (LOS) conditions as described in **C.1.6.2, V2X Communication Model**.

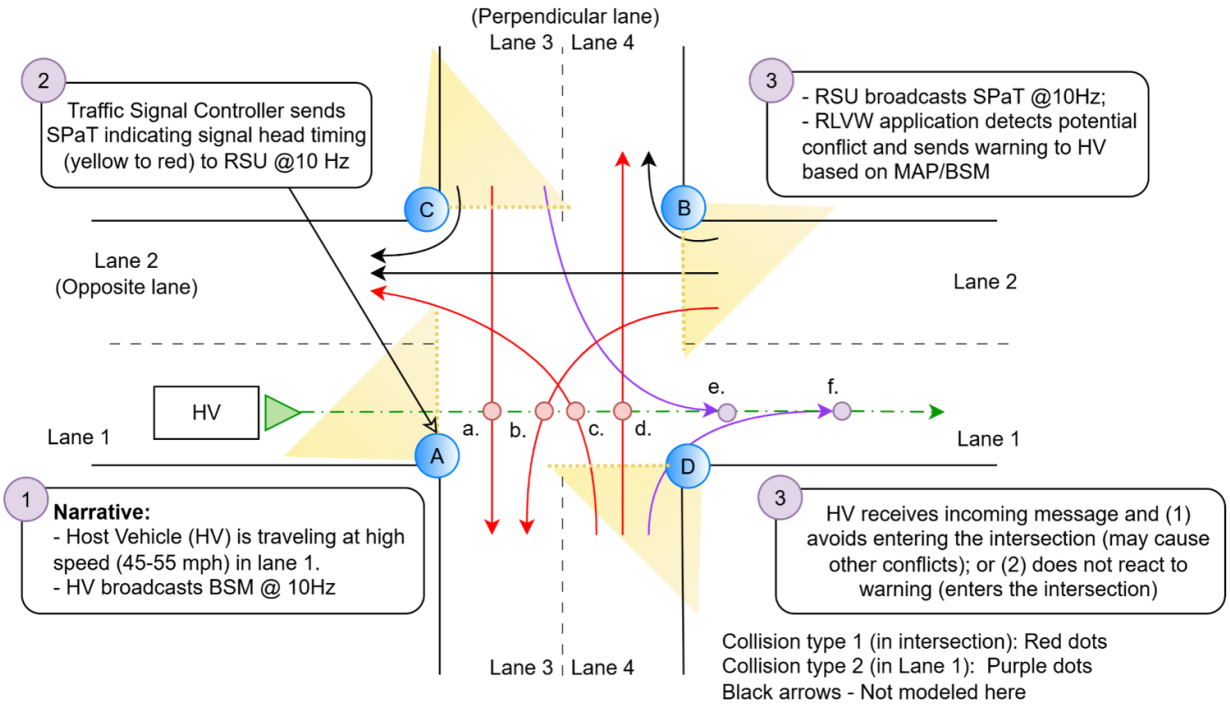

Figure 3.1: RLVW Scenario Narrative.

3.1.2.2. Driver Failure Behavior

The RLVW Concept of Operations document[31] specifies a design detection onset of up to 10 seconds before the vehicle reaches the stop bar, with the system re-evaluating the vehicle's conflict trajectory at 10 Hz based on received SPaT/MAP messages and updating the driver-facing alert state at every cycle. In practice, the time available to deliver a warning and have the driver act on it (i.e., the useful warning window) is physically constrained by approach speed, driver perception-reaction time (PRT), and the vehicle's braking distance under prevailing road conditions. This model sets driver PRT at $1.00 \pm 0.39\ s$ and deceleration at $0.4g$ under nominal conditions and $0.7g$ under hard braking; **Section C.1.1** derives the warning window from standard stopping-distance kinematics and reviews the literature basis for these parameter choices.

[31] Vehicle-to-Infrastructure (V2I-4) Consortium (CAMP). (2021). Red Light Violation Warning (RLVW) Application Vehicle System: Concept of Operations, Version 2.4. CAMP LLC. Available [online]: https://www.campllc.org/wp-content/uploads/sites/2896/2021/02/RLVW_ConOps_Ver_2_4_20200222.pdf?nocdn

For vehicles approaching within the 35-50 mph range typical of this study's signalized intersections, the useful warning window ranges from approximately 5.6 seconds (35 mph) down to 3.1 seconds (50 mph) under nominal braking and remains above 5 seconds under hard braking across this range (**Table 7.7, C.1.1**). This range motivates three discrete modeling scenarios: high availability (warning windows greater than 5 seconds), low availability (between 3 and 5 seconds), and no availability (less than 3 seconds, which is treated as no warning transmitted, or transmitted too late for the driver to act on). Driver compliance also depends on where the warning falls relative to the Type II dilemma zone, the roughly 2-5.5 second window before the stop line within which drivers are ambivalent about stopping versus proceeding through the intersection; warnings delivered within this zone show measurably lower compliance.

3.1.2.3. Level 4 Failure Behavior

The L4 ADS failure model follows the same structure as the L0 driver model: whether the vehicle fails to stop before the intersection decomposes into a message-reception failure branch and an OEDR (perception/planning/execution)-level failure branch. For ADS, the OEDR branch captures perception-based failures and software integration failures. Representative incident statistics at the same level of specificity as driver behavior models are not available in the literature as standardized ADS incident data is limited, and traffic-signal misinterpretation specifically is not broken out from broader disengagement categories in the data that does exist (**Section C.1.2** reviews the available evidence, including California DMV disengagement records).

For this model, the dominant ADS failure mode is assumed to be perception-based, stemming from camera-based misclassification or missed detection of traffic signal state. Camera-based computer vision remains the primary channel for signal-state classification in currently deployed ADS vehicles even with multi-sensor fusion, as LiDAR does not contribute to traffic signal detection. Drawing on computer-vision benchmarks for traffic light detection (reviewed in **Section C.1.2**), a mature L4 system operating within its designed operational design domain (ODD) is assumed to have a per-encounter perception error probability of 0.1-1% under normal conditions, rising to 2-10% or higher in adverse conditions or at the edges of the ODD.

Beyond perception, two V2X-related failure modes are relevant: the warning message is received but not acted upon by the ADS decision layer, or in the case of a traffic-signal misclassification, received too late for a physically feasible braking response. The same early/late/no-warning ESD branching used for L0 applies to L4, with the same physics-based stopping model. The key difference is reaction time: end-to-end system reaction time for an L4 ADS is approximately 50-100ms from V2X message reception to brake

actuation, compared to 1.25 s for an L0 driver under unexpected braking conditions[32]. At 50 km/h under 0.4g deceleration, this reduces total stopping time from approximately 4.8 s (L0) to approximately 3.7 s (L4) when the vehicle has not independently detected the signal change or potential conflict. At typical urban approach speeds, both the high- and low-availability warning windows provide sufficient time for the ADS to initiate braking actions before onboard sensors alone would detect the signal change under nominal conditions[33],[34]. The reduction in reaction times and deceleration profiles is considered to estimate effective stopping distances compared to the L0 baseline. Additional details are described in **Section C.1.6.1 (Crash Exposure Model)**.

3.1.2.4. Level 2 Failure Behavior

The L2 failure model combines the L0 and L4 models. It is assumed that the host vehicle's baseline red-light running probability (no warning, or warning not received) depends only on the human driver and matches the L0 baseline. When the RLVW warning is received, compliance remains a driver decision: the driver may ignore the warning, with the same timing- and dilemma-zone-dependent compliance used in the L0 model. However, either the driver or the L2 system can initiate braking once a warning has been received. A failure to stop requires both response paths to fail. The driver path uses the L0 perception-reaction time and deceleration parameters. The L2 path uses the L4 end-to-end reaction time (approximately 50–100 ms from message reception to brake actuation). Both paths are applied to the same early/late/no-warning ESD branching and physics-based stopping model. The same structure applies to encountering vehicles: the driver may disregard the warning, but either the driver or the L2 system can respond to it.

The L2 sub-scenario also adds a recovery path that is not modeled in the L0 or L4 cases. Forward collision warning and automatic emergency braking (AEB) bound the plausible benefit of well-timed warnings, with documented rear-end crash-rate reductions on the order of 25–50% depending on system configuration[35]. If the host or encountering vehicle fails to stop, under warned or unwarned conditions, the host vehicle's automatic emergency braking (AEB) acts as a final safety barrier that does not depend on V2X messages. AEB is modeled as a sequential recovery event that follows the driver and L2

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[32] "5G; Service requirements for enhanced V2X scenarios," ETSI TS 122 186, v 18.0.1, May 2024, Available [online] at: https://www.etsi.org/deliver/etsi_ts/122100_122199/122186/18.00.01_60/ts_122186v180001p.pdf

[33] A. Aniculaesei and Y. Elhajji, "Runtime Monitoring Approach to Safeguard Behavior of Autonomous Vehicles at Traffic Lights," Electronics, vol. 14, no. 12, p. 2366, June 2025, doi: 10.3390/electronics14122366.

[34] Z. Dai, A. Wolf, P. P. Ley, T. Glück, M. C. Sundermeier, and R. Lachmayer, "Requirements for Automotive LiDAR Systems," Sensors, vol. 22, no. 19, p. 7532, Oct. 2022, doi: 10.3390/s22197532.

[35] Partnership for Analytics Research in Traffic Safety (PARTS), "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

failure rather than replacing it. Its success probability is conditioned on light condition, vehicle-side line of sight (LOS/NLOS), and weather[36]. Additional details are described in **Section C.1.6.1 (Crash Exposure Model)**.

3.2. Scenario B: PED-CP

3.2.1. Scenario Summary

In this scenario, we have modeled vehicle-pedestrian conflicts at intersection and midblock crossings, including cases with several vehicles approaching the same crossing at the same time. In this case, we assume that the infrastructure is equipped with a communication device (RSU), a sensor system (camera and/or LiDAR), and an edge device capable of generating sensor data sharing messages (SDSM), as defined by SAE J3224 Sensor Data Sharing Message (SDSM)[37].

These messages include detected object lists and do not constitute a warning on their own: it requires an onboard vehicle system to interpret the information and determine whether to warn the driver (L0) or act in response to it (L2, L4). When pedestrians are detected, the RSU broadcasts SDSMs to oncoming vehicles, prompting the onboard systems from all vehicles to determine if the warning should be communicated to the driver (L0). As in RLVW, this application can warn multiple vehicles simultaneously.

Differences across automation levels: At L0, the warning response depends on the driver. Factors such as timing, warning compliance, and braking feasibility have been incorporated into the driver's response. At L2, we have assumed the automation and/or the driver can intervene based on the warning and the response's baseline is grounded on reported PAEB performance (pedestrian-conflict specific automated emergency braking), which acts as a backup system, independent of the warning. At L4, we have assumed that the automation directly acts in response to the warning. When automation is engaged (L2, L4), timing and braking feasibility have been considered. Factors affecting all automation levels and connectivity performance include weather, light conditions, road/intersection type, and line-of-sight effects.

[36] Partnership for Analytics Research in Traffic Safety (PARTS), "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

[37] SAE International Technical Standard, V2X Sensor-Sharing for Cooperative and Automated Driving, SAE Standard J3224_202208, Issued August 2022, https://doi.org/10.4271/J3224_202208.

3.2.2. Modeling Overview

Vehicle conflicts with vulnerable road users (VRUs), including pedestrians and cyclists, represent a significant and disproportionately high severity share of traffic injuries and fatalities, and have shown an increasing trend over the past decade. In 2024, pedestrian deaths accounted for 18% of all traffic fatalities, while pedestrians made up only 3% of all people injured in traffic crashes[38]. Pedestrian fatalities in the United States increased by 59% between 2009 and 2020, outpacing the 4% increase in vehicle occupant fatalities over the same period[39], and rising from 15% to 18% of all traffic fatalities in the period 2015-2024.

Conditions that degrade both driver perception and pedestrian behavior predictability are factors frequently reported to contribute to pedestrian crash risk, including occlusions from parked vehicles, adverse lighting, and complex geometric configurations at and between intersections[40,41]. In 2024, more than three-quarters of pedestrian fatalities (76%) occurred in dark conditions and 84% occurred in urban areas. Regarding location, 73% occurred at non-intersection locations, while 18% occurred at intersections, suggesting that conditions at midblock crossings lead to higher crash risk exposure.

Advanced driver assistance systems (ADAS) have targeted vehicle-side risk factors through technologies such as forward collision warning (FCW) and automated emergency braking (AEB), with effectiveness that varies substantially by operating conditions[42]. Specifically, pedestrian automatic emergency braking (PAEB), as a concrete example, has demonstrated meaningful effectiveness in reducing pedestrian crash involvement, with estimated reductions on the order of 25–27% under daytime conditions in real-world studies[43]. However, PAEB performance degrades substantially in nighttime, low-contrast

[38] National Highway Traffic Safety Administration, "2024 Pedestrians Traffic Safety Facts," U.S. Department of Transportation, Washington, DC, Rep. DOT HS 813 818, 2026. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813818

[39] A. Mallory, R. Ramachandra, A. Valek, B. Suntay, and J. Stammen, “Pedestrian injuries in the United States: Shifting injury patterns with the introduction of pedestrian protection into the passenger vehicle fleet,” Traffic Injury Prevention, vol. 25, no. 3, pp. 463–471, Jan. 2024, doi: 10.1080/15389588.2023.2281271.

[40] A. Karami, H. Karami, A. R. Mamdoohi, and M. Allahviranloo, “Pedestrian safety at urban intersections: lighting conditions is the question,” International Journal of Crashworthiness, vol. 28, no. 6, pp. 750–759, Oct. 2022, doi: 10.1080/13588265.2022.2130598.

[41] K. Kavee, K. A. Flanigan, and S. L. Quick, “Human-centered simulation of intersection lighting: a parametric study of design tradeoffs,” Internet of Things, vol. 37, p. 101936, Apr. 2026, doi: 10.1016/j.iot.2026.101936.

[42] Partnership for Analytics Research in Traffic Safety, "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

[43] J. B. Cicchino, “Effects of automatic emergency braking systems on pedestrian crash risk,” Accident Analysis & Prevention, vol. 172, p. 106686, July 2022, doi: 10.1016/j.aap.2022.106686.

backgrounds, and scenarios where a pedestrian enters the vehicle's path at short range. Higher levels of driving automation (L4) offer the potential for more substantial reductions through shorter reaction times and more consistent and robust perception systems[44]. However, fundamental limitations remain for vehicle-mounted sensors regarding occlusion effects[45]. These constraints will persist as a central concern in mixed traffic environments, where human drivers and vehicles equipped with ADAS/ADS vehicles interact with pedestrians under imperfect geometric and lighting conditions.

Infrastructure-side sensor systems, while also subject to similar weather and lighting conditions, offer a complementary detection geometry to vehicle-mounted systems that can contribute further to crash reduction. Scenario B involves infrastructure sensor systems equipped with communication devices to broadcast SDSMs to approaching vehicles with information about pedestrians in intersections and midblock crossings. An overview of the scenario is presented for intersections pedestrian crossings in **Figure 3.2**.

This assumes that equipped RSUs are installed at the intersections, with coverage extending to adjacent midblock crossings. This case involves both sensing and communication elements from infrastructure and assumes that connected vehicles can process SDSM to inform their downstream processing, either to generate in-vehicle alerts for drivers (L0, L2) or provide additional information for automated responses (L4).

Current CP-type deployments remain limited, and the underlying technology is still evolving. The Utah Department of Transportation (UDOT) has deployed LiDAR-based sensing for intersection safety, using the technology to detect and track pedestrians, vehicles, and other road users at signalized intersections[46,47]. Ohio has piloted camera-based pedestrian detection using thermal cameras, predating the introduction of SDSM as a standardized message set[48]. The University of Michigan's Mcity test facility has

[44] K. D. Kusano, J. M. Scanlon, Y.-H. Chen, T. L. McMurry, T. Gode, and T. Victor, “Comparison of Waymo Rider-Only crash rates by crash type to human benchmarks at 56.7 million miles,” Traffic Injury Prevention, pp. 1–13, May 2025, doi: 10.1080/15389588.2025.2499887.

[45] H. Zhu, M. Iryo-Asano, W. K. M. Alhajyaseen, H. Nakamura, and C. Dias, “Interactions between autonomous vehicles and pedestrians at unsignalized mid-block crosswalks considering occlusions by opposing vehicles,” Accident Analysis & Prevention, vol. 163, p. 106468, Dec. 2021, doi: 10.1016/j.aap.2021.106468.

[46] Li, Taylor et al. (2023). New LiDAR System Pinpoints Pedestrian Behavior to Improve Efficiency and Safety at Intersections. Available [online]: https://rosap.ntl.bts.gov/view/dot/68473

[47] Saldivar-Carranza, E. D., Desai, J., Thompson, A., Taylor, M., Sturdevant, J., & Bullock, D. M. (2024). Vehicle and Pedestrian Traffic Signal Performance Measures Using LiDAR-Derived Trajectory Data. Sensors, 24(19), 6410. https://doi.org/10.3390/s24196410

[48] U.S. Department of Transportation (USDOT) Intelligent Transportation Systems Joint Program Office (ITS JPO). U.S. 33 Smart Mobility Corridor Program Final Report (Reference ID: 2024-L01243). Available [online]: https://www.itskrs.its.dot.gov/2024-l01243

explored combined camera-and-LiDAR sensor configurations for pedestrian detection[49]. These deployments illustrate the range of sensor modalities under consideration for infrastructure-based pedestrian detection, though none yet operate at the scale or with the standardized SDSM messaging assumed in this scenario.

Scenario logic has some analogies to RLVW, and this model will reuse structures and values unless explicitly stated. Driver stopping logic is different, based on warnings generated from received SDSMs, implying that CVs are equipped to process incoming messages and trigger respective warnings. The specific warning modality, frequency, and urgency escalation mechanisms are assumed to differ across OEMs, literature on audible crash warnings are used to anchor the analysis as technology is not mature.

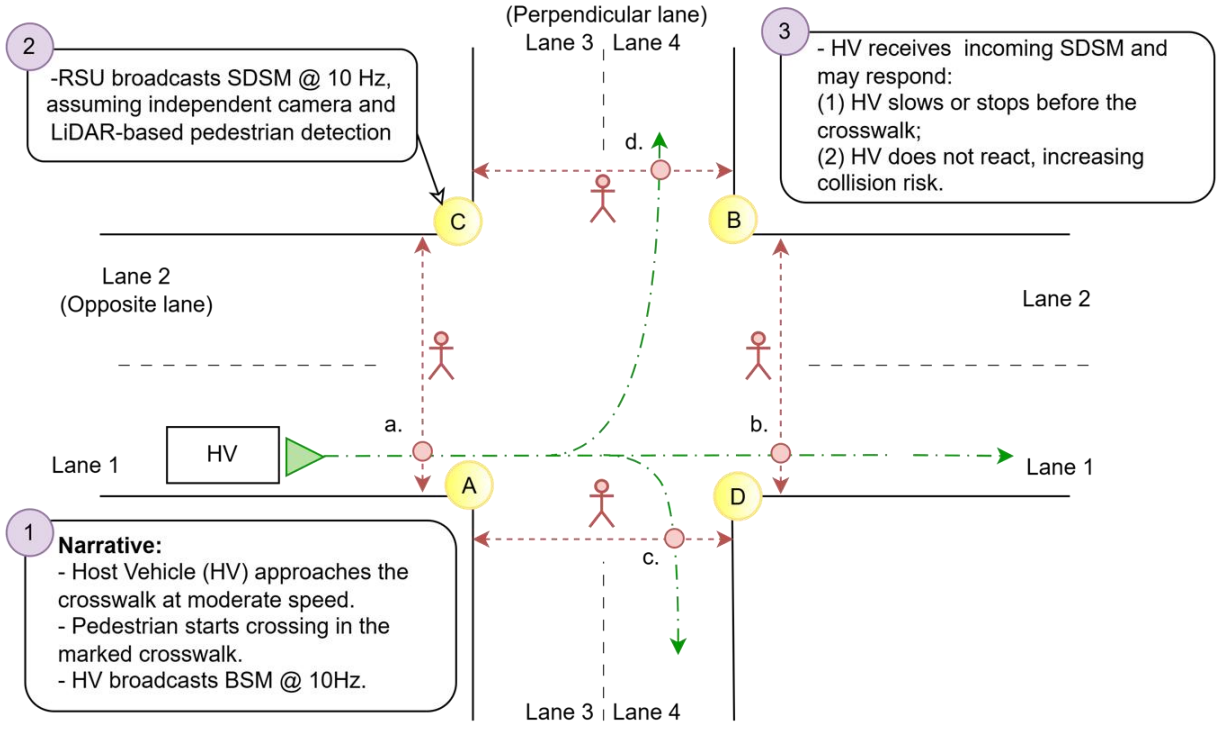


Figure 3.2: Pedestrian Collision Warning Scenario Narrative.

3.2.2.1. V2X Failure Behavior

In this scenario, the V2X failure behavior stems from two pathways. The first is data-related: SDSM generation begins with the infrastructure sensor systems detecting a pedestrian. Independent camera and LiDAR detection streams are considered, such that

[49] University of Michigan Transportation Research Institute (UMTRI). Connected/Automated Vehicle and Infrastructure Research. Report No. SPR-1695. Available [online]: https://www.michigan.gov/MDOT/-/media/Project/Websites/MDOT/Programs/Research-Administration/Final-Reports/SPR-1695-Report.pdf

a pedestrian is considered detected if either modality registers it. This mainly refers to the perception errors (detection, localization, tracking) that involve detecting a pedestrian. Factors that impeded or degrade camera and/or LiDAR perception, including occlusion from queued vehicles, buses, or other infrastructure elements, is the dominant source of missed detections for both sensor types, and its effect is treated as correlated between the two modalities through shared weather and line-of-sight parent nodes **(Section C.2.6.1, Sensor-System Failures)**.

The second failure pathway is related to V2X communication. Once a pedestrian is detected, the RSU must still assemble a valid SDSM and transmit it to the host vehicle; failures at this stage stem from onboard processing errors and roadside-to-vehicle connectivity or device-reliability issues. These infrastructure-side failure modes are detailed in **Section C.2.5.1 (Infrastructure-sensing and communication-related failure modes**) and in **Section C.2.6.2 (V2X Communication Model)**.

Intersection and midblock crossings share the same driver and vehicle failure logic downstream but differ in exposure: occlusion levels and detection/communication geometry vary by location type, which shifts the infrastructure sensor system's effective detection performance without changing how the driver or vehicle responds once a warning is generated.

3.2.2.2. Driver Failure Behavior

Driver-warning and collision-avoidance literature is used as the main anchor to frame the driver failure model in Scenario B, since the underlying reliability of pedestrian detection is addressed separately in the sensor-effectiveness nodes in **Section C.2.6.1 (Sensor-System Failures)**. This section focuses on the impact of the timing of the resulting driver-facing alert. As SDSM messages are broadcast continuously at 10 Hz, alert timing is not governed by message reception, as it is in RLVW, but by the OEM's onboard HMI logic. The scope here is limited to time-constrained conflict-avoidance warnings, with representative horizons of 3-7s prior to potential conflicts, as distinct from other SDSM use cases (e.g., advance advisories for work zones, lane closures, or incidents) that operate on longer timescales.

Driver warnings in current ADAS systems use different modalities, employing visual (e.g., dashboards alerts), audible (alarms), and/or tactile (e.g., steering wheel, seat belt or seat vibrations) cues, aimed at providing timely information about the driving environment. The design, calibration, and effectiveness of driver warnings (related to FCW or other alerts) have been extensively studied, as well as the impact on driver behavior beyond crash

scenarios[50,51,52]. Collision-warning research broadly converges on a time-to-collision (TTC) threshold near 5 seconds across forward, lateral, and rear-end conflicts, while pedestrian-specific driving-simulator studies converge on 4s as the minimum lead time producing a measurable protective effect. On this basis, as in RLVW, the model adopts 4s/6.5s as the representative low-time/high-time warning scenarios. Supporting studies are described in **Section C.2.1.**

3.2.2.3. Level 4 Failure Behavior

The L4 ADS failure model follows a similar structure to the L0/L2 driver models. Whether the vehicle fails to avoid a crash with a pedestrian, either at an intersection or a midblock crossing, decomposes into message-reception failure and OEDR-level failure branches. As in RLVW, OEDR-level failures encompass perception, planning, and execution failure modes; for this model, the dominant failure mode is assumed to be perception-based, stemming from pedestrian misclassification or missed detection rather than planning or control errors.

Unlike RLVW, where ADS perception performance is anchored to third-party traffic-signal-detection benchmarks, Scenario B parameterizes ADS pedestrian detection directly from independent, per-modality camera and LiDAR detection probabilities (**Table 7.33-Table 7.34**), following the same conservative independent-sensor-fusion logic used for the infrastructure RSU node (**Table 7.29**): a pedestrian is considered detected if either the camera or the LiDAR registers it. Detection performance for both modalities is conditioned on weather, light condition, and vehicle-side line-of-sight (occlusion), following the same general treatment as the infrastructure-mounted sensors. However, vehicle-mounted sensors are parameterized from a separate literature base given differing sensor height, viewing geometry, and range (**Section C.2.6.1, Crash Exposure Model**).

As with RLVW, ADS reaction time following a successful detection or a received SDSM is modeled as $t_r \sim N(0.10, 0.02^2)$ s, reflecting end-to-end ADS latency from perception or message receipt through brake actuation. The reduction in reaction time relative to an L0 driver (1.00–1.25 s) is the primary mechanism by which the L4 stopping-feasibility branch

[50] A. S. Mueller, J. B. Cicchino, J. Singer, and J. W. Jenness, “Effects of training and display content on Level 2 driving automation interface usability,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 69, pp. 61–71, Jan. 2020, doi: 10.1016/j.trf.2019.12.010.

[51] L. Yue, M. Abdel-Aty, Y. Wu, J. Ugan, and C. Yuan, “Effects of forward collision warning technology in different pre-crash scenarios,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 76, pp. 336–352, Jan. 2021, doi: 10.1016/j.trf.2020.12.004.

[52] M. Zhu, X. Wang, and J. Hu, “Impact on car following behavior of a forward collision warning system with headway monitoring,” Transportation Research Part C: Emerging Technologies, vol. 111, pp. 226–244, Jan. 2020, doi: 10.1016/j.trc.2019.12.015.

differs from the L0/L2 branches; full parameterization of stopping probability under warned and unwarned conditions is described in **Section C.2.6.1.**

3.2.2.4. Level 2 Failure Behavior

The L2 failure model combines the L0 driver model and the L4 ADS model. Unlike RLVW, where the host vehicle's baseline depends only on the human driver, in Scenario B the L2 system's onboard sensors can detect the pedestrian independently of the SDSM. A pedestrian is considered detected if either the driver or the L2 system registers it. L2 detection is parameterized from the L4 vehicle-mounted camera detection probabilities only (**Table 7.33**), conditioned on weather, light condition, and vehicle-side line of sight. When the SDSM-based warning is received, braking can therefore be initiated by either the driver or the L2 system, and a failure to avoid the conflict requires both response paths to fail. The driver path uses the L0 perception-reaction time and the 4 s/6.5 s low-time/high-time warning scenarios, while the L2 path reuses the L4 braking model. Both paths are applied to the same warned/unwarned stopping-feasibility branches described in **Section C.2.6.1**.

If both response paths fail, PAEB acts as the final, message-independent barrier. In this model, PAEB acts as a safety-net against a driver's late or missed reaction to a warning, rather than as a channel through which the SDSM message itself reaches the vehicle's automated braking response. The pedestrian-specific effectiveness of PAEB under warned conditions is further addressed in **Section C.2.6.1 (Crash Exposure Model)**.

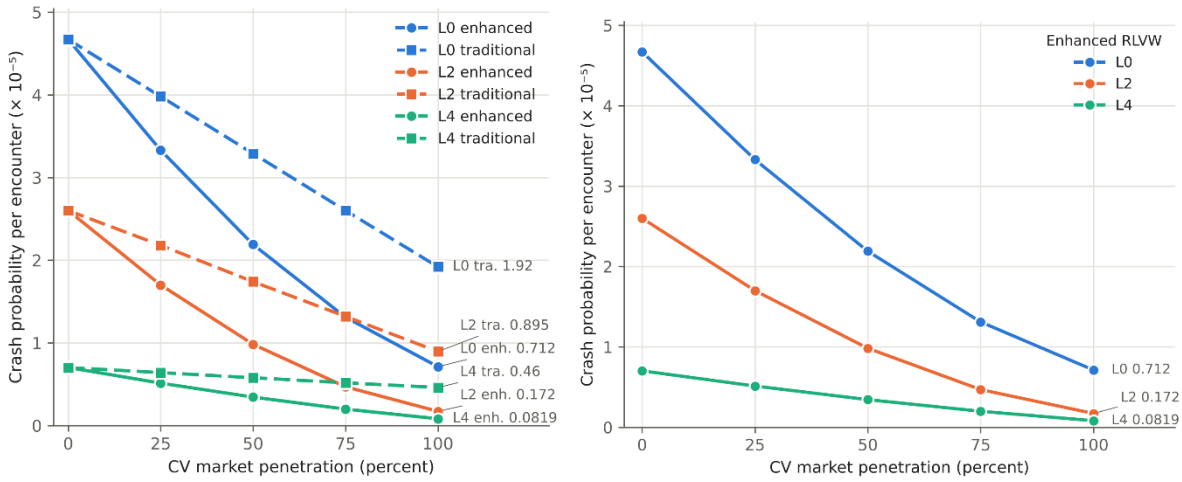
4. Results and Analysis

4.1. Safety and Economic Benefits

4.1.1. Scenario A: Red Light Violation Warning (RLVW)

4.1.1.1. RLVW collision probability reduction per-encounter (CV% Lever)

Figure 4.1-Figure 4.3 give the per-encounter probability of a crash-producing red-light-running conflict, averaged over all conditioning factors (weather, light condition, speeding, intersection type), as a function of connected vehicle market penetration (CV%). Figure 4.1 shows the crash probability, Figure 4.2 shows the reduction relative to CV=0% in relative and absolute terms, and Figure 4.3 shows the reduction added by each 25-point increase in CV% (incremental reduction), in percentage points of the CV=0% probability. The corresponding values are listed in Table 4.1-Table 4.3.



(a) Traditional vs enhanced RLVW *(b) Enhanced RLVW*

Figure 4.1: Per-encounter crash probability by CV market penetration for enhanced and traditional RLVW (Scenario A).

At CV = 0%, values represent the no-V2X baseline in which the encounter reduces to the base red-light running, insufficient stopping feasibility, and the crash-exposure conditional probabilities. Two implementations are explored: enhanced RLVW, accounting for RSU- and OBU-generated warnings targeting both the host vehicle (HV) and all encountering vehicles (EV) at the intersection, and traditional RLVW, with only OBU-generated warnings targeting the host vehicle (HV). On a per-encounter basis, CV market

penetration is the probability that a vehicle approaching the intersection is equipped to receive RLVW. In L0, the warning acts on the driver only. In L2, either the driver or the partial automation can respond to the RLVW warning, and the base AEB functionality is also included. In L4, the ADS receives and acts on the warning.

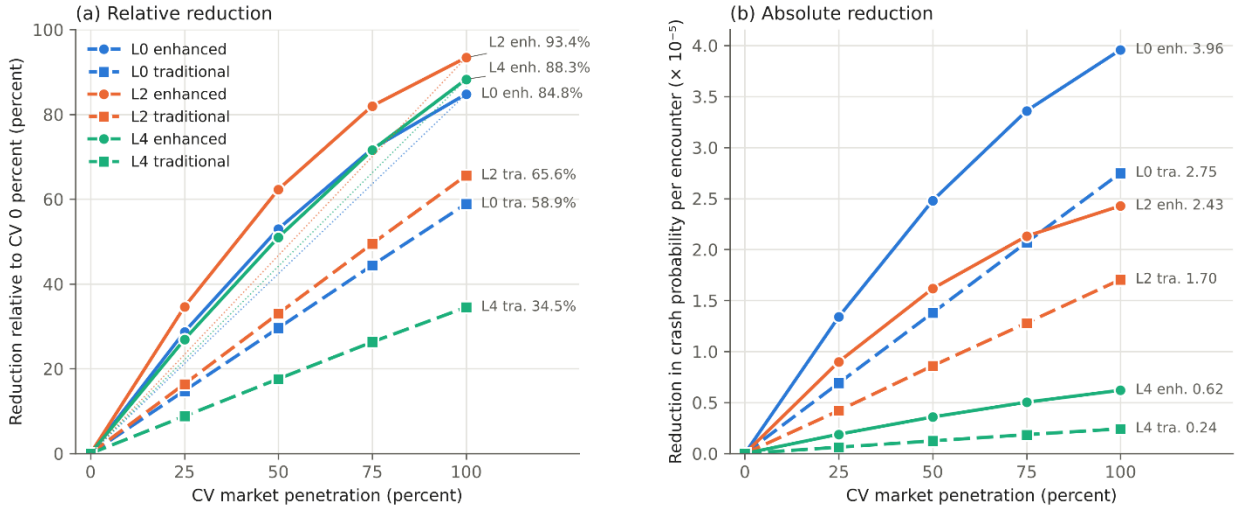


Figure 4.2: Reduction in per-encounter crash probability by CV market penetration for enhanced and traditional RLVW (Scenario A): (a) relative reduction, with proportional reference lines; (b) absolute reduction.

Figure 4.1 shows two effects: the impact of automation (L0/L2/L4 baselines) and the impact of enhanced RLVW compared to traditional RLVW. Automation lowers the no-V2X baseline crash rate by approximately 44% (L2) and 85% (L4). These baselines are model assumptions based on reported AEB performance (L2) and reported intersection-crash reductions for L4 vehicles. Within each level, enhanced RLVW lowers the crash probability faster than traditional RLVW.

For L0, enhanced RLVW reduces the per-encounter crash probability monotonically with CV penetration (Figure 4.2, Table 4.2). The incremental reduction is largest at low penetration, with CV 25% delivering about one third of the full-penetration reduction (Figure 4.3, Table 4.3). This non-linearity comes from notifying multiple vehicles about the same red-light runner: a conflict can be mitigated if either the host vehicle or any encountering vehicle is warned and responds, so the probability that at least one vehicle in the conflict is warned rises faster than CV% itself. The residual risk at full connectivity reflects line-of-sight effects, driver non-compliance with a received warning, and stopping-feasibility failures under adverse weather and high approach speed.

Traditional RLVW, which warns only the host vehicle, has no multi-vehicle effect, and its reduction is approximately proportional to CV%. Enhanced RLVW therefore outperforms

traditional RLVW at every penetration level, with the largest relative advantage at low CV (about twice the traditional reduction at CV 25%). The corresponding crash modification factors are listed in Table 4.4.

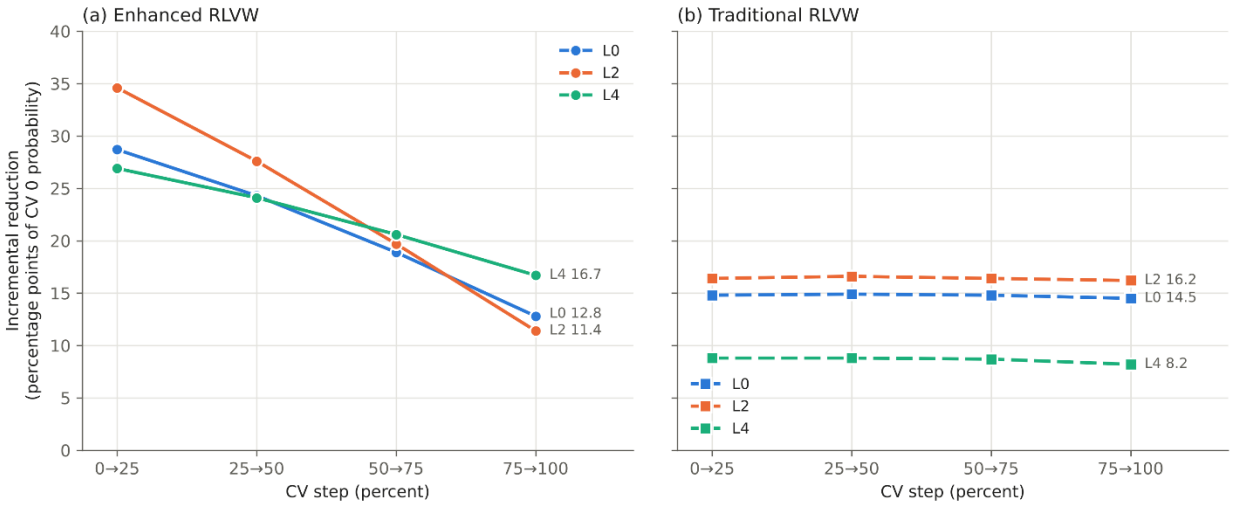


Figure 4.3: Incremental reduction in per-encounter crash probability (reduction added by each 25-point increase in CV penetration) for enhanced and traditional RLVW, by automation level (Scenario A).

For L2, the lower baseline reflects the additional response path provided by the partial automation and the AEB function. With V2X, L2 achieves the largest relative reduction of the three levels at every CV level, because a warned conflict becomes a crash only if both the driver and the partial automation fail to respond, and AEB remains a message-independent crash avoidance mechanism. The incremental reduction shows the same multi-vehicle non-linearity as L0, and the advantage of enhanced over traditional RLVW is larger than at L0 (about 2.1 times at CV25%). In CMF terms, traditional versus enhanced RLVW is 0.84 vs. 0.65 at CV 25% and 0.34 vs. 0.07 at CV 100%.

For L4, the lower baseline follows from the residual crash rates reported for vehicle-to-vehicle intersection crashes. For an ADS-equipped host vehicle, the unwarned failure is dominated by camera-based signal misclassification, while for encountering vehicles the main failure mode is detecting and reacting to a red-light runner. The response to CV penetration is closer to proportional than at L0/L2, and the residual risk is dominated by communication and device failures rather than the stopping maneuver. The gap between enhanced and traditional RLVW is largest at L4: At CV25, the enhanced reduction is 3.1 times the traditional reduction. In CMF terms, traditional versus enhanced RLVW is 0.91 vs. 0.73 at CV 25% and 0.66 vs. 0.12 at CV 100%.

Comparing across automation levels: In relative terms (Figure 4.2a), at low CV penetration rates for the sample test area, the biggest crash reduction is achieved at L2 (CV25=34.6%), followed by L0 (CV25=28.7%) and L4 (CV25=26.9%). At high CV penetration rates, L2 exhibits the biggest relative crash reduction (CV100%=93.4%), followed by L4 (CV100=88.3%) and L0 (CV100=84.8%). In absolute benefit terms, more safety gains are expected from increasing CV% for L0, followed by L2, and L4 (reflecting the staggered baseline expected crashes). The multi-vehicle non-linearity of enhanced RLVW is present at all three levels (Figure 4.3): CV 25% delivers 34% (L0), 37% (L2), and 30% (L4) of the full-penetration reduction, compared with traditional RLVW, whose incremental reduction is constant. The gap between traditional and enhanced RLVW is largest at L4 (CMF 0.66 vs. 0.12 at CV 100%). Each CMF is relative to its own level's no-V2X baseline, so a lower CMF indicates a larger relative effect.

Table 4.1: Average per-encounter crash probabilities by connected vehicle deployment rate for Scenario A.

Connected Vehicle %	L0-RLVW		L2-RLVW		L4-RLVW	
	Enhanced	Traditional	Enhanced	Traditional	Enhanced	Traditional
CV:0%	4.67E-05	4.67E-05	2.60E-05	2.60E-05	7.02E-06	7.02E-06
CV:25%	3.33E-05	3.98E-05	1.70E-05	2.18E-05	5.13E-06	6.40E-06
CV:50%	2.19E-05	3.29E-05	9.83E-06	1.74E-05	3.44E-06	5.78E-06
CV:75%	1.31E-05	2.60E-05	4.69E-06	1.32E-05	1.99E-06	5.17E-06
CV:100%	7.12E-06	1.92E-05	1.72E-06	8.95E-06	8.19E-07	4.60E-06

Table 4.2: Reduction in average per-encounter crash probability by connected vehicle deployment rate for Scenario A (RLVW).

Connected Vehicle %	L0-RLVW		L2-RLVW		L4-RLVW	
	Enhanced	Traditional	Enhanced	Traditional	Enhanced	Traditional
CV:25%	28.7%	14.8%	34.6%	16.4%	26.9%	8.8%
CV:50%	53.0%	29.6%	62.3%	33.0%	51.0%	17.6%
CV:75%	71.9%	44.4%	82.0%	49.5%	71.6%	26.3%
CV:100%	84.8%	58.9%	93.4%	65.6%	88.3%	34.5%

Table 4.3: Incremental reduction in average per-encounter crash probability by connected vehicle deployment rate for Scenario A (RLVW).

Connected Vehicle %	L0-RLVW		L2-RLVW		L4-RLVW	
	Enhanced	Traditional	Enhanced	Traditional	Enhanced	Traditional
CV:25%	28.7%	14.8%	34.6%	16.4%	26.9%	8.8%
CV:50%	24.3%	14.9%	27.6%	16.6%	24.1%	8.8%
CV:75%	18.9%	14.8%	19.7%	16.4%	20.6%	8.7%
CV:100%	12.8%	14.5%	11.4%	16.2%	16.7%	8.2%

Table 4.4: Per-encounter crash modification factor, CMF (CRF), by connected vehicle deployment rate for Scenario A (RLVW).

Connected Vehicle %	L0-RLVW		L2-RLVW		L4-RLVW	
	Enhanced	Traditional	Enhanced	Traditional	Enhanced	Traditional
CV:25%	0.71 (28.7)	0.85 (14.8)	0.65 (34.6)	0.84 (16.4)	0.73 (26.9)	0.91 (8.8)
CV:50%	0.47 (53.0)	0.70 (29.6)	0.38 (62.3)	0.67 (33.0)	0.49 (51.0)	0.82 (17.6)
CV:75%	0.28 (71.9)	0.56 (44.4)	0.18 (82.0)	0.51 (49.5)	0.28 (71.6)	0.74 (26.3)
CV:100%	0.15 (84.8)	0.41 (58.9)	0.07 (93.4)	0.34 (65.6)	0.12 (88.3)	0.66 (34.5)

4.1.1.2. RLVW Estimated Crashes and Costs Avoided (CV% and V2I% Levers)

Figure 4.4 compares L0, L2, and L4 automation levels on a common basis, using annual total Study Area crash counts[53]. The estimated baseline declines with automation: 116.57 crashes per year ($16.84M) for L0, 64.81 ($9.36M) for L2, and 17.49 ($2.53M) for L4. The starting height of each line shows the effect of automation alone, and the slope shows the effect of V2X.

Figure 4.5 shows the same results relative to each level's own no-V2X baseline. All three surfaces increase almost linearly along the V2I axis, as more locations are equipped, and at a decreasing rate along the CV axis. The L2 surface lies above the other two at every V2I/CV combination, reaching 93.4% at V2I/CV 100%. The L0 and L4 surfaces nearly coincide, differing by at most 3.6 percentage points, and reach 84.8% and 88.3% at V2I/CV 100%.

However, L0 and L4 differ mainly in the shape of the CV response: L0 gains more from the first connected vehicles, consistent with warnings reaching both the host and encountering vehicles, whereas the L4 response is closer to proportional and reaches a lower residual at full penetration. In absolute terms, L2 avoids 61–67% and L4 14–16% of the crashes avoided at L0, since their relative reductions apply to lower baselines.

Results per Automation Level

Table 4.5-Table 4.6 report the estimated crashes avoided and equivalent economic savings for the L0, L2, and L4, for the enhanced RLVW implementation, translating the area-level reductions into annual terms for the 92-intersection DTLA reference deployment. The estimated crashes and resulting costs are provided for the Equipped

[53] **Study Area**: the CV=0% crash probability is replaced with the CV=25% crash probability at the equipped road segments (e.g., 25%) and kept at the remaining segments (e.g., 75%). Crashes are summed over all segments.

Locations (dependent on V2I%)[54] and the Study Area. Note that at the equipped locations, the CMF is the same at every V2I level and equals the per-encounter CMF in Table 4.4. Detailed crash and cost results can be found in Table 7.47-Table 7.49 (Appendix D).

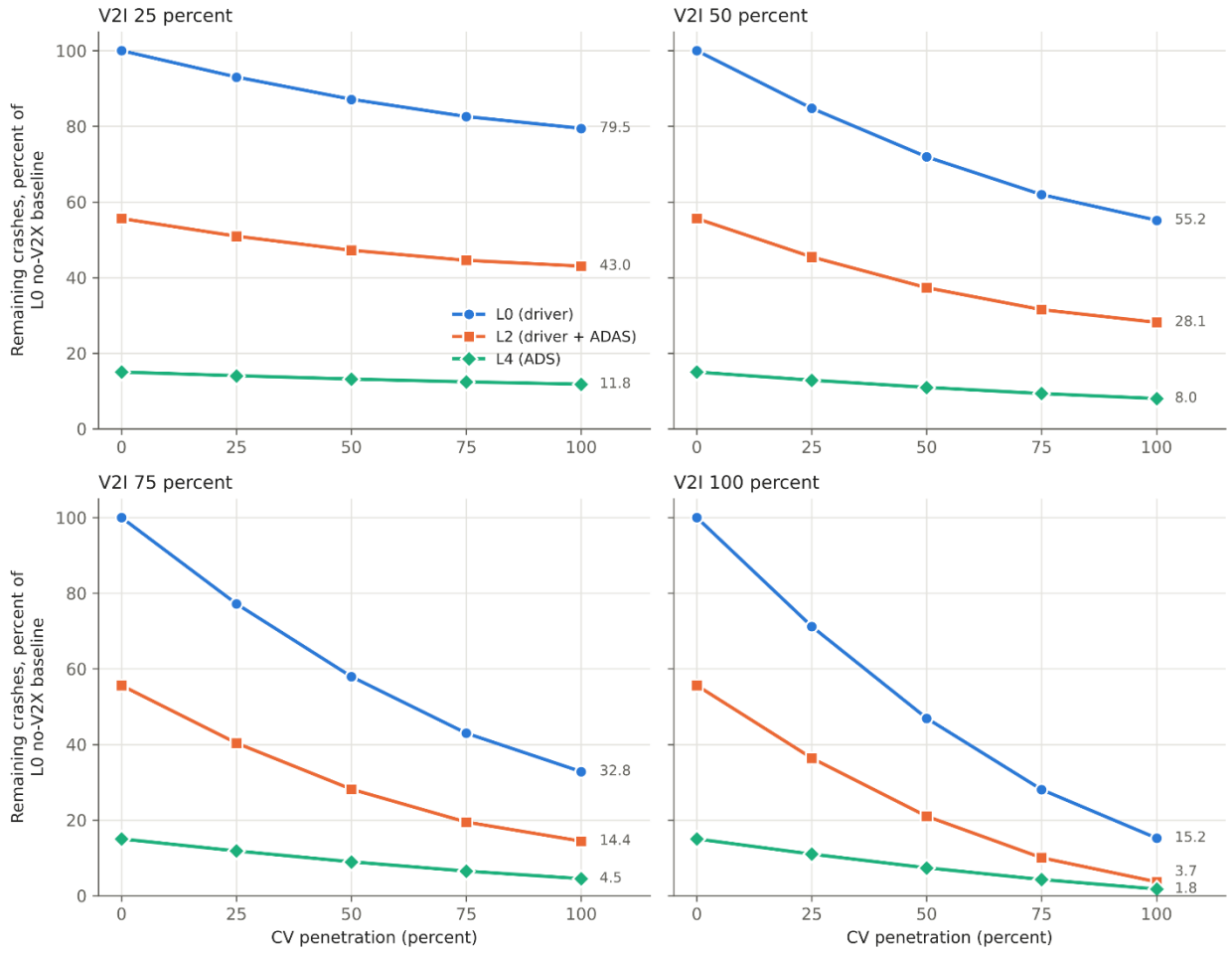


Figure 4.4: Remaining Study Area crashes as a percentage of the L0 no-V2X baseline, by CV penetration and V2I deployment, for L0, L2, and L4 (Scenario A - RLVW). At L2, ADAS functions include AEB as an additional safety mechanism.

At L0 (Figure 4.6), crashes avoided and savings increase with both levers. At the Equipped Locations, the reduction equals the per-encounter enhanced RLVW reduction at every V2I level, and the CV non-linearity carries over to the area level: at V2I 100%, the first 25-point CV step delivers about one third of the full-penetration benefit. Full deployment with full penetration yields an estimated 98.81 crashes avoided and $14.28M

[54] **Equipped Locations:** the CV=0% crash probability is replaced with the CV=25% crash probability at the equipped road segments (V2I%), and crashes are summed over those segments only.

in annual savings, declining to 8.13 crashes and $1.17M at the lowest deployment (V2I:25%/CV:25%).

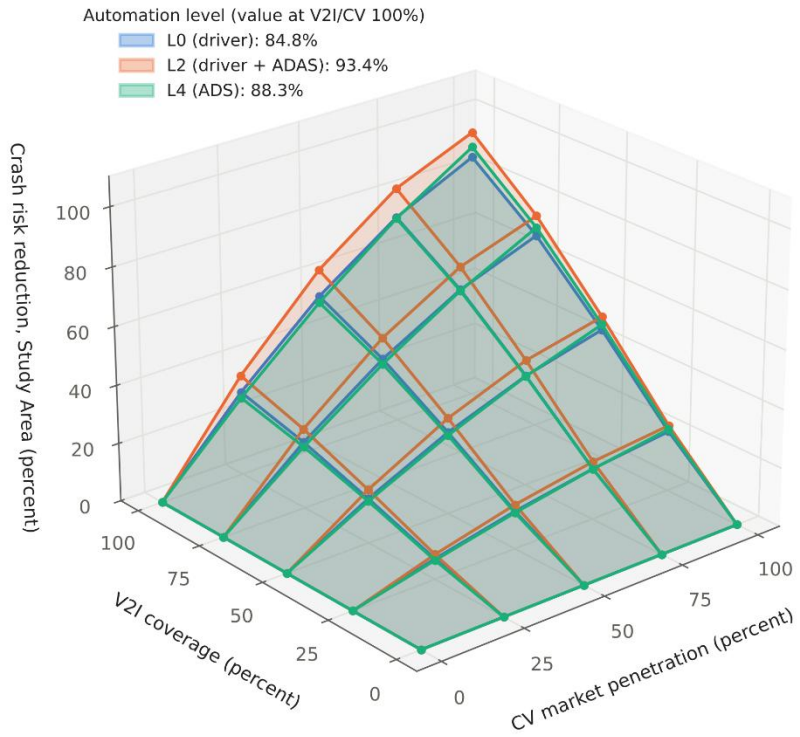


Figure 4.5: Study Area crash risk reduction (percent) by CV market penetration and V2I coverage for L0 (blue), L2 (orange), and L4 (green), Scenario A (enhanced RLVW). Legend values are the reductions at V2I/CV 100%.

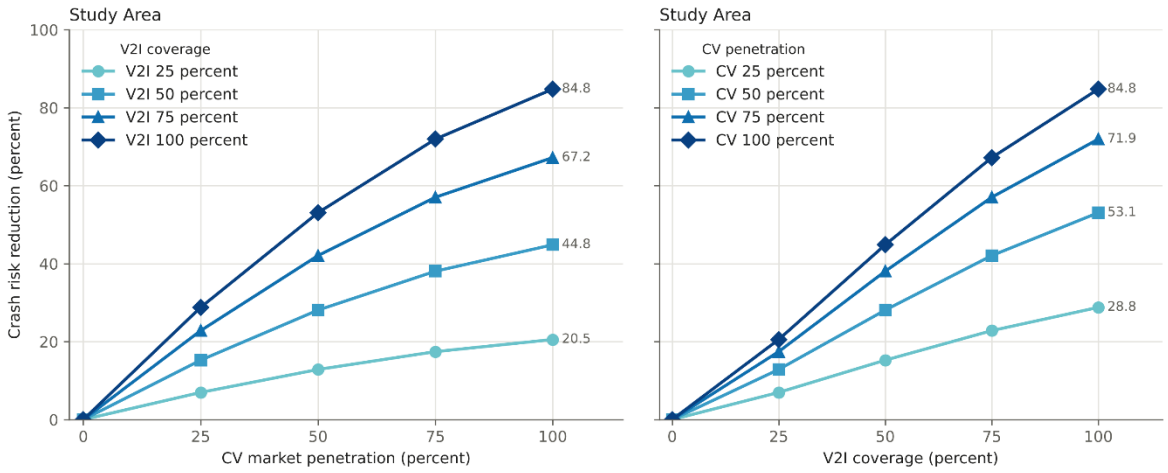


Figure 4.6: Crash risk reduction vs. CV penetration (left) and V2I deployment (right) for the Study Area, no automation (L0), enhanced RLVW.

Figure 4.7 combines both levers for the Study Area. V2I% determines how many intersections receive the benefit and CV% how large the benefit is at each one; the V2I steps follow the share of baseline crashes at the equipped intersections, which is close to the nominal V2I%. Partial deployment caps the Study Area benefit: at V2I 25%, about three quarters of the baseline crashes occur at unequipped intersections, so even at CV 100% only about one fifth of the Study Area baseline is avoided (Table 7.47).

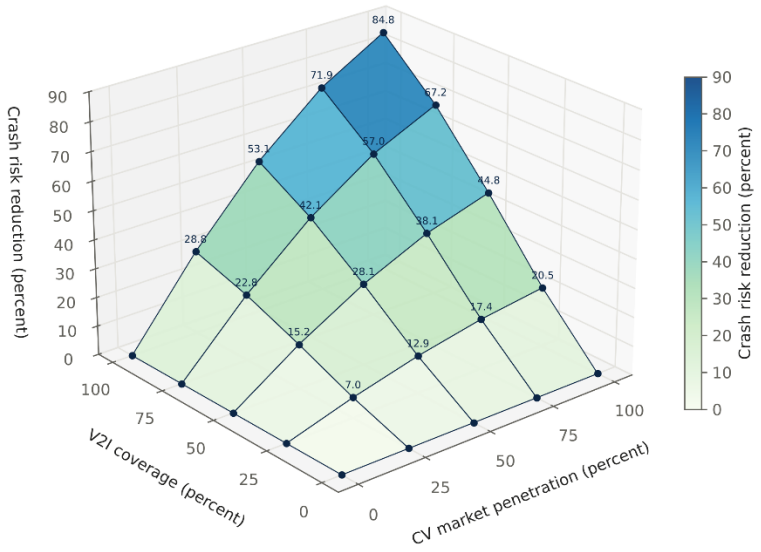


Figure 4.7: Crash risk reduction vs. CV penetration and V2I deployment for the Study Area, no automation (L0), enhanced RLVW.

For L2 (Figure 4.8–Figure 4.9), the crash risk reduction is the largest of the three automation levels at every V2I level, and the first 25-point CV step delivers slightly more than one third of the full-penetration benefit (34.6%). Because the baseline is 44% lower, the absolute benefit is 61–67% of the L0 values. Full deployment with full penetration yields 60.53 crashes avoided and $8.75M in annual savings, declining to 5.43 crashes and $0.79M at V2I:25%/CV:25%. As for L0, the Study Area benefit is capped by the share of baseline crashes at equipped intersections (Table 7.48).

For L4 (Figure 4.10–Figure 4.11), the relative benefit follows the L0 pattern for both levers. Because the baseline is small, the absolute benefit for L4 is about 14–16% of the L0 values, even though the relative benefit at CV 100% is higher for L4 than for L0. Full deployment with full penetration yields 15.44 crashes avoided and $2.23M in annual savings (compared to a baseline of 17.49 crashes and $2.53M per year (Table 7.49).

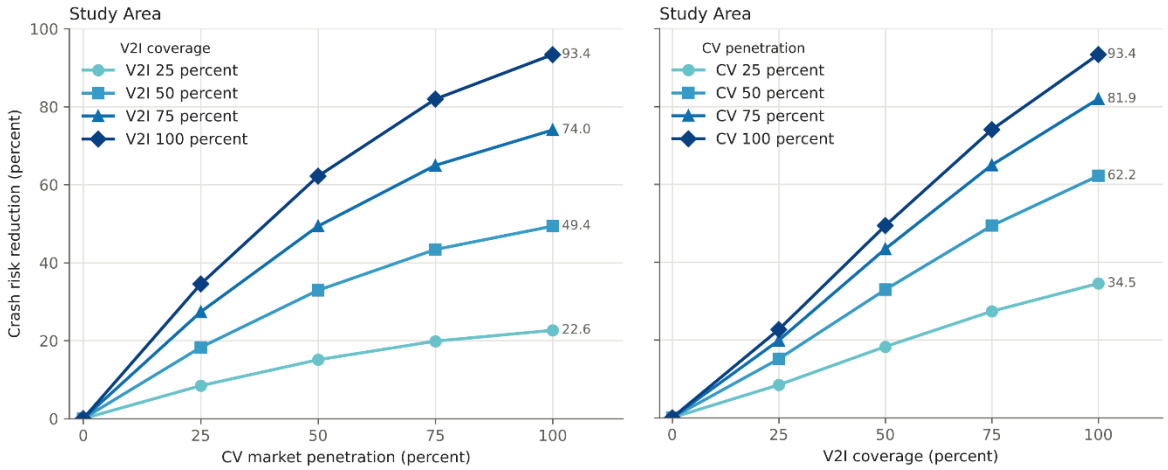


Figure 4.8: Crash risk reduction vs. CV penetration (left) and V2I deployment (right) for the Study Area, Level 2 automation (L2), enhanced RLVW.

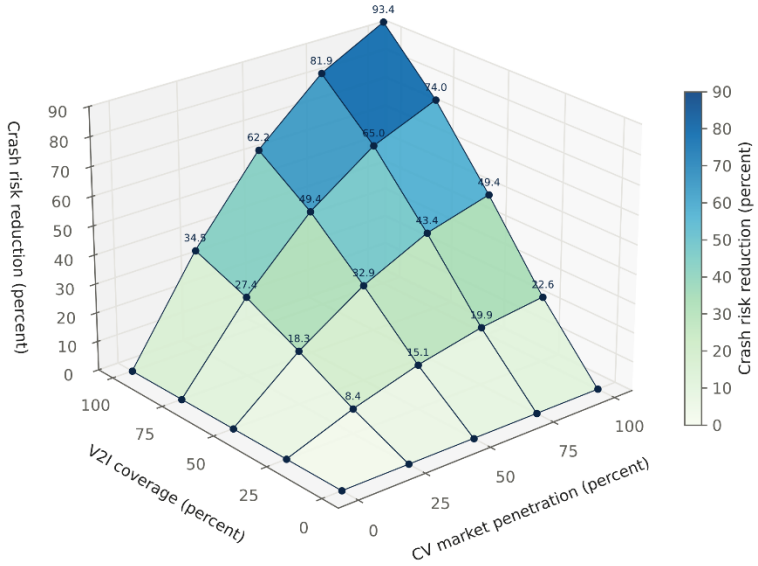


Figure 4.9: Crash risk reduction vs. CV penetration and V2I deployment for the Study Area, Level 2 automation (L2), enhanced RLVW.

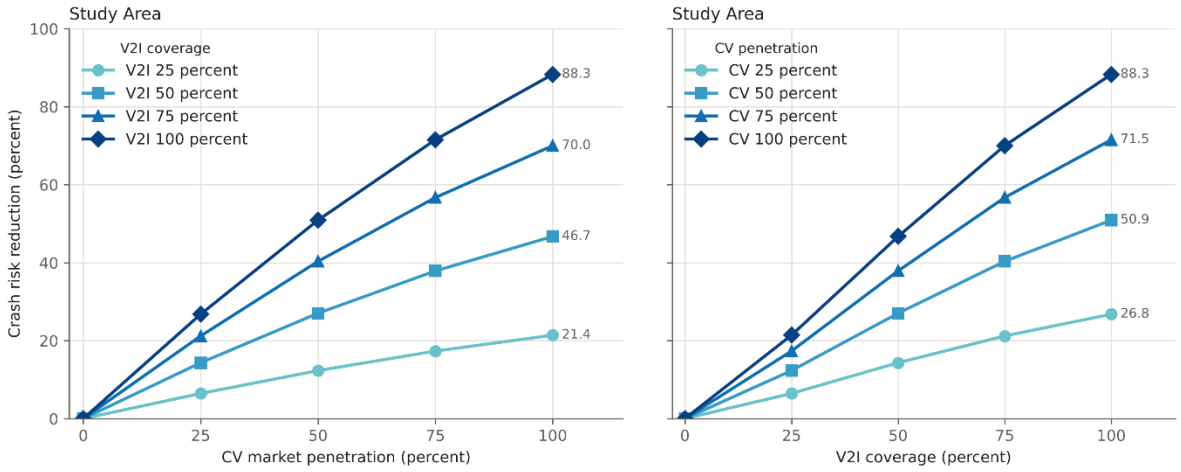


Figure 4.10: Crash risk reduction vs. CV penetration (left) and V2I deployment (right) for the Study Area, Level 4 automation (L4), enhanced RLVW.

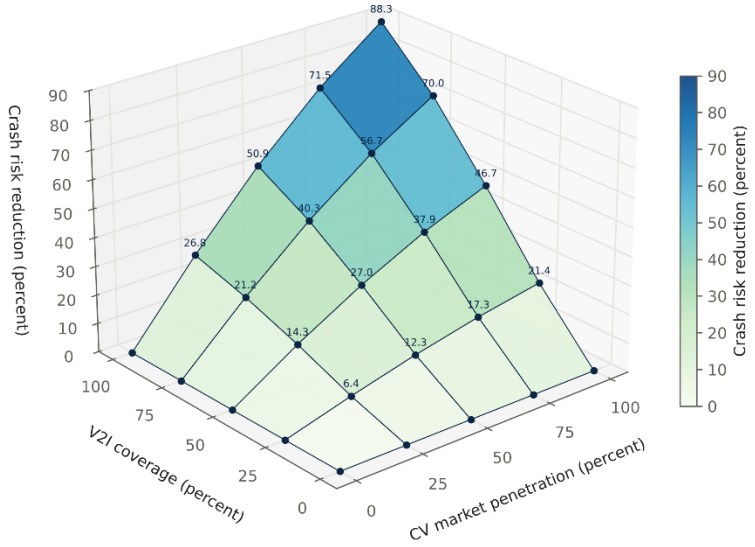


Figure 4.11: Crash risk reduction vs. CV penetration and V2I deployment for the Study Area, Level 4 automation (L4), enhanced RLVW.

Table 4.5: Crashes averted per year and study-area crash reduction (CRF%) by V2I and CV deployment level, RLVW (Enhanced).

Level	V2I	Baseline crashes at equipped locations*	Crashes Averted (CRF %)			
			CV 25%	CV 50%	CV 75%	CV 100%
L0	25%	28.25	8.13 (7.0)	14.99 (12.9)	20.32 (17.4)	23.95 (20.5)
	50%	61.64	17.77 (15.2)	32.74 (28.1)	44.37 (38.1)	52.27 (44.8)
	75%	92.42	26.60 (22.8)	49.04 (42.1)	66.48 (57.0)	78.34 (67.2)
	100%	116.57	33.56 (28.8)	61.86 (53.1)	83.86 (71.9)	98.81 (84.8)
L2	25%	15.71	5.43 (8.4)	9.78 (15.1)	12.88 (19.9)	14.67 (22.6)
	50%	34.27	11.84 (18.3)	21.32 (32.9)	28.09 (43.3)	32.01 (49.4)
	75%	51.39	17.77 (27.4)	31.98 (49.3)	42.12 (65.0)	47.99 (74.0)
	100%	64.81	22.41 (34.6)	40.33 (62.2)	53.12 (82.0)	60.53 (93.4)
L4	25%	4.24	1.13 (6.5)	2.15 (12.3)	3.03 (17.3)	3.74 (21.4)
	50%	9.25	2.50 (14.3)	4.72 (27.0)	6.62 (37.9)	8.17 (46.7)
	75%	13.86	3.71 (21.2)	7.05 (40.3)	9.91 (56.7)	12.24 (70.0)
	100%	17.49	4.68 (26.8)	8.90 (50.9)	12.51 (71.5)	15.44 (88.3)

* CRF is relative to each automation level's own study-area no-V2X baseline: 116.57 (L0), 64.81 (L2) and 17.49 (L4) crashes/yr. Crashes averted are the same for equipped locations and the study area. At V2I 100%, CRF equals the values in Table.

Table 4.6: Crash costs avoided per year (million USD) by V2I and CV deployment level, RLVW (Enhanced).

Level	V2I	Baseline cost at equipped locations*	Costs Avoided			
			CV 25%	CV 50%	CV 75%	CV 100%
L0	25%	$4.08	$1.17	$2.17	$2.94	$3.46
	50%	$8.91	$2.57	$4.73	$6.41	$7.55
	75%	$13.35	$3.84	$7.09	$9.60	$11.32
	100%	$16.84	$4.85	$8.94	$12.12	$14.28
L2	25%	$2.27	$0.79	$1.41	$1.86	$2.12
	50%	$4.95	$1.71	$3.08	$4.06	$4.62
	75%	$7.42	$2.57	$4.62	$6.08	$6.93
	100%	$9.36	$3.24	$5.83	$7.67	$8.75
L4	25%	$0.61	$0.16	$0.31	$0.44	$0.54
	50%	$1.34	$0.36	$0.68	$0.96	$1.18
	75%	$2.00	$0.54	$1.02	$1.43	$1.77
	100%	$2.53	$0.68	$1.29	$1.81	$2.23

* Baseline at equipped locations is the no-V2X crash cost at the V2I-equipped intersections. Study-area no-V2X crash costs are $16.84M (L0), $9.36M (L2), and $2.53M (L4) per year.

4.1.2. Scenario B: Pedestrian Collision Warning (PED-CP)

4.1.2.1. PED-CP collision probability reduction per-encounter (CV% Lever)

Figure 4.12-Figure 4.14 give the per-encounter probability for a vehicle–pedestrian conflict, averaged over all conditioning factors (weather, light condition, speeding, intersection or road type), as a function of connected vehicle market penetration (CV%). Figure 4.12 shows the crash probability, Figure 4.13 shows the reduction relative to CV=0% in relative and absolute terms, and Figure 4.14 shows the reduction added by each 25-point increase in CV% (incremental reduction), in percentage points of the CV=0% probability. The corresponding values are listed in Table 4.7-Table 4.9.

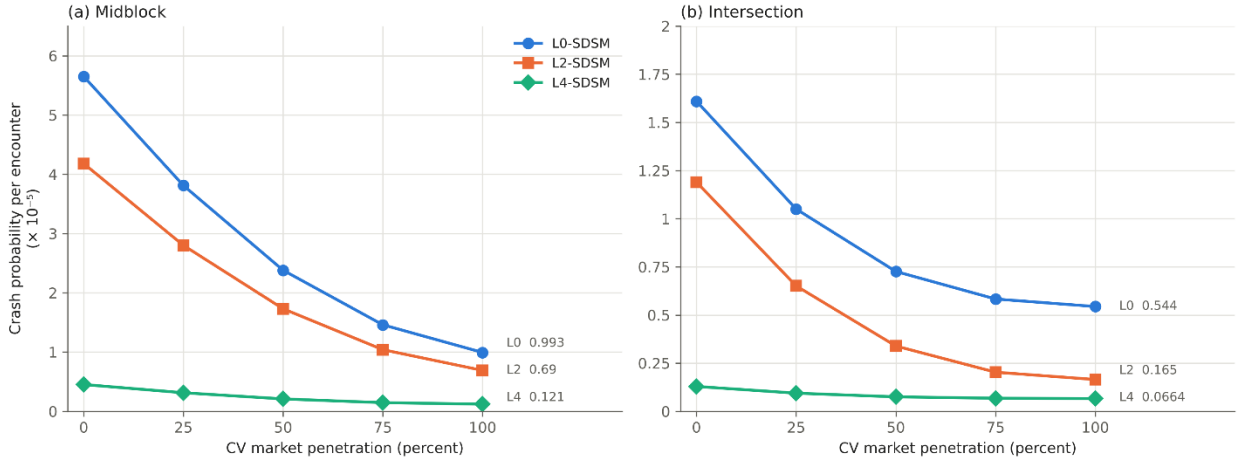


Figure 4.12: Per-encounter crash probability by CV market penetration for L0, L2, and L4 (Scenario B): (a) midblock and (b) intersection crossings. The y-axes of (a) and (b) use different scales to show the non-linear behavior at each crossing type; per encounter, crashes are less likely at intersections than at midblock crossings.

At CV = 0%, values represent the no-V2X baseline: the historic crash-calibrated probabilities, stemming from missed pedestrian detections, infeasible stopping, and conditional crash-exposure probabilities. Two sub-scenarios are explored: intersection crossing crashes and midblock crossing crashes. On a per-encounter basis, CV market penetration is the probability that a vehicle approaching the crossing is equipped to receive the SDSM. Because a single SDSM warning can protect multiple pedestrians from multiple vehicles approaching the same crossing simultaneously, the per-encounter crash probability does not decrease in proportion to CV%: the reduction added by each increase in CV% is largest at low penetration and declines as more encounters already involve a warned vehicle.

Figure 4.12 shows two effects: the impact of automation and how benefits vary by crossing type. Automation lowers the no-V2X baseline by about the same proportion at

both crossing types (approximately 26% for L2 and 92% for L4). These baselines are model assumptions based on reported PAEB performance (L2) and pedestrian-crash reductions for L4 vehicles. For L0 and L4, the SDSM warning reduces the crash probability more at midblock crossings than at intersections (82.4% and 73.1% at midblock crossings; 66.2% and 48.6% at intersection crossings, respectively), whereas for L2 the two crossing types reach similar reductions (83.5% at midblock crossings, 86.1% at intersections). At both crossing types, the improvement is greatest at low CV and plateaus at higher penetration.

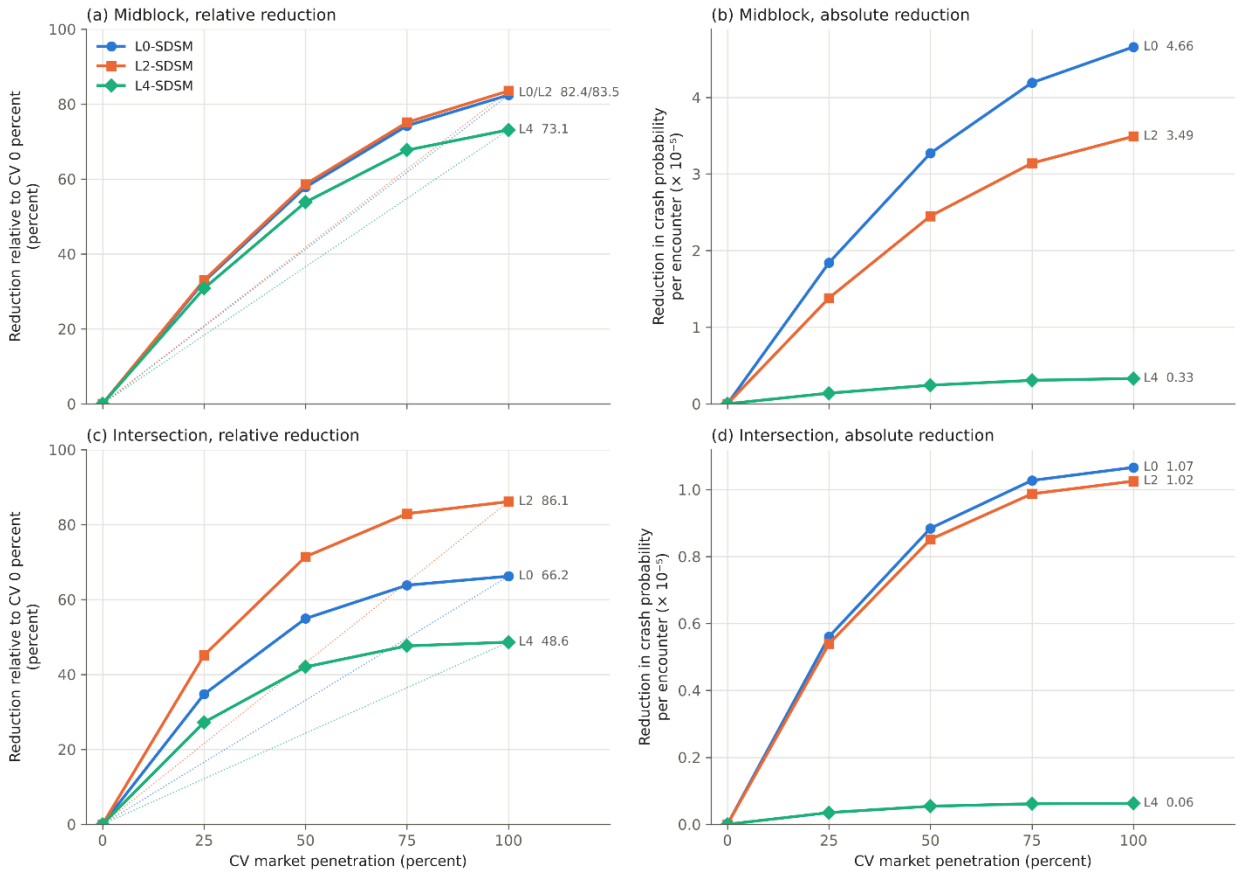


Figure 4.13: Reduction in per-encounter crash probability by CV market penetration for L0, L2, and L4 (Scenario B): relative reduction for (a) midblock and (c) intersection crossings, with proportional reference lines; absolute reduction for (b) midblock and (d) intersection crossings.

For L0 (Figure 4.13, Table 4.8), the reduction rises with CV penetration at a decreasing rate at both crossing types (Figure 4.14, Table 4.9). The incremental reduction declines with each step (Table 4.9, Figure 4.14), such that CV 25% already delivers about 40% of the full-penetration reduction at midblock crossings and 52% at intersections (Table 4.10).

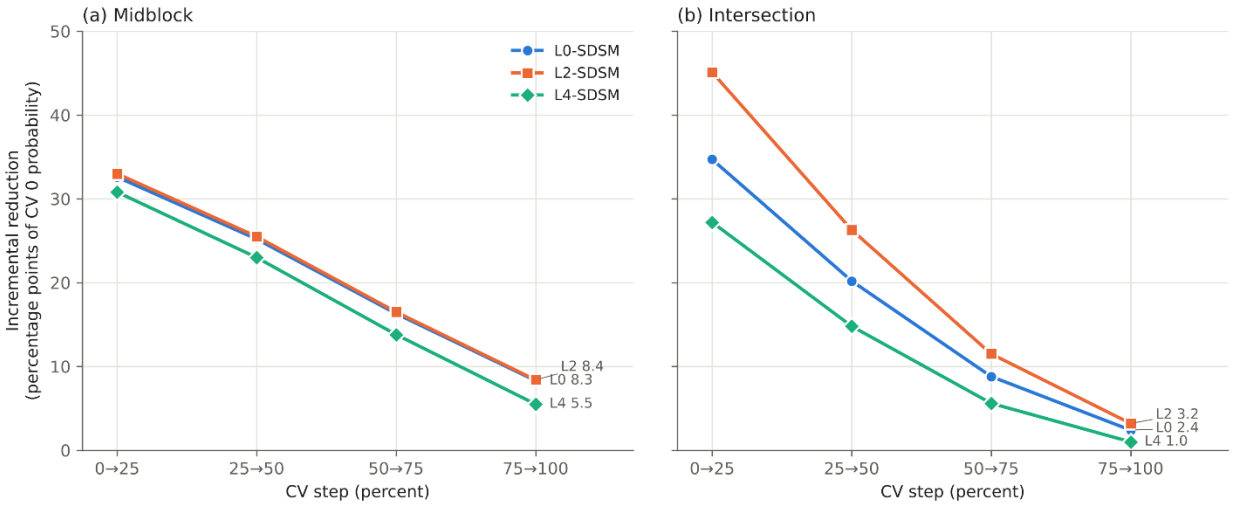


Figure 4.14: Incremental reduction in per-encounter crash probability (reduction added by each 25-point increase in CV penetration) for L0, L2, and L4 (Scenario B): (a) midblock and (b) intersection crossings.

As for RLVW, the non-linearity comes from notifying multiple vehicles about the same pedestrian detection and crash probability reduction is heavily impacted by increasing the share of connected vehicles (CV%); however, safety benefits scale differently per crossing type. The residual risk at CV 100% reflects encounters in which the warning is received but the driver does not respond in time or cannot stop, which is estimated to be higher at intersections as these can potentially involve more conflicts. These results are subject to multiple assumptions, including high (but not total) occlusion from the vehicle or infrastructure sensor system, and driver response rates to crash warnings at urban speeds, with distraction and pedestrian occlusions assumed as the main cause of potential conflicts. Expressed as crash modification factors (CMF) for midblock versus intersection crossings, at L0 the values are 0.67 vs. 0.65 at CV 25% and 0.18 vs. 0.34 at CV 100%.

For L2, the baseline reduction (compared to L0) reflects the additional response path provided by the partial automation and base PAEB functionality. Either the driver or the partial automation can respond to the SDSM warning and PAEB-type functions provide an additional safety barrier that is independent of the warning (but also subject to weather, light, and line-of-sight conditions). At midblock crossings, the L2 reduction follows L0 closely, while at intersections it is larger than for L0 at every penetration level, so the additional response path removes the largest share of risk where the driver's response alone leaves the largest residual. The efficacy of SDSM-based warnings is expected to decrease under challenging environmental conditions, which also affect the effective braking probabilities. In terms of CMFs, the value for midblock versus intersection crossings is 0.67 vs. 0.55 at CV 25% and 0.17 vs. 0.14 at CV 100%.

For L4, the baseline is approximately 92% lower than for L0, following the substantially lower unwarned conflict rate for an ADS-equipped host vehicle. V2X produces a further reduction on top of this low baseline, but the smallest relative reduction of the three levels at full penetration, and the response levels off fastest, particularly at intersections: (Figure 4.14, Table 4.9) This is consistent with the ADS already preventing most of the conflicts it can detect with onboard sensors, so the L4 baseline is concentrated in difficult conflicts, where SDSM information may also be more uncertain. While line-of-sight effects affect vehicle sensors more than infrastructure-mounted sensors, common failure modes triggered by weather and light conditions affect both sensor systems. In terms of CMFs, the value midblock versus intersection crossings is 0.69 vs. 0.73 at CV 25% and 0.27 vs. 0.51 at CV 100%.

Comparing across automation levels: In relative terms (Figure 4.13a, c; Table 4.8), at low CV penetration rates the differences depend on the crossing type. At midblock crossings, the three levels are within 2.2 percentage points (CV25: L0=32.6%, L2=33.0%, L4=30.8%), whereas at intersections the biggest crash reduction is achieved at L2 (CV25=45.1%), followed by L0 (CV25=34.7%) and L4 (CV25=27.2%). At high CV penetration rates, L2 and L0 exhibit similar reductions at midblock crossings (CV100=83.5% and 82.4%), while at intersections L2 remains well above L0 (86.1% vs. 66.2%). L4 exhibits the smallest (but still substantial) decrease (CV100=73.1% and 48.6% at midblock and intersections, respectively). The non-linearity of the SDSM response is present at all three levels and at both crossing types (Figure 4.14, Table 4.9): CV 25% delivers about 40% of the full-penetration reduction at midblock crossings for every level, and 52% (L0), 52% (L2), and 56% (L4) at intersections. The intersection response levels off faster as connectivity increases, and more than 80% of the full-penetration reduction is reached by CV 50%. In CMF terms at CV 100%, V2X is most effective for L2 at intersections (0.14) and least effective for L4 at intersections (0.51). At midblock crossings, the CMFs are close for L0 and L2 (0.18 and 0.17) and higher for L4 (0.27).

Table 4.7: Average per-encounter crash probabilities by connected vehicle deployment rate for scenario B across all automation levels.

Connected Vehicle %	L0-SDSM		L2-SDSM		L4-SDSM	
	Midblock	Intersection	Midblock	Intersection	Midblock	Intersection
CV:0%	5.65E-05	1.61E-05	4.18E-05	1.19E-05	4.52E-06	1.29E-06
CV:25%	3.81E-05	1.05E-05	2.80E-05	6.51E-06	3.13E-06	9.42E-07
CV:50%	2.38E-05	7.26E-06	1.73E-05	3.39E-06	2.09E-06	7.51E-07
CV:75%	1.46E-05	5.83E-06	1.04E-05	2.03E-06	1.46E-06	6.78E-07
CV:100%	9.93E-06	5.44E-06	6.90E-06	1.65E-06	1.21E-06	6.64E-07

Table 4.8: Reduction in average per-encounter crash probability by connected vehicle deployment rate for scenario B across all automation levels.

Connected Vehicle %	L0-SDSM		L2-SDSM		L4-SDSM	
	Midblock	Intersection	Midblock	Intersection	Midblock	Intersection
CV:25%	32.6%	34.7%	33.0%	45.1%	30.8%	27.2%
CV:50%	57.8%	54.9%	58.6%	71.4%	53.8%	42.0%
CV:75%	74.2%	63.8%	75.1%	82.9%	67.7%	47.6%
CV:100%	82.4%	66.2%	83.5%	86.1%	73.1%	48.6%

Table 4.9: Incremental reduction in average per-encounter crash probability by connected vehicle deployment rate for Scenario B.

Connected Vehicle %	L0-SDSM		L2-SDSM		L4-SDSM	
	Midblock	Intersection	Midblock	Intersection	Midblock	Intersection
CV:25%	32.6%	34.7%	33.0%	45.1%	30.8%	27.2%
CV:50%	25.2%	20.2%	25.5%	26.3%	23.0%	14.8%
CV:75%	16.3%	8.8%	16.5%	11.5%	13.8%	5.6%
CV:100%	8.3%	2.4%	8.4%	3.2%	5.5%	1.0%

Table 4.10: Per-encounter crash modification factor, CMF (CRF), by connected vehicle deployment rate for Scenario B (PED-CP).

Connected Vehicle %	L0-SDSM		L2-SDSM		L4-SDSM	
	Midblock	Intersection	Midblock	Intersection	Midblock	Intersection
CV:25%	0.67 (32.6)	0.65 (34.7)	0.67 (33.0)	0.55 (45.1)	0.69 (30.8)	0.73 (27.2)
CV:50%	0.42 (57.8)	0.45 (54.9)	0.41 (58.6)	0.29 (71.4)	0.46 (53.8)	0.58 (42.0)
CV:75%	0.26 (74.2)	0.36 (63.8)	0.25 (75.1)	0.17 (82.9)	0.32 (67.7)	0.52 (47.6)
CV:100%	0.18 (82.4)	0.34 (66.2)	0.17 (83.5)	0.14 (86.1)	0.27 (73.1)	0.51 (48.6)

4.1.2.2. PED-CP Estimated Crashes and Costs Avoided (CV% and V2I% Levers)

Figure 4.15 compares the three automation levels on a common basis, using annual Study Area crash counts; the no-V2X baseline is approximately 26% (L2) and 92% (L4) below L0, consistent with the per-encounter baselines in Table 4.7. Table 4.11 expresses the Equipped Locations results as crash modification factors, combining midblock and intersection crossings weighted by their baseline crashes. At V2I 100%, the CMF is 0.66 at CV 25% and 0.29 at CV 100% for L0, 0.58 and 0.15 for L2, and 0.72 and 0.44 for L4.

Figure 4.16 shows the same results relative to each level's own no-V2X baseline. Unlike in RLVW, the three surfaces separate clearly: L2 lies above L0, and L0 above L4, at every V2I/CV combination, and the gaps widen as CV increases. At V2I/CV 100%, the

reductions are 84.8% (L2), 74.3% (L0), and 60.7% (L4). All surfaces increase almost linearly along the V2I axis and level off along the CV axis, most strongly for L4.

Table 4.11: Crash modification factor, CMF (CRF), at the Equipped Locations, midblock and intersection crossings combined, Scenario B (PED-CP), V2I 100%. Values vary by at most 0.02 across V2I levels.

Connected Vehicle %	L0-SDSM	L2-SDSM	L4-SDSM
CV:25%	0.66 (33.8)	0.58 (41.6)	0.72 (27.7)
CV:50%	0.44 (55.6)	0.33 (67.5)	0.55 (45.1)
CV:75%	0.33 (66.8)	0.20 (80.5)	0.47 (53.3)
CV:100%	0.29 (71.0)	0.15 (85.3)	0.44 (55.7)

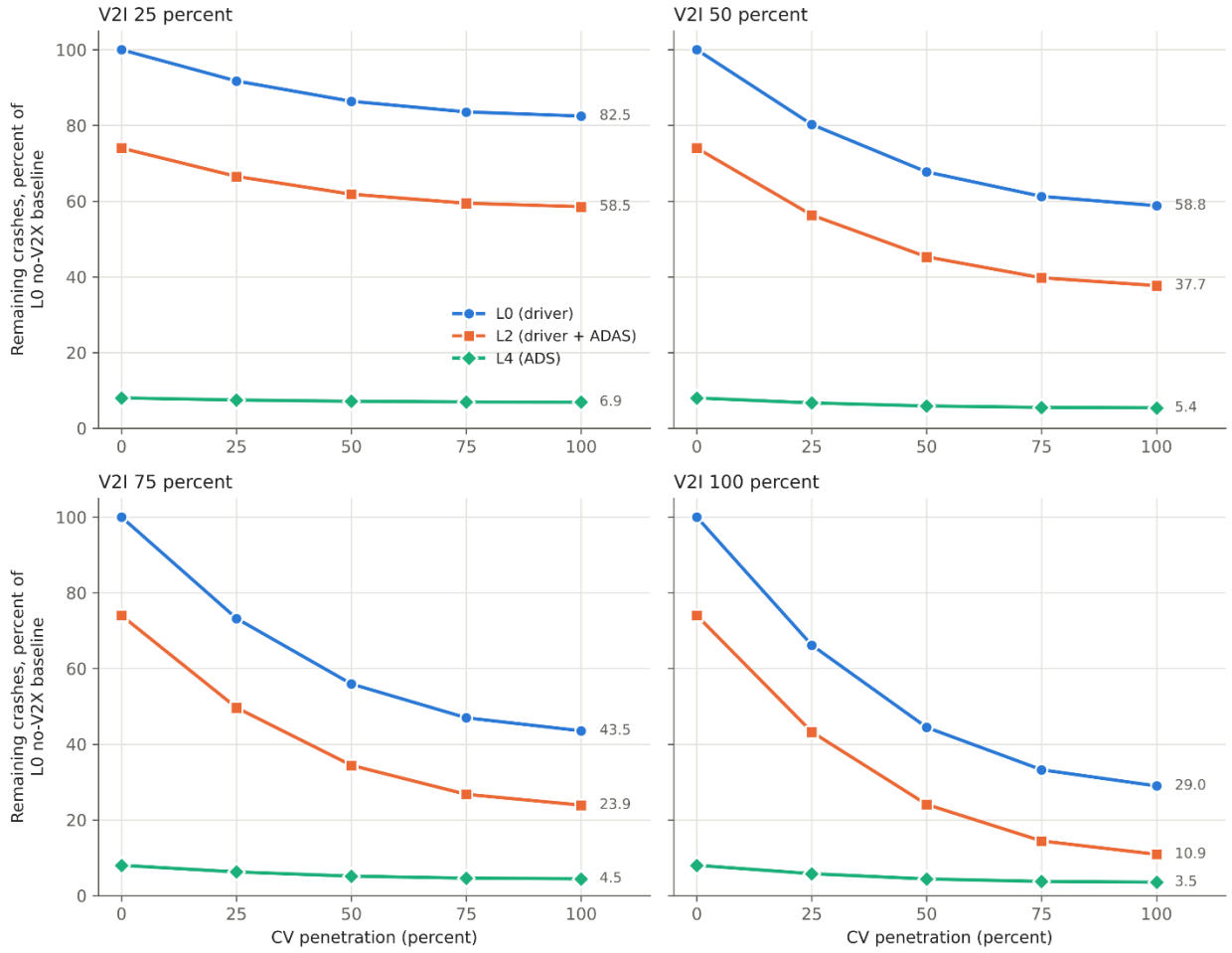


Figure 4.15: Remaining Study Area pedestrian crashes as a percentage of the L0 no-V2X baseline, by CV penetration and V2I deployment, for L0, L2, and L4. At L2, ADAS functions include PAEB as an additional safety mechanism.

Across all combinations, L2 shows a larger crash risk reduction than L0 at every V2I/CV combination (84.8% vs. 74.3% at full deployment), consistent with the larger per-encounter reduction at intersections (Figure 4.13). L4 shows a smaller crash risk reduction than L0 at every V2I/CV combination. This is consistent with the per-encounter results: the ADS already prevents most of the conflicts it can detect with onboard sensors, so the conflicts that remain are those where the SDSM warning is also less effective.

In absolute terms, L2 avoids 88–91% of the crashes that L0 avoids, since its larger relative reduction applies to a 26% lower baseline, while L4 avoids only 6–7%. At full deployment, L0, L2, and L4 avoid 39.61, 35.19, and 2.49 crashes per year, or $58.73M, $49.61M, and $3.84M in annual savings. The V2X benefit is therefore largest where the human driver remains the main risk contributor, and targeting V2X applications to human-driven vehicles would provide the largest absolute benefits.

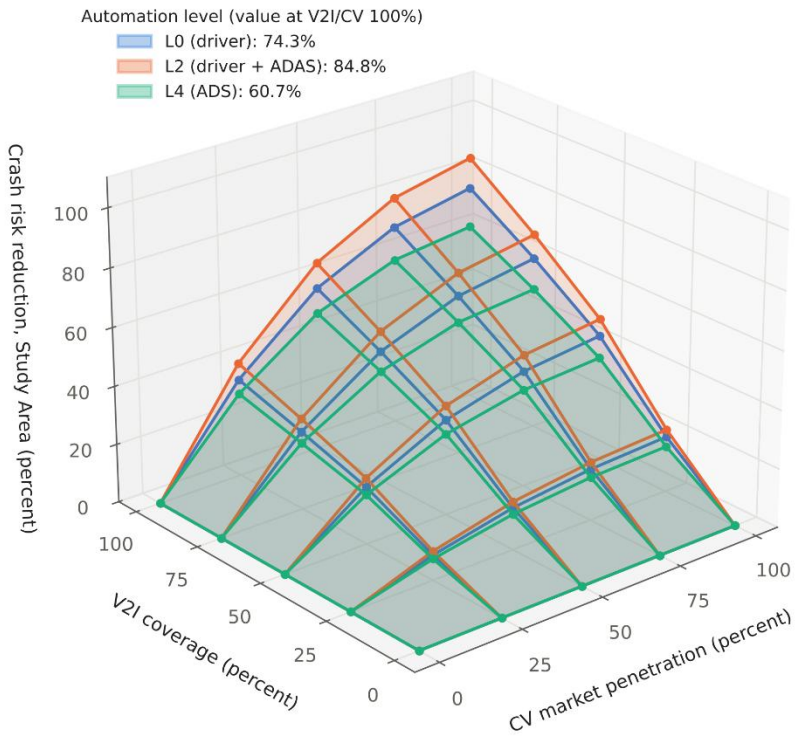


Figure 4.16: Study Area crash risk reduction (percent) by CV market penetration and V2I coverage for L0 (blue), L2 (orange), and L4 (green), Scenario B (PED-CP). Legend values are the reductions at V2I/CV 100%.

Results per Automation Level

Table 4.12-Table 4.13 report the estimated crashes avoided and equivalent economic savings for the L0, L2, and L4, translating the area-level reductions into annual terms for the 92-intersection DTLA reference deployment, combining intersection and midblock crossing exposure. The estimated crashes and resulting costs are provided for the Equipped Locations (dependent on V2I%) and the Study Area. Detailed crash and cost results can be found in Table 7.53-Table 7.55 (Appendix D).

At L0 (Figure 4.17), crashes avoided and savings increase with both levers. At a fixed V2I level, the Equipped Locations reduction rises with CV penetration at a decreasing rate, and CV 25% delivers about 45% of the full-penetration reduction. At CV 100%, this reduction lies between the per-encounter reductions for midblock crossings (82.4%) and intersections (66.2%), since the equipped locations include both crossing types. Because crash risk reduction is cost-weighted, it slightly exceeds the crash-count reduction: the avoided crashes have a higher average cost than the baseline mix. At a fixed CV level, the benefit increases with the share of baseline crashes at the equipped locations. Full deployment with full penetration yields an estimated 39.61 crashes avoided and $58.73M in annual savings, declining to 4.61 crashes and $6.76M at the lowest modeled deployment (V2I:25%/CV:25%).

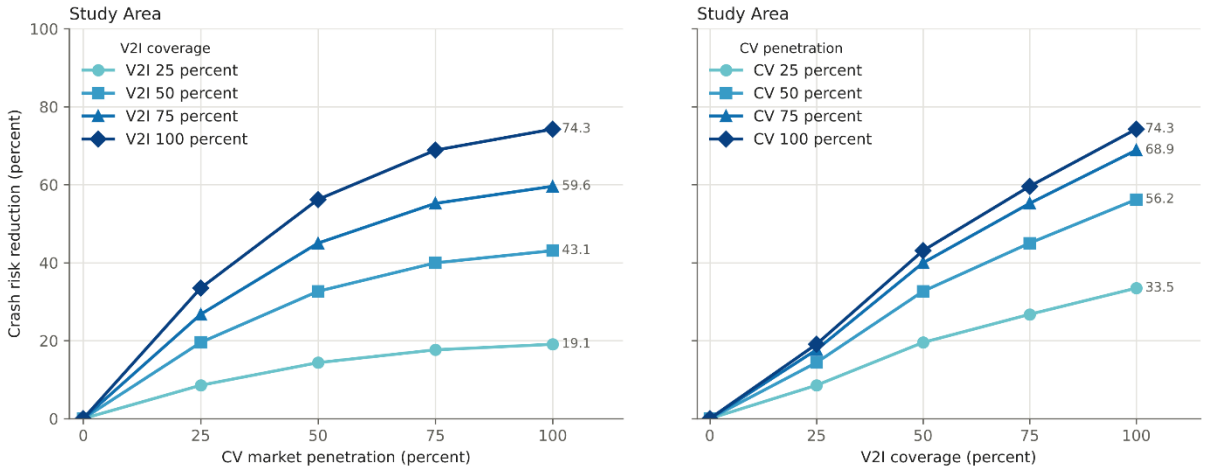


Figure 4.17: Crash risk reduction vs. CV penetration (left) and V2I deployment (right) for the Study Area, no automation (L0).

Figure 4.18 combines both levers in the Study Area view. The V2I steps are uneven because they follow the share of baseline crashes at the equipped locations, and partial deployment caps the Study Area benefit: at V2I 25%, about three quarters of the baseline crashes occur at unequipped locations (Table 7.54).

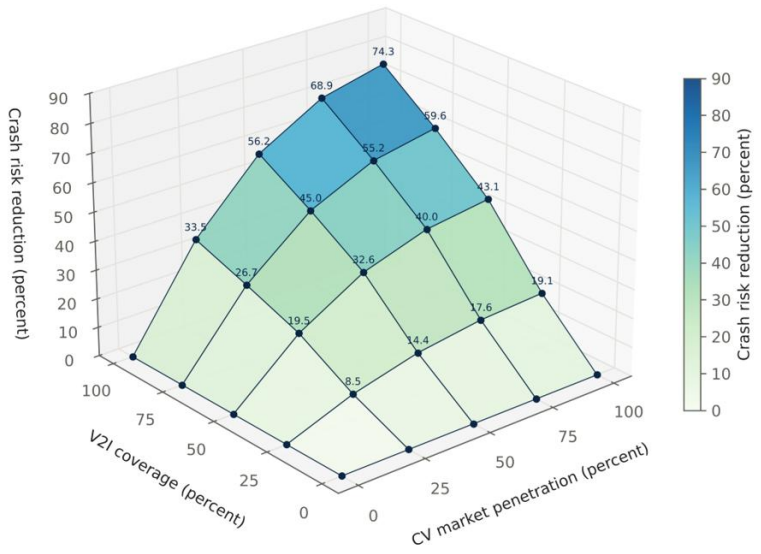


Figure 4.18: Crash risk reduction vs. CV penetration and V2I deployment for Study Area, no automation (L0).

For L2 (Figure 4.19–Figure 4.20), the Equipped Locations reduction is higher than for L0 at every V2I/CV combination, consistent with the per-encounter results, where either the driver or the partial automation with PAEB can respond to the warning. CV 25% delivers about 46% of the full-penetration reduction. Unlike L0, the crash-count reduction slightly exceeds the cost-weighted reduction, because the L2 benefit is concentrated at intersections, where crashes have a lower average cost. The absolute benefit is close to that of L0: full deployment yields 35.19 crashes avoided and $49.61M in annual savings, 89% and 84% of the L0 values (Table 7.55).

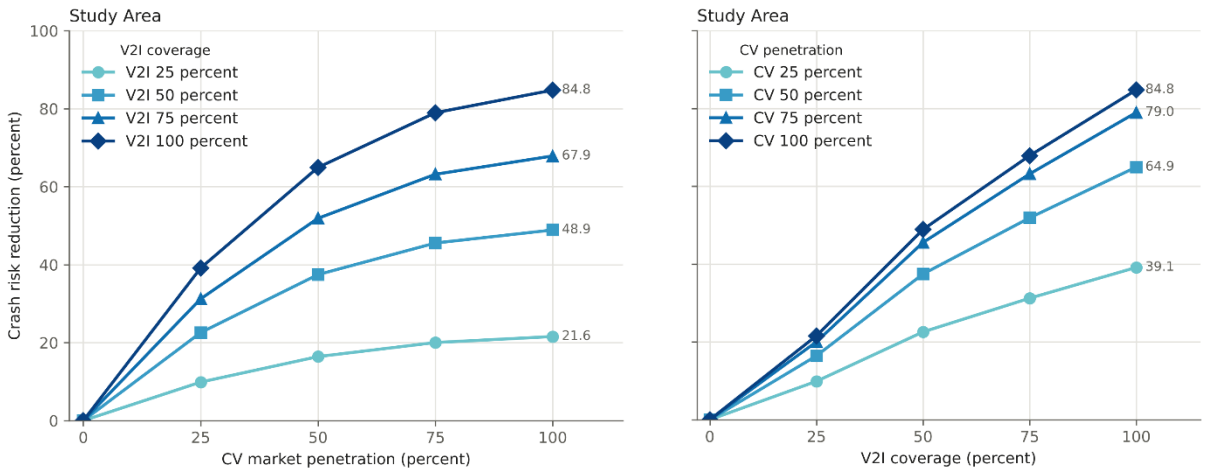


Figure 4.19: Crash risk reduction vs. CV penetration (left) and V2I deployment (right) for the Study Area, Level 2 automation (L2).

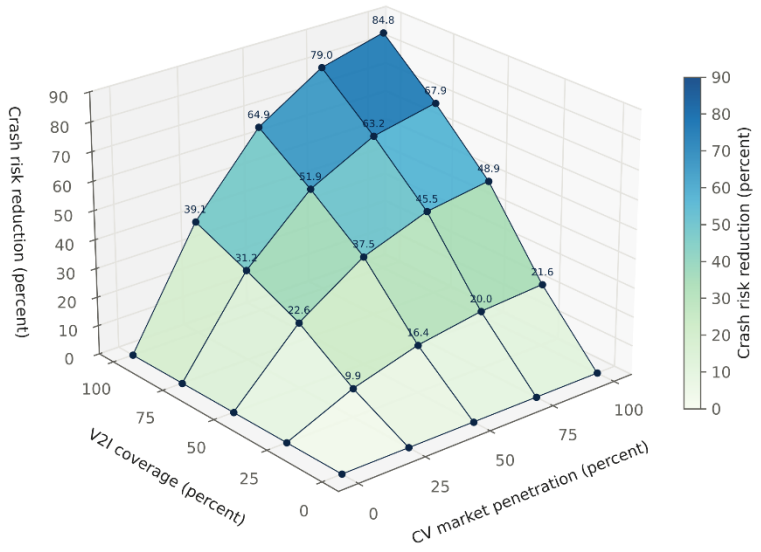


Figure 4.20: Crash risk reduction vs. CV penetration and V2I deployment for Study Area, Level 2 automation (L2).

For L4 (Figure 4.21–Figure 4.22), the Equipped Locations reduction is lower than for L0 and L2 at every V2I/CV combination. This is consistent with the per-encounter results: the ADS already prevents most of the conflicts it can detect with onboard sensors, so the L4 baseline is concentrated in occluded or otherwise difficult conflicts, where the SDSM warning is less effective. Because the baseline is also small, the absolute benefit is much smaller than for L0 (Table 7.56): full deployment yields 2.49 crashes avoided and $3.84M in annual savings.

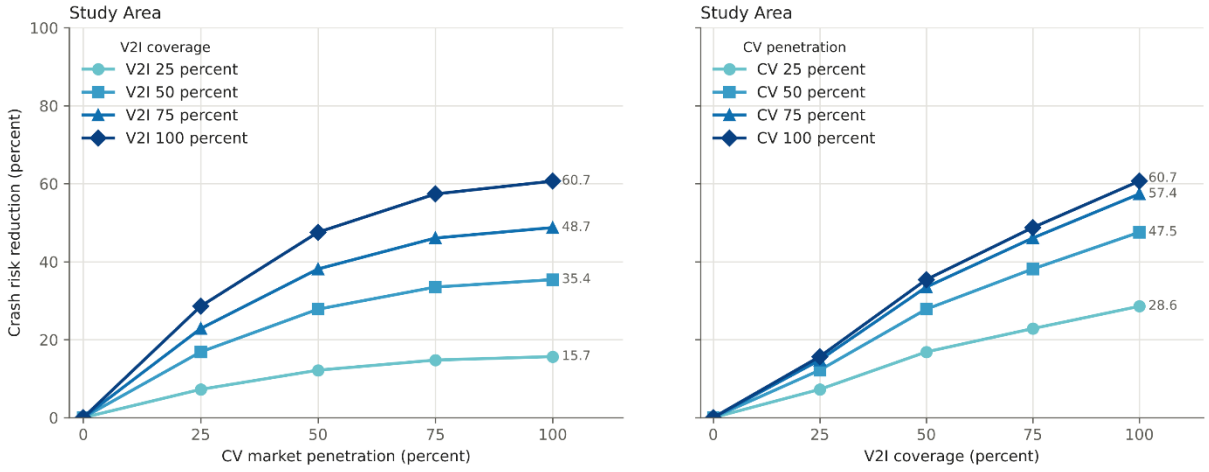


Figure 4.21: Crash risk reduction vs. CV penetration (left) and V2I deployment (right) for the Study Area, Level 4 automation (L4).

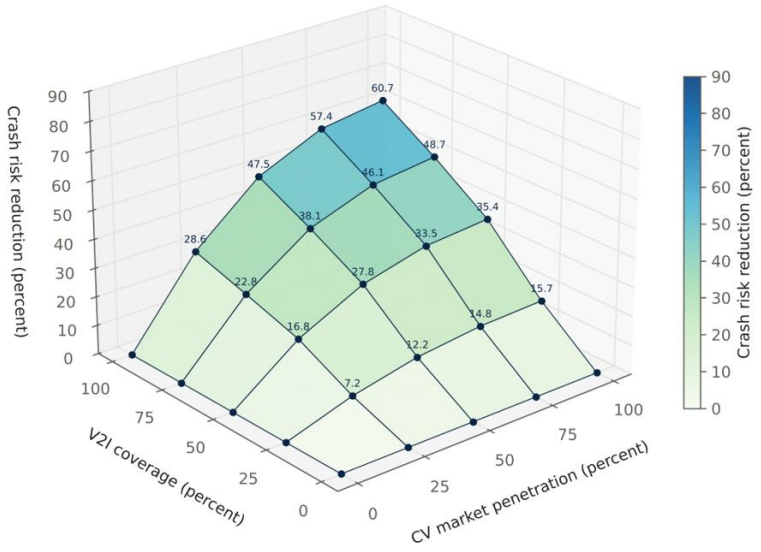


Figure 4.22: Crash risk reduction vs. CV penetration and V2I deployment for Study Area, Level 4 automation (L4).

Table 4.12: Crashes averted per year and study-area crash reduction (CRF%, in parentheses) by V2I and CV deployment level, PED-CP.

Level	V2I	Baseline crashes at equipped locations*	Crashes Averted (CRF %) CV 25%	CV 50%	CV 75%	CV 100%
L0	25%	13.69	4.61 (8.3)	7.60 (13.6)	9.16 (16.4)	9.78 (17.5)
	50%	32.07	11.01 (19.7)	18.00 (32.3)	21.60 (38.7)	22.98 (41.2)
	75%	44.29	14.93 (26.8)	24.58 (44.1)	29.57 (53.0)	31.49 (56.5)
	100%	55.77	18.85 (33.8)	30.98 (55.5)	37.22 (66.7)	39.61 (71.0)
L2	25%	10.13	4.17 (10.1)	6.78 (16.4)	8.12 (19.7)	8.63 (20.9)
	50%	23.73	9.87 (23.9)	16.02 (38.8)	19.12 (46.3)	20.26 (49.1)
	75%	32.78	13.57 (32.9)	22.06 (53.5)	26.35 (63.8)	27.94 (67.7)
	100%	41.27	17.15 (41.6)	27.84 (67.5)	33.21 (80.5)	35.19 (85.3)
L4	25%	1.09	0.30 (6.7)	0.49 (11.0)	0.59 (13.2)	0.62 (13.9)
	50%	2.57	0.73 (16.4)	1.18 (26.5)	1.39 (31.2)	1.46 (32.7)
	75%	3.54	0.98 (22.0)	1.60 (35.9)	1.89 (42.4)	1.98 (44.4)
	100%	4.46	1.23 (27.6)	2.01 (45.1)	2.38 (53.4)	2.49 (55.8)

* Baseline at equipped locations is the no-V2X crash count at the V2I-equipped locations. CRF is relative to each automation level's own study-area no-V2X baseline: 55.77 (L0), 41.27 (L2) and 4.46 (L4) crashes/yr. At V2I 100%, CRF equals the values in Table.

Table 4.13: Crash costs avoided per year (million USD) and study-area crash cost reduction (%) by V2I and CV deployment level, PED-CP

Level	V2I	Baseline cost at equipped locations*	Costs Avoided (Reduction %)			
			CV 25%	CV 50%	CV 75%	CV 100%
L0	25%	$20.14	$6.76 (8.5)	$11.35 (14.4)	$13.95 (17.6)	$15.08 (19.1)
	50%	$45.59	$15.44 (19.5)	$25.82 (32.6)	$31.60 (40.0)	$34.07 (43.1)
	75%	$63.37	$21.15 (26.7)	$35.59 (45.0)	$43.66 (55.2)	$47.13 (59.6)
	100%	$79.09	$26.47 (33.5)	$44.45 (56.2)	$54.45 (68.8)	$58.73 (74.3)
L2	25%	$14.90	$5.78 (9.9)	$9.61 (16.4)	$11.72 (20.0)	$12.62 (21.6)
	50%	$33.74	$13.21 (22.6)	$21.92 (37.5)	$26.65 (45.5)	$28.62 (48.9)
	75%	$46.89	$18.28 (31.2)	$30.38 (51.9)	$36.98 (63.2)	$39.73 (67.9)
	100%	$58.53	$22.90 (39.1)	$38.01 (64.9)	$46.21 (79.0)	$49.61 (84.8)
L4	25%	$1.61	$0.46 (7.3)	$0.77 (12.2)	$0.93 (14.7)	$0.99 (15.6)
	50%	$3.65	$1.07 (16.9)	$1.76 (27.8)	$2.12 (33.5)	$2.24 (35.4)
	75%	$5.07	$1.44 (22.7)	$2.41 (38.1)	$2.91 (46.0)	$3.08 (48.7)
	100%	$6.33	$1.81 (28.6)	$3.01 (47.6)	$3.63 (57.3)	$3.84 (60.7)

* Baseline at equipped locations is the no-V2X crash cost at the V2I-equipped locations. Cost reduction is relative to each automation level's own study-area no-V2X crash cost: $79.09M (L0), $58.53M (L2) and $6.33M (L4) per year. Unlike RLVW, cost reductions differ from the crash reductions.

4.2. Comparison Across Scenarios

Figure 4.23 compares the two scenarios at full V2I deployment across automation levels in absolute terms. RLVW avoids more crashes and PED-CP yields larger savings at every automation level, because the average pedestrian crash costs about ten times a red-light-running crash In both scenarios, the absolute benefit is largest for vehicles with a human driver (L0, L2), while L4 avoids about 14–16% (RLVW) and 6–7% (PED-CP) of the crashes avoided at L0.

Figure 4.24 shows the same results relative to each series' own no-V2X baseline. The relative benefit is largest at L2 in both scenarios, where either the driver or the automation can respond to a warning. For RLVW, L4 removes a larger share of its own baseline than L0 at full penetration (88.3% vs. 84.8%), whereas for PED-CP it removes a smaller share at every V2I/CV combination (60.7% vs. 74.3% at full deployment), because the conflicts that remain for an ADS are those in which the SDSM warning is also less effective.

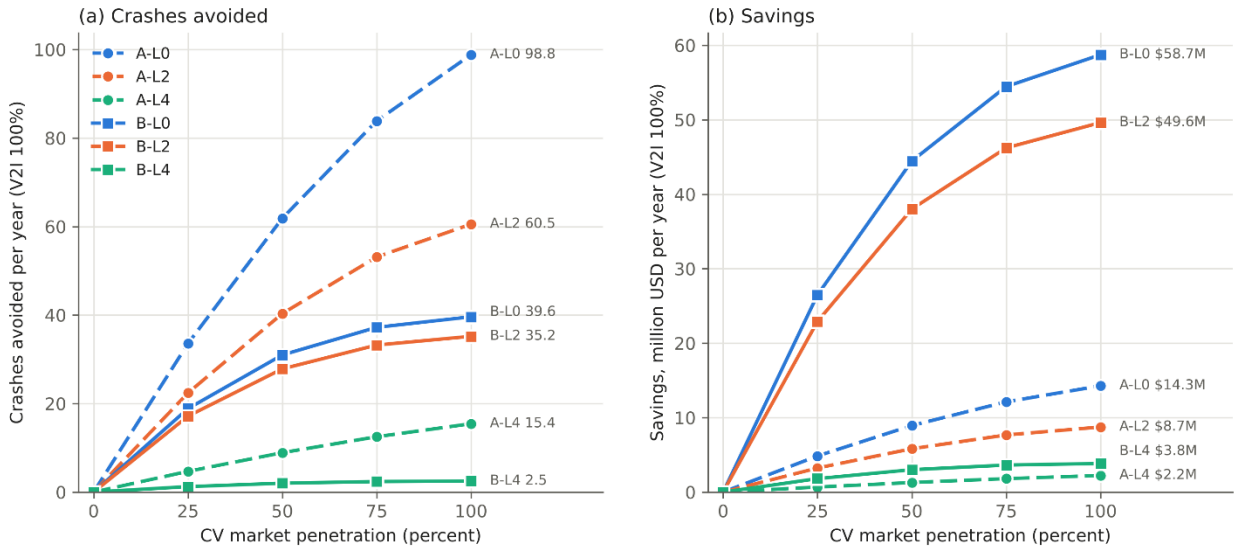


Figure 4.23: Annual (a) crashes avoided (b) and savings by CV penetration at V2I 100%, Scenario A (enhanced RLVW, dashed) and Scenario B (PED-CP, solid), by automation level.

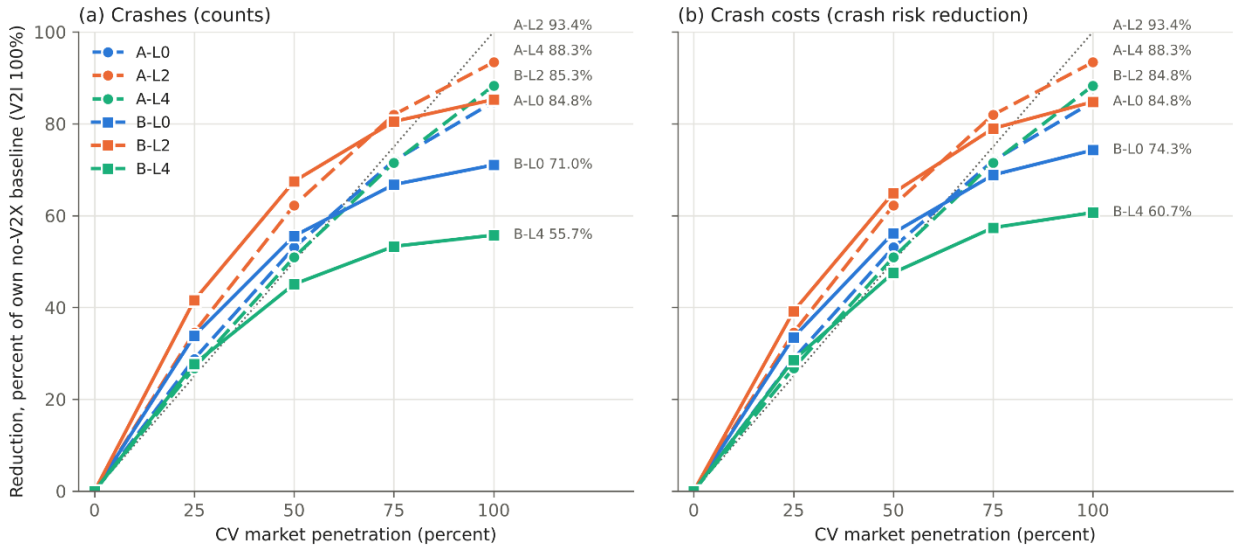


Figure 4.24: Crash reduction by CV penetration at V2I 100%, as a percentage of the corresponding no-V2X Study Area baseline: (a) crash counts and (b) crash costs (crash risk reduction), Scenario A (enhanced RLVW, dashed) and Scenario B (PED-CP, solid), by automation level. The dotted line indicates a reduction proportional to CV%.

Figure 4.25 compares the shape of the CV response across scenarios, using per-encounter reductions normalized to each series' CV 100% value; curves above the dotted proportional line add more benefit at low CV%. Both applications deliver more than a proportional share of their benefit at low penetration, because a single warning can

protect more than one road user: enhanced RLVW warns both the host and encountering vehicles, and an SDSM warning protects several pedestrians from simultaneous vehicle approaches. The effect is stronger for PED-CP, where CV 25% delivers about 40% of the full-penetration crashes avoided at midblock crossings and 52-56% at intersection crossings, compared with 30–37% for enhanced RLVW.

To compare the scenarios at an early stage of deployment, Table 4.14 lists the results at V2I 25% and CV 25%. At his deployment level, enhanced RLVW avoids more crashes and PED-CP yields larger savings at every automation level.

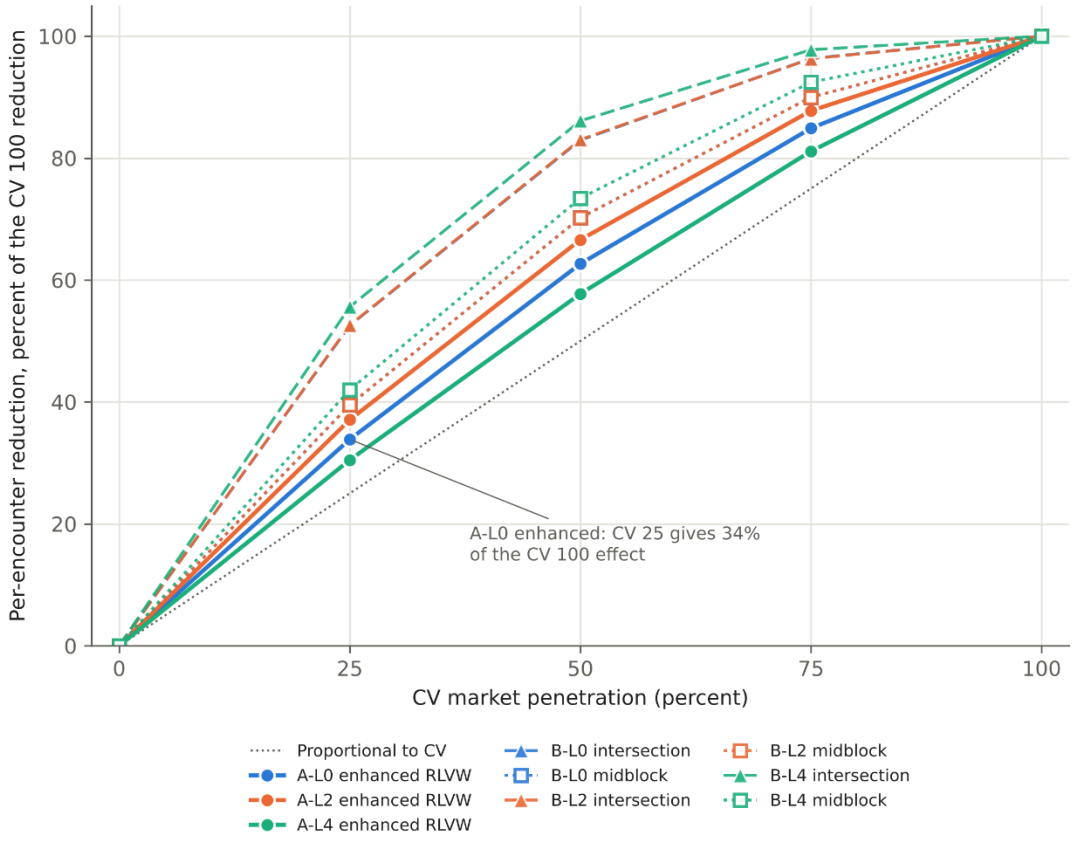


Figure 4.25: Per-encounter crash probability reduction normalized to each series' CV 100% value, for Scenario A (enhanced RLVW) and Scenario B (midblock and intersection), by automation level.

Figure 4.26 compares the remaining crashes for human-driven vehicles (L0) with V2X against the L2 and L4 baseline without V2X, in absolute terms. In RLVW, full deployment (V2I 100%/CV 100%) brings L0 to 17.76 crashes per year, approximately the expected L4 no-V2X baseline (17.49).

Table 4.14: Study Area results at low deployment (V2I 25%, CV 25%), Scenario A (enhanced RLVW) and Scenario B (PED-CP).

Scenario, level	Baseline No-V2X Study Area crashes per year	Crashes avoided per year	Savings per year ($M)	CMF (CRF), Equipped Locations*	Crash risk reduction, Equipped Locations Only (%)	Crash risk reduction, Total Study Area (%)	Share of full-deployment crashes avoided (%)
A-L0 (enhanced RLVW)	116.57	8.13	1.17	0.71 (28.8)	28.8	7.0	8.2
A-L2 (enhanced RLVW)	64.81	5.43	0.79	0.65 (34.6)	34.8	8.4	9.0
A-L4 (enhanced RLVW)	17.49	1.13	0.16	0.73 (26.6)	26.6	6.4	7.3
B-L0 (PED-CP)	55.77	4.61	6.76	0.66 (33.7)	33.6	8.5	11.6
B-L2 (PED-CP)	41.27	4.17	5.78	0.59 (41.2)	38.8	9.9	11.8
B-L4 (PED-CP)	4.46	0.30	0.46	0.73 (27.3)	28.4	7.2	12.0

* CMF (CRF) is calculated from crash counts at the Equipped Locations; crash risk reduction is cost-weighted. Both are relative to each level's no-V2X baseline. The share of full-deployment crashes avoided is relative to V2I 100% / CV 100%.

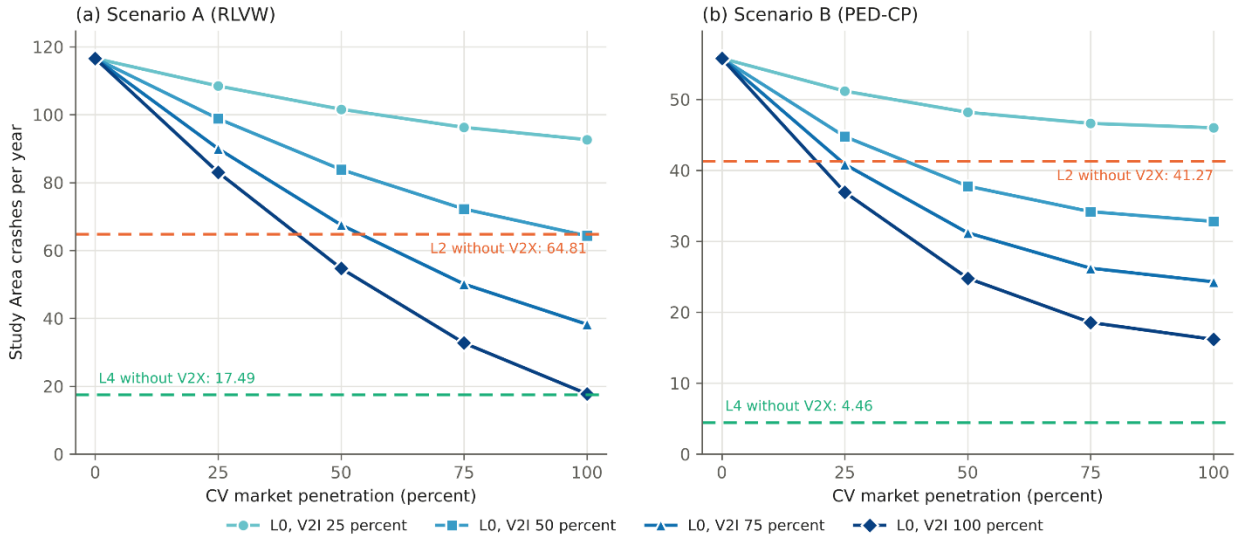


Figure 4.26: Remaining Study Area crashes per year for L0 by CV penetration and V2I deployment, compared with the L2 and L4 no-V2X baselines (dashed): (a) Scenario A (enhanced RLVW) and (b) Scenario B (PED-CP).

In PED-CP, L0 at full deployment (16.16) remains 3.6 times the L4 baseline (4.46), so for pedestrian crashes V2X on human-driven vehicles does not close the gap to automation.

However, because real-world fleets are mixed (L0, L2-L4 vehicles) and heavily skewed towards L0, the highest safety benefits in the short-to-medium term would be driven by enabling V2X applications for low/no-automation vehicles (L0, L2).

Figure 4.27 normalizes the crashes avoided by the number of equipped intersections. Per equipped intersection, enhanced RLVW avoids 1.8–2.5 times as many crashes as PED-CP at L0, while PED-CP yields larger savings ($0.64M vs. $0.16M per equipped intersection per year at full deployment).

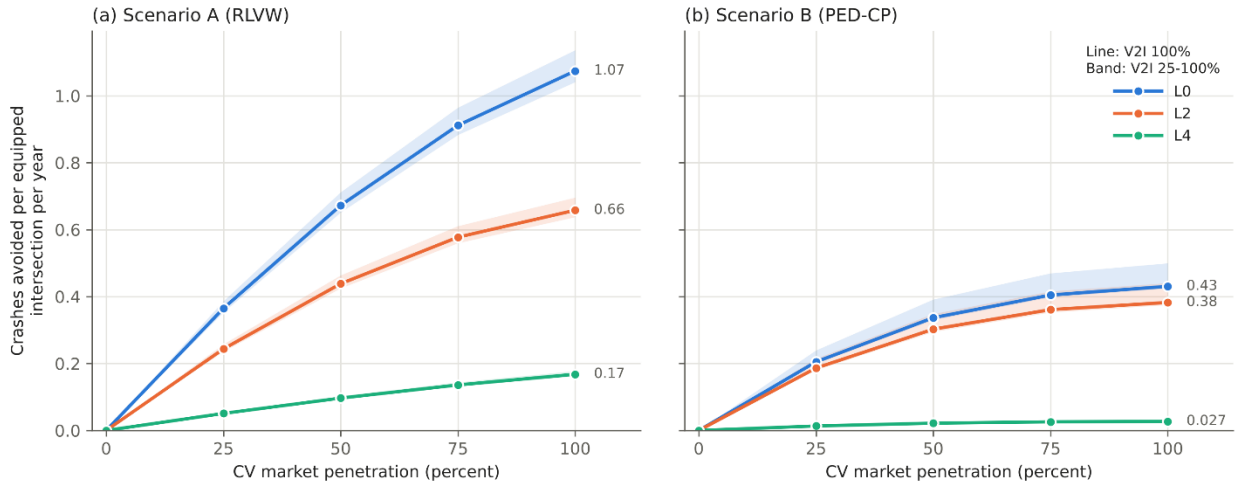


Figure 4.27: Crashes avoided per equipped intersection per year by CV penetration at V2I 100% (band indicates range across V2I 25–100%): (a) Scenario A (enhanced RLVW) and (b) Scenario B (PED-CP).

Because the warning acts only on vehicles approaching an equipped location, V2I coverage determines how many locations receive the benefit, and the Study Area benefit scales close to linearly with the share of equipped locations. **Wide V2I coverage with partial CV penetration therefore outperforms full CV penetration with partial V2I coverage**, as shown in Figure 4.28: V2I 100%/CV 25% avoids 27–35% (RLVW) and 28–42% (PED-CP) of Study Area crashes, compared with 21–23% and 14–21% at V2I 25%/CV 100%. The advantage of wide coverage with partial penetration is larger for PED-CP because the SDSM response levels off faster with CV%: additional CV penetration adds less than additional equipped locations, whose benefit scales with the share of baseline crashes they cover.

Figure 4.29 shows iso-benefit contours of Study Area crashes avoided over the full V2I–CV range. For RLVW, the contours are roughly symmetric about the diagonal, so a given benefit is reached most efficiently by raising V2I and CV together. For PED-CP, contours are steeper on the low-CV side of the line, which means that beyond about 25–35% CV,

extra CV adds little unless V2I also increases. With full V2I coverage (along the top edge), half of the full-deployment benefit is reached at CV 36–43% (RLVW) and 25–27% (PED-CP). With full CV penetration (along the right edge), it requires about 44–48% V2I coverage.

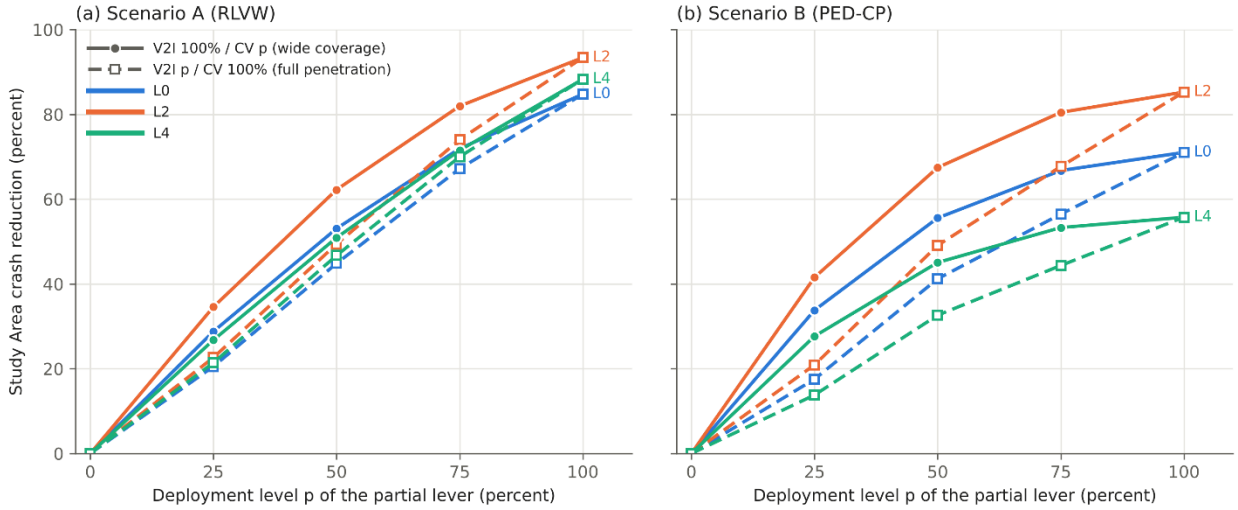


Figure 4.28: Study Area crash reduction (crash counts, percent of each level's no-V2X baseline) for deployment pairs with the same V2I x CV product: wide V2I deployment with partial CV penetration (V2I 100% / CV p, solid) vs. full CV penetration with partial V2I deployment (V2I p / CV 100%, dashed), by automation level: (a) Scenario A (enhanced RLVW) and (b) Scenario B (PED-CP).

For both applications, the area-level benefits depend on which locations are equipped as much as on CV penetration. In this case study, at 25% V2I coverage, at most 14–23% of total crashes are avoided even at full CV penetration. In the short term, the largest benefit per deployed unit is therefore expected from equipping high-crash locations first, combined with about 25% CV penetration among the vehicles that use them, which captures about one third (RLVW) to one half (PED-CP) of the full-penetration benefit at those locations. Location-specific estimates reflect local traffic exposure, road type, and intersection type; weather, lighting, and line-of-sight conditions are applied as study-area averages, so locations where adverse conditions are more frequent may see benefits that differ from those reported.

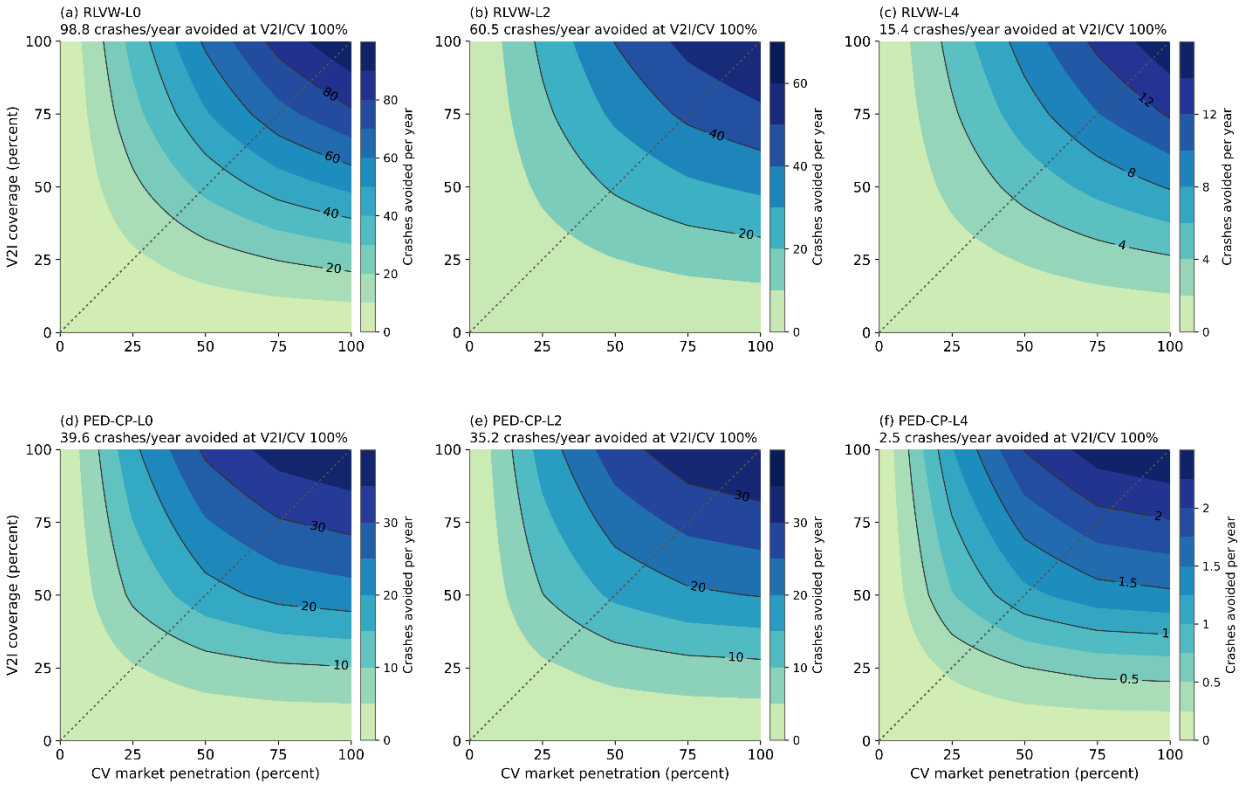


Figure 4.29: Iso-benefit contours of Study Area crashes avoided per year by CV penetration and V2I deployment (linear interpolation between modeled points): (a) A-L0, (b) A-L2, (c) A-L4, (d) B-L0, (e) B-L2, and (f) B-L4. The dotted line indicates equal V2I and CV deployment.

4.3. Sensitivity Analysis: Importance Measures

This section reports Risk Reduction Worth (RRW) and Risk Achievement Worth (RAW) importance measures for the basic events contributing to each scenario's top-level crash probability. These importance measures help prioritize which system elements' performance improvements can provide the most safety benefit:

- RRW quantifies the relative decrease in crash probability if a given system component were perfectly reliable, indicating where further improvement offers the greatest risk reduction.
- RAW quantifies the relative increase in crash probability if a given element were to fail entirely, indicating how consequential the element's current (imperfect) reliability already is to overall system risk.

An element can rank high on one measure without ranking high on the other; the two are discussed together below because their combination indicates whether a system element

is worth further investment, already at acceptable risk, or currently reliable but critical to preserve.

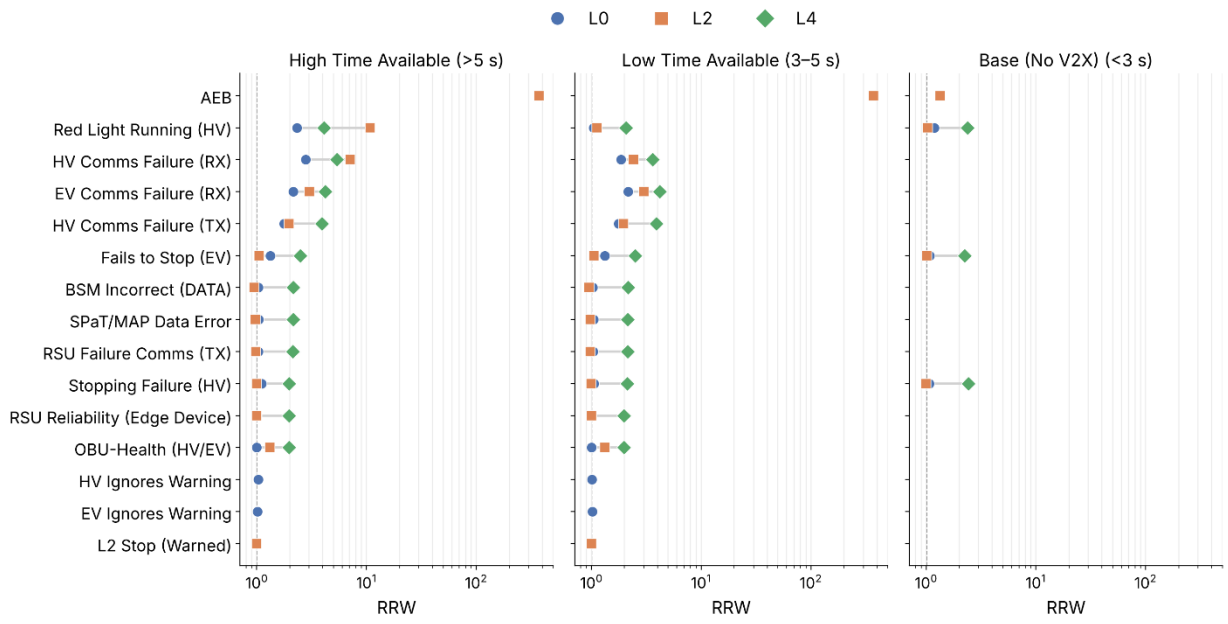
4.3.1. RLVW Analysis

Figure 4.30 reports RRW and RAW values for each basic event across automation levels (L0, L2, L4) and ESD time-availability branches (High Time, Low Time, Base (No V2X)). Nodes upstream of the time split, or otherwise branch-invariant, show identical High and Low Time values, and Base values are reported only for nodes in the No V2X branch. Tabulated data are provided in Appendix D.1.2.

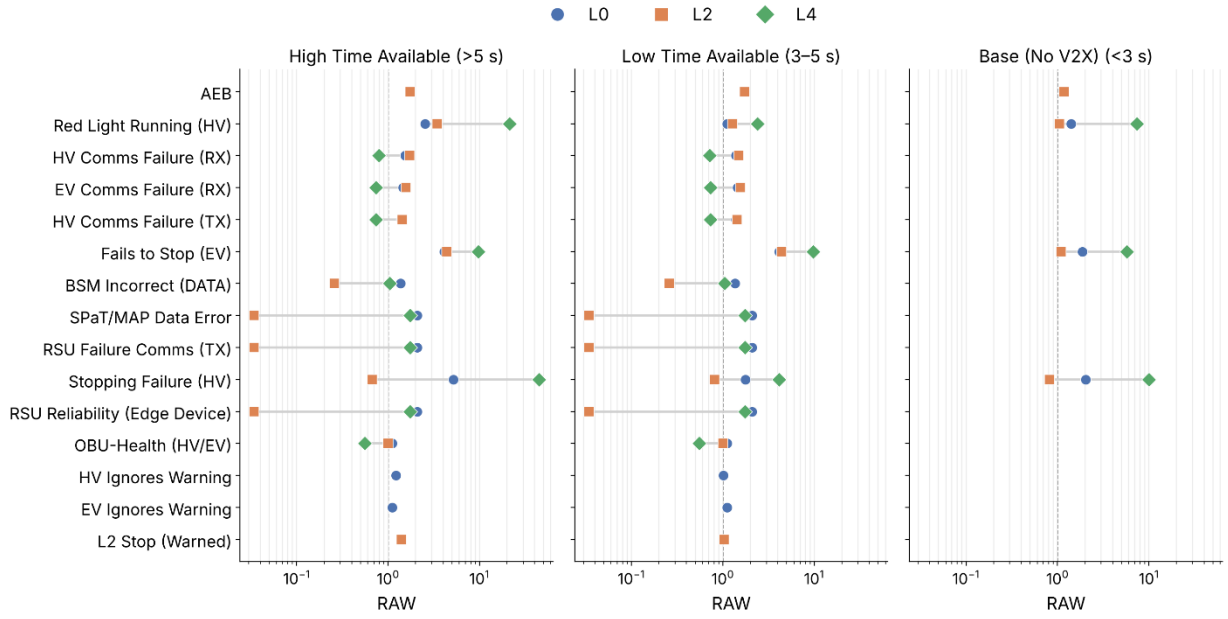
4.3.1.1. RLVW Level 0 Scenario

At L0, the HV's failure to receive the RSU broadcast (HV comms failure (RX)) ranks highest on RRW, confirming that reliable message reception (either the RSU-generated RLVW or the SPaT required to trigger onboard warnings) is the largest lever for reducing crash risk, while its moderate RAW indicates that the currently assumed failure rate is not itself a large driver of risk. The underlying red-light-running rate (Red Light Running (HV)) ranks second on RRW and is also sensitive to its current value, particularly in the high time-availability branch. The encountering vehicle's failure to receive the warning (EV comms failure (RX)) shows a similar profile, while the HV's transmission failure (HV comms failure (TX)) is a smaller lever.

The underlying red-light-running rate (Red Light Running (HV)) ranks second on RRW, with a moderate RAW, indicating both room for improvement and sensitivity to the current failure rate, particularly in high time-availability scenarios (>5 s). The encountering vehicle's reception failure (EV comms failure (RX)) shows a similar profile, while the HV's transmission failure (HV comms failure (TX)) is a smaller lever than either reception failure. Stopping-related nodes show the opposite profile. The EV's failure to yield to a red-light runner under unwarned conditions (Driver Fails to Stop (EV)), which is relevant to the Enhanced RLVW application, and the HV's stopping failure (Stopping Failure (HV)) have low RRW but the highest RAW values in the L0 model. This is the profile of components that are fairly reliable in the model but whose failure contributes disproportionately to the modeled crash probability.



(a) RRW



(b) RAW

Figure 4.30: Importance Measures (a) RRW (b) RAW – RLVW, L0, L2 and L4.

The RSU and OBU reliability nodes, the communication and data nodes (SPaT/MAP Data Error, RSU Failure Comms (TX), BSM Incorrect (DATA)), and the warning-compliance nodes (HV Ignores Warning, EV Ignores Warning) all have RRW close to 1, indicating that no single communication link or warning-response failure dominates the RLVW-

related failure sequence. The RSU-related nodes share an elevated RAW, consistent with their acting through the same RSU message path. **In summary, these results indicate that for automation level 0, the greatest return on further data collection to refine estimated safety benefits are (in prioritized order):**

- **V2X message reception reliability (both RSU-to-HV and RSU-to-EV)**
- **Red-light-running base rate**
- **Stopping behavior: host vehicle driver stopping performance and encountering vehicle driver-yield behavior under unwarned conditions**

4.3.1.2. RLVW Level 2 Scenario

At L2, AEB dominates the RRW ranking. Because AEB is modeled as the last barrier after both the driver and the L2 function have failed to stop, nearly all of the residual crash probability in the V2X branches passes through an AEB failure, so a perfectly reliable AEB would remove almost all residual risk. Its modest RAW reflects the node's current conflict probability, derived from PARTS (2025) (Section C.1.3). Among the V2X-related nodes, the ranking follows L0, with larger RRW values in the high time-availability branch: the red-light-running base rate (*Red Light Running (HV))* ranks first (with the largest RRW of any automation level), followed by HV message reception (*HV comms failure (RX)*), EV message reception (*EV comms failure (RX)*), and HV transmission (*HV comms failure (TX)*). The encountering vehicle's failure to stop (*Fails to Stop (EV)*) shows the highest RAW in the L2 model with an RRW near 1, the same profile observed at L0. Unlike L0 and L4, the RSU-side nodes, BSM data errors (*BSM Incorrect (DATA)*), and the HV stopping failure (*Stopping Failure (HV)*) show RRW and RAW values slightly below 1, i.e., in this model their failure does not increase the crash probability once the L2 response and AEB paths are included.

In summary, these results indicate that for automation level 2, the greatest return on further data collection to refine estimated safety benefits are (in prioritized order):

- **AEB performance as the last barrier**
- **Red-light-running base rate**
- **V2X message reception reliability (RSU-to-HV, then RSU-to-EV)**
- **EV stopping behavior**

4.3.1.3. RLVW Level 4 Scenario

At L4, the HV's failure to receive the RLVW (*HV comms failure (RX)*) remains the top-ranked RRW node, followed by the encountering vehicle's failure to receive the Enhanced

RLVW warning of a red-light runner (*EV comms failure (RX)*), the underlying red-light-running rate (Red Light Running (HV)), and the HV's transmission failure (*HV comms failure (TX)*). This reflects the ADS's greater reliance, relative to the L0 driver, on receiving V2X messages when it has failed to detect the conflict on its own.

The most notable shift from L0 is in RAW: the ADS stopping failure (*Stopping Failure (HV)*) under warned conditions and the red-light-running base rate (*Red Light Running (HV)*) reach RAW values close to an order of magnitude above their L0 counterparts, with a smaller increase for the encountering vehicle's failure to stop (*ADS Fails to Stop (EV)*). This follows from the low L4 baseline failure rates: because the ADS is expected to rarely misclassify traffic signals (absent external causes), that failure mode accounts for a disproportionately large share of the reduced crash probability. This implies that **while further risk reduction remains achievable through improvements to these V2X functions, it is more important to validate how automated features contribute to overall improved safety performance.**

In summary, these results indicate that for automation level 4, the greatest return on further data collection to refine estimated safety benefits are (in prioritized order):

- **V2X message reception and transmission reliability (RSU-to-HV, RSU-to-EV, and HV transmission)**
- **Red-light-running base rate**
- **ADS stopping performance (HV under warned conditions and EV in response to a red-light runner)**

4.3.2. PED-CP Analysis

This section reports RRW and RAW importance measures for Scenario B (PED-CP), following the same convention as Section 4.3.1. Figure 4.31 and Figure 4.32 report RRW and RAW, respectively, for each basic event across automation levels and time-availability branches, for intersection and midblock crossings. Tabulated data are provided in Appendix D.2.2.

4.3.2.1. PED-CP Level 0 Scenario

At L0, the dominant node differs by crossing geometry. At midblock crossings, the driver's failure to detect a potential pedestrian conflict under unwarned conditions (*Driver Detection Failure*) ranks highest on RRW in all branches, consistent with pedestrian detection being the main bottleneck in an unassisted crossing conflict, while its modest RAW indicates that the currently assumed failure rate is not itself a large driver of risk. At

intersections, the warned driver's failure to stop (*Stopping Failure (HV)*) ranks highest on both measures, followed by the driver's detection failure (*Driver Detection Failure*). The HV's failure to receive the SDSM (*HV Comms Failure (RX)*) ranks next on RRW at both geometries. The remaining infrastructure-side and device nodes have RRW close to 1, although at midblock crossings the RSU-side nodes carry the highest RAW values in the L0 model. **In summary, these results indicate that for automation Level 0, the greatest return on further data collection to refine estimated safety benefits are (in prioritized order):**

- **Pedestrian detection reliability (driver), particularly at midblock crossings**
- **Driver stopping performance under warned conditions, particularly at intersections**
- **V2X message reception reliability (RSU-to-HV)**

4.3.2.2. PED-CP Level 2 Scenario

The Level 2 model retains the L0 failure modes and adds three nodes: the L2 function's pedestrian detection (*L2 Detection Failure (Camera)*), its stopping (*L2 Fails to Stop*), and *PAEB Failure* as the last barrier. The importance of the L0 nodes shifts as a result.

At intersections, the PAEB failure (*PAEB Failure*) ranks highest on RRW, but only in the high time-availability branch, indicating that automated braking plays a significant role in preventing crashes only when there is sufficient time margin. SDSM reception (*HV Comms Failure (RX)*), which enables both fallback mechanisms, ranks second, followed by the L2 camera's detection failure (*L2 Detection Failure (Camera)*). The warned driver's and the L2 function's failures to stop (*Stopping Failure (HV), L2 Fails to Stop*) show moderate RRW but high RAW: they are not large levers for further risk reduction, but the model remains highly sensitive to their current reliability. The remaining infrastructure-side and device nodes have RRW close to 1.

At midblock crossings, the driver's detection failure (*Driver Detection Failure*) remains the top-ranked RRW node, although lower than at L0, followed by the PAEB failure (*PAEB Failure*) and SDSM reception (*HV Comms Failure (RX)*). PAEB Failure has a low RAW at both geometries. The stopping nodes show RRW and RAW close to or below 1 at midblock crossings, i.e., in this model their failure does not increase the crash probability once the L2 response and PAEB paths are included. As at L0, the RSU-side nodes carry the highest RAW values at midblock crossings, whereas at intersections they fall below 1.

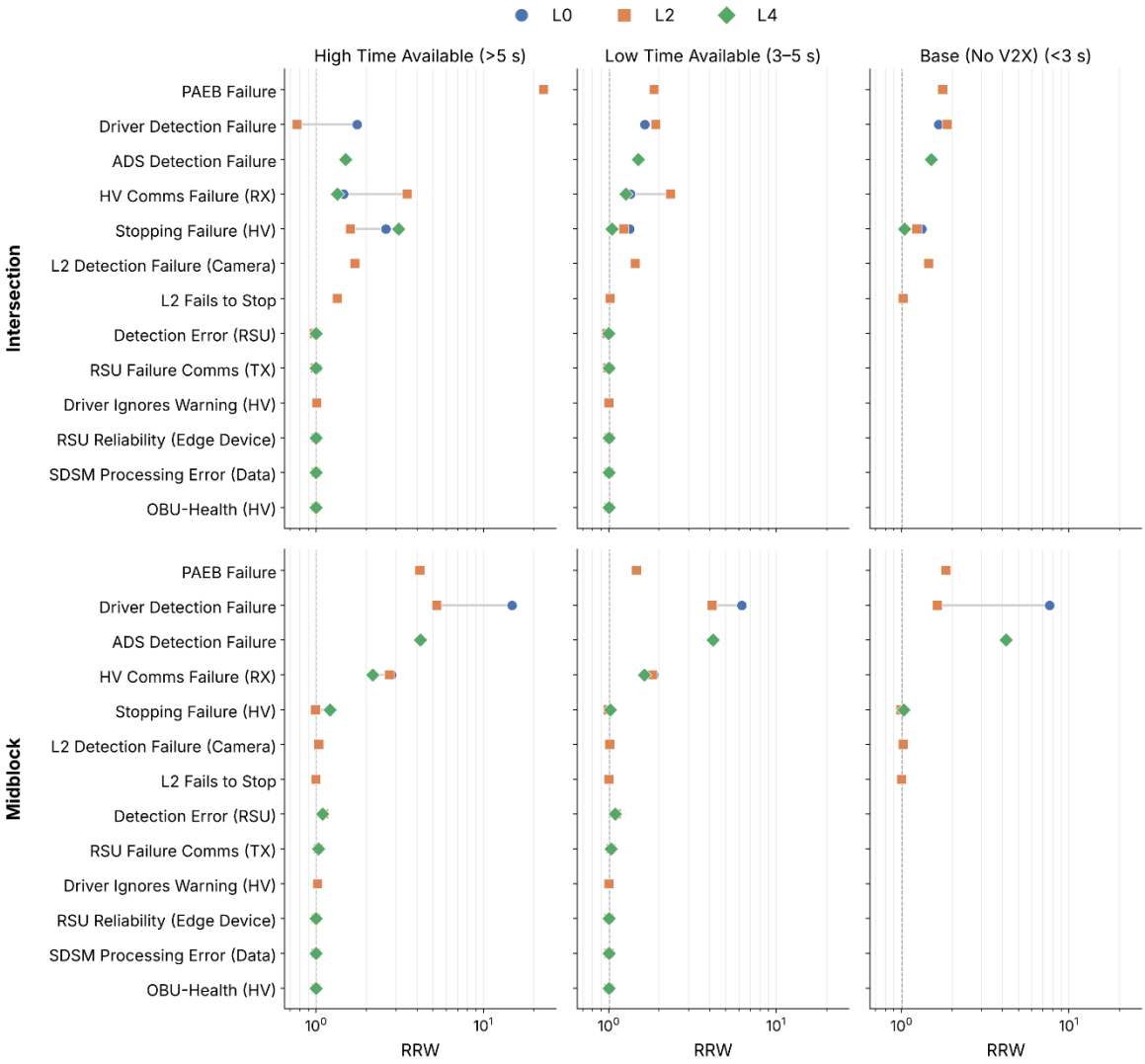


Figure 4.31: Importance Measures, RRW – PED-CP, L0, L2 and L4.

In summary, these results indicate that for automation level 2, the greatest return on further data collection to refine estimated safety benefits are (in prioritized order):

- **PAEB performance, particularly at intersections and in combination with V2X warnings**
- **Pedestrian detection reliability (driver and L2 camera), particularly at midblock crossings**
- **V2X message reception reliability (RSU-to-HV)**
- **Driver and L2 stopping performance at intersections**

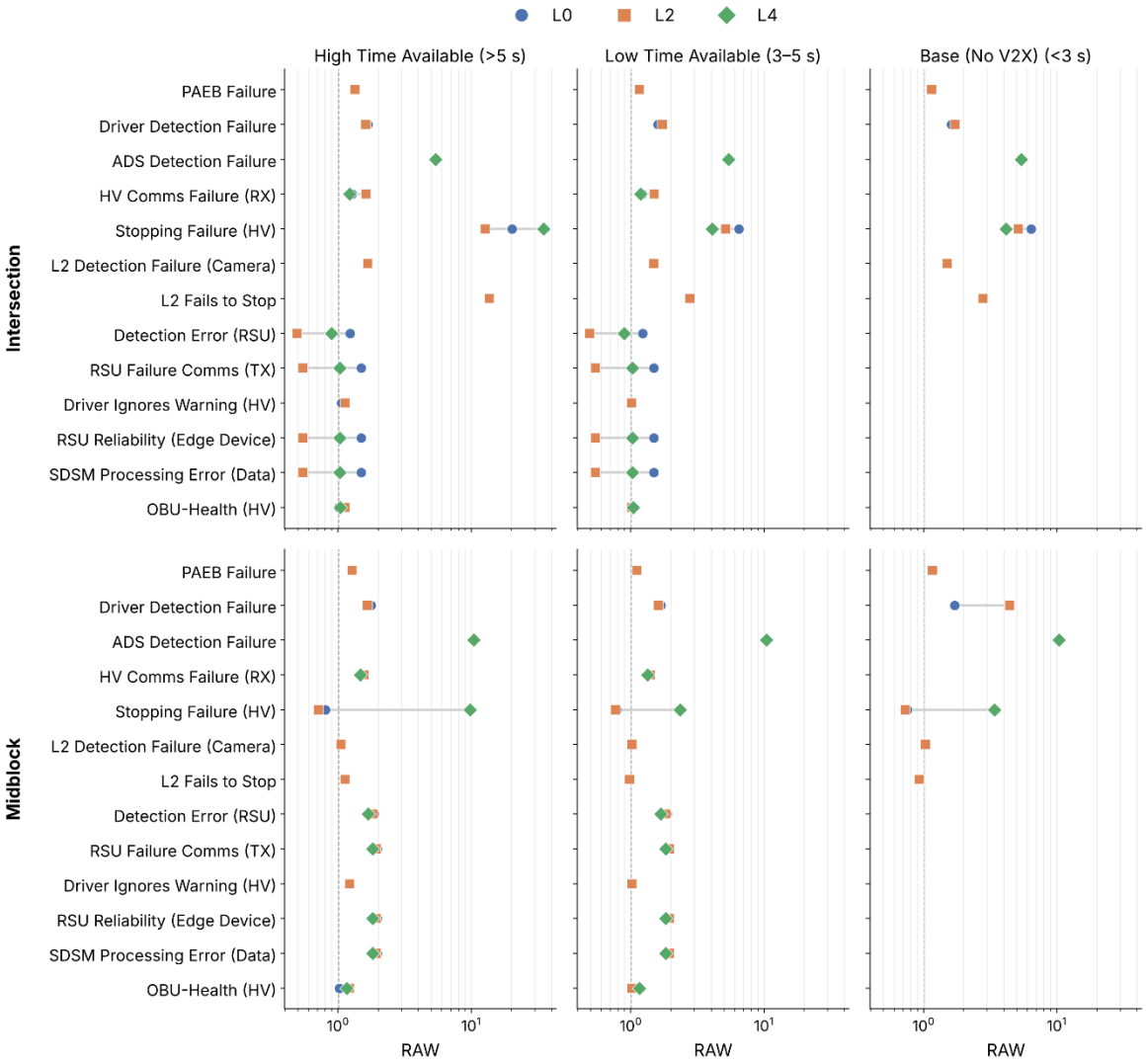


Figure 4.32: Importance Measures, RAW – PED-CP, L0, L2 and L4.

4.3.2.3. PED-CP Level 4 Scenario

At L4 intersections, the ADS's failure to stop under warned conditions (*Stopping/Weather Failure (HV)*) ranks highest on RRW and has the highest RAW in the model, concentrated in the high time-availability branch, the same rare-event pattern observed for RLVW at L4. The ADS's failure to detect the pedestrian (*ADS Detection Failure*) follows, with a flat profile across time-availability branches, and SDSM reception (*HV Comms Failure (RX)*) ranks third.

At midblock crossings, the ADS's detection failure (ADS Detection Failure) leads on both RRW and RAW, followed on RRW by SDSM reception (*HV Comms Failure (RX)*), while the ADS stopping failure (*Stopping/Weather Failure (HV)*) shows a low RRW but a high

RAW. The dominance of the ADS detection and stopping nodes indicates that empirical ADS failure-rate data remains the primary source of uncertainty in this model; the remaining infrastructure and device nodes have RRW close to 1 at both crossing geometries.

In summary, these results indicate that for automation level 4, the greatest return on further data collection to refine estimated safety benefits are (in prioritized order):

- **ADS pedestrian detection reliability, particularly at midblock crossings**
- **ADS stopping performance under warned conditions, particularly at intersections**
- **V2X message reception reliability (RSU-to-HV)**

4.4. Discussion & Limitations

4.4.1. Technology Deployment

At full deployment (V2I:100%/CV:100%), RLVW avoids more crashes annually than PED-CP at every automation level, while PED-CP produces higher economic savings (Section 4.2). This reflects the severity composition of each conflict type: pedestrian-vehicle conflicts carry a higher weighted share of fatality and injury outcomes than the vehicle-vehicle conflicts modeled in RLVW, so each avoided PED-CP crash is valued more highly based on the reference comprehensive crash costs.

Both applications' benefits scale with V2I deployment and CV penetration, but not at the same rate. V2I coverage determines how many locations receive the benefit, and the Study Area benefit scales close to linearly with the share of equipped locations. CV penetration determines how large the benefit is at each equipped location, and its effect is non-linear because a single warning can protect more than one road user. The PED-CP response levels off faster with CV% (CV 25% delivers 48–50% of the full-penetration crashes avoided, compared with 30–37% for RLVW), so additional equipped locations add more to PED-CP benefits than additional CV penetration (Section 4.2). The difference between scenarios may be traced to the baseline, non-V2X collision-avoidance capability. Vehicle-vehicle detection (either from drivers or ADS-equipped vehicles), as modeled in Scenario A (red light violation warning), is a more tractable problem for existing onboard technology. Pedestrian detection is documented to degrade substantially under occlusion, low light, and short-range entry; therefore, infrastructure-based detection provides a complementary detection path in PED-CP (pedestrian collision warning stemming from SDSM). The importance measures nonetheless show that the dominant

sources of residual risk in PED-CP remain vehicle-side detection and stopping performance, with RSU-side nodes contributing little individually (Section 4.3.2).

V2X benefits for L4 are small in absolute terms for both scenarios, since the baseline L4 crash rates are significantly lower based on currently reported data[55] (Section 4.2). In relative terms, V2X still removes an estimated 88% (RLVW) and 56–61% (PED-CP) of the remaining L4 crashes at full deployment (Section 4.3.2).

The relative benefit is largest at L2 in both scenarios, where either the driver or the partial automation can respond to a warning (Section 4.2). Because its baseline is also lower, the absolute benefit at L2 is close to that of L0 for PED-CP and about two thirds of it for RLVW. The importance measures show that the last-barrier functions (AEB for RLVW and PAEB for PED-CP at intersections) dominate the L2 rankings (Section 4.3). This result depends on the assumption that the L2 system can act on a received V2X warning with a reaction time comparable to an ADS (approximately 50–100 ms; Sections 3.1.2.4 and 3.2.2.4).

Based on these findings, **prioritizing Pedestrian Collision Warning (Scenario B) deployment at high-severity, high-exposure midblock locations offers the highest return, given its higher dollar value per crash avoided** and because it captures about half of its full-penetration benefit at CV 25%, so early returns depend mainly on how many high-exposure locations are equipped. However, this application also depends on detection and communication technology (SDSM, occlusion-robust perception) that is less mature and less field-validated than RLVW's, which argues for planning the locations for infrastructure-based sensor and communication systems now while phasing in deployment as the underlying technology matures. RLVW (Scenario A) deployment reaches a larger crash population in absolute terms and draws on more established, standardized infrastructure. Thus, **RLVW remains the more immediately actionable priority for broad near-term deployment**, with benefits that continue to grow with CV penetration (CV 25% captures about one third of the full-penetration benefit) and are reached most efficiently by increasing V2I coverage and CV penetration together (Section 4.2).

4.4.2. Modeling Limitations

The results presented in Section 4.1-4.2 are based on a set of assumptions, modeling choices, and limited data sources given the early stage of real-world V2X applications.

[55] K. D. Kusano, J. M. Scanlon, Y.-H. Chen, T. L. McMurry, T. Gode, and T. Victor, “Comparison of Waymo Rider-Only crash rates by crash type to human benchmarks at 56.7 million miles,” Traffic Injury Prevention, pp. 1–13, May 2025, doi: 10.1080/15389588.2025.2499887

4.4.2.1. Scenario A: RLVW

The main limitation of this model arises from the nature of the potential red-light runner's population. The underlying rate of vehicle-to-vehicle intersection crashes stemming from red-light running conflicts is estimated to be approximately 27% (see **Section 3.1.2**). This figure represents a driver population (L0/L2) that covers unintentional ones (inattention, distraction, inability to stop given speed/weather/visibility) and intentional traffic violations (low perceived enforcement risk, congestion, queue-following). The model does not distinguish between these types of red-light runners beyond assuming a time-dependent rate of warning non-compliance (**C.1.5.2**). The Enhanced RLVW concept, which layers infrastructure-side warnings onto the traditional onboard RLVW warning, is a key safety mechanism to account for intentional traffic violations; however, it requires additional processing at the RSU that was not evaluated for computational or maintenance cost in this analysis.

Red light running arises from a wide range of driver behavior and roadway geometry factors that this model does not attempt to fully capture. No specific assumptions were implemented to represent the driver's states (see Phase 1 report for discussions on data limitations representing driver states[56]), and intersection geometric characteristics are currently simplified as intersection type (4-way vs. 3-way), while other key factors known to influence dilemma zone behavior, such as width and lane count, are not represented. Further, AADT/total entering volume is used as a proxy for conflict exposure, which is a reasonable first-order approximation but does not capture turning-movement-specific exposure or time-of-day variation in conflict rates. Regarding L4 ADS modeling, it should be noted that standardized ADS incident data at the specificity needed for this kind of model is limited, e.g., traffic-signal misinterpretation is not systematically traced as a root cause for vehicle disengagement during testing or fallback during operation.

Regarding L2 modeling, the AEB recovery path is anchored to the PARTS (2025) effectiveness estimate for crashes at intersections (44.4%), which refers to front-to-rear crashes; no comparable estimate is available for the angle crashes that dominate red-light-running conflicts, so this value is adopted as a ceiling of AEB performance. In addition, the L2 response to a received warning reuses the L4 end-to-end reaction time, while warning compliance and the unwarned red-light-running rate follow the L0 driver model. The AEB node determines the lower L2 no-V2X baseline (approximately 44% below L0), while the L2 response path determines the larger L2 relative benefit with V2X;

[56] Correa-Jullian, C., Mosleh, A., Zhu, D., & Ma, J. (2025). Quantifying Safety Impacts of V2X-Enabled Traffic Systems (Phase 1). *UCLA: Mobility Center of Excellence*. http://dx.doi.org/10.82903/B2CC78 Retrieved from https://escholarship.org/uc/item/6tz6n000

both should be revisited as field evidence on L2 responses to V2X warnings become available.

V2X communication reliability estimates rely on nominal per-packet delivery rate (≈0.97–0.99), degraded by weather and LOS/NLOS conditions. These estimations are not calibrated against DTLA-specific field measurements, particularly under high traffic congestion. The model also does not represent the time-dependent reliability of SPaT data. Field testing has documented failure modes in which RSU-broadcast SPaT no longer reflects the actual signal state due to controller/RSU processing timing, independent of transmission reliability. This is a distinct failure mode from the communications-link failures already represented in the model (RSU Failure Comms (TX), HV/EV reception failures) and is not currently included. Collecting field data on SPaT data-integrity failure rates, separate from transmission reliability, is a prerequisite for a complete cost-benefit case for Enhanced RLVW, including the maintenance burden associated with keeping SPaT accuracy over time.

The model is anchored in empirical studies on driver warnings and vehicle kinematics. The warning-timing brackets (3s/5s no-availability/low-high boundary) come from stopping-distance kinematics for the 35-50 mph approach speed range modeled (**Section 3.1.2**). Driver compliance is also already conditioned on dilemma-zone position through the high/low-availability branch structure, rather than applied as a flat compliance-rate discount. False positives have been documented to degrade drivers' trust in warnings, and the potential effect of repeated false-positive warnings on compliance over time is not considered in this model (i.e., the warning compliance rate only applied to true positive warnings).

Two benefits fall outside the model's scope. First, reducing red-light-running events at an intersection plausibly reduces VRU exposure at that same intersection, a collateral safety benefit outside the modeled vehicle-vehicle conflicts. Second, infrastructure-generated warnings can potentially recognize conflicts beyond a vehicle's own onboard collision-avoidance system (L2+), given their lower exposure to NLOS conditions. This complementary role, rather than a purely redundant one, is part of why V2X-side nodes remain important even as onboard automation improves (see the Level 4 RRW/RAW discussion in **Section 4.3.1**).

4.4.2.2. Scenario B: Pedestrian Collision Warning

The main limitation of this model arises from the nature of the high-risk VRU conflicts stemming from unexpected behaviors, such as jaywalking or dart-outs from occlusions. The occlusion modeling in this analysis represents partial occlusion; true dart-out events, where a pedestrian or other VRU is entirely hidden until immediately before the conflict,

are difficult to represent with the same framework and are not well reported in available literature. The analysis is also limited to two generic crossing geometries (intersection and midblock crossings) as a simplification of the much larger variety of real-world crossing configurations (curb extensions, medians, multi-stage crossings, etc.).

Occlusion impact estimates draw on published literature rather than field-measured detection, localization, and tracking performance (from either infrastructure-mounted or vehicle-mounted sensors) under occlusion. This is one of the larger data gaps in the model, since detection failure (driver at L0/L2, ADS at L4), which is driven primarily by occlusion in the model, is the top-ranked RRW node at midblock crossings at every automation level and remains among the top-ranked nodes at intersections (**Section 4.3.2**), implying that the model's overall precision is disproportionately sensitive to the estimated detection performance for camera- and LiDAR-based systems.

As in Scenario A, the host vehicle's (driver at L0/L2, or ADS at L4) reaction is modeled as a function of warning timing without assuming a specific warning mechanism or SDSM-ingestion mechanism. It should be noted that real-world performance will depend on the OEM's specific implementation. The modeled SDSM response is front-loaded in CV penetration: CV 25% delivers about 40% of the full-penetration per-encounter reduction at midblock crossings and 52–56% at intersections, and the intersection response levels off beyond about 50% CV, while midblock crossings continue to benefit at higher penetration. As a result, the near-term benefit estimate is more sensitive to which locations are equipped than to the CV penetration trajectory, whereas in Scenario A (RLVW) the benefit continues to grow with CV penetration. For L2, onboard pedestrian detection is parameterized from the L4 vehicle-mounted camera detection probabilities only, and the L2 braking response reuses the L4 stopping model. Similar to RLVW, PAEB is anchored to Cicchino (2022) and PARTS (2025), with substantially reduced performance at night and under occlusion. These assumptions bound the L2 results until field data on L2 pedestrian detection and response to SDSM-derived warnings become available.

In addition, signal timing at intersections is not modeled as a factor in VRU crossing behavior; the analysis treats a pedestrian-vehicle conflict as a surprise-level event rather than modeling how a pedestrian's crossing decision might vary with signal phase. Similarly, VRU-specific factors such as speed, size, and crossing trajectory (all relevant to real SDSM generation performance) are abstracted to function-level performance rather than modeled explicitly. Therefore, the analysis evaluates whether detection/warning succeeds or fails, not how detection performance varies with these VRU characteristics. Data trustworthiness is a separate concern the model does not address: SDSM accuracy depends on IOOs maintaining infrastructure sensor systems

over time, and this maintenance burden is not represented. The model also handles message veracity differently by automation level, consistent with how the fault trees are structured: at L0/L2, the analysis abstracts the question of whether an SDSM is accurate to a driver-warning-response problem (does the driver comply with what may or may not be a valid warning); while at L4, the analysis assumes the vehicle has some independent capacity to assess SDSM veracity before acting on it. This is a reasonable simplification given the current state of SDSM deployment maturity. RSU-based sensing can plausibly provide the largest relative benefit in conditions where onboard vehicle sensing is degraded (e.g., nighttime), but it is unclear what verification mechanism or strategy will be implemented in the future.

4.4.2.3. Cross-Scenario Discussion

Both models assume that a warning delivered with less than approximately 3 seconds of time remaining is no longer useful to the driver or system. Collision-avoidance benefit is not necessarily zero below this threshold, but delayed or absent driver action becomes increasingly likely as available time decreases below this threshold, for reasons this model does not disaggregate (attention, distraction, indecision, etc.). Refining this threshold (along with the broader question of false-positive rates and their effect on long-term technology adoption and trust) is one of the clearer opportunities for further study (**Section 4.4.3**).

Communications reliability is treated relatively optimistically in both scenarios. Message reception and transmission rates used do not account for degraded conditions such as heavy traffic density or dense urban canyon environments, both of which are known to affect V2X link reliability in practice. Sensitivity to perception-reaction time and achievable braking deceleration is significant, and approach speed has an outsized effect on outcomes. The current models evaluate a small number of discrete speed states (30-40 mph) under specific weather and lighting conditions rather than a continuous or more broadly sampled range. More sophisticated braking and PRT models, calibrated against a wider range of conditions, would narrow this source of uncertainty.

Absolute benefits are consistently smaller for the ADS (L4) scenarios in both cases, since the modeled L4 no-V2X baselines are 85% (RLVW) and 92% (PED-CP) lower than the L0 baselines, figures that are expected to shift as ADS fleets grow and more real-world evidence accumulates. Representative, standardized ADS incident data at a level of specificity comparable to what exists for human-driver behavior is not currently available in the literature. In relative terms, the two scenarios diverge. For RLVW, L4 removes a larger share of its own baseline than L0 at full penetration (88.3% vs. 84.8%), since the residual ADS risk is dominated by communication and device failures that full connectivity addresses. For PED-CP, L4 removes the smallest share of the three automation levels

(60.7% vs. 74.3% for L0), because the conflicts that remain for an ADS are concentrated in occluded or low-light conditions, in which infrastructure-mounted sensing is also degraded. This is consistent with the importance measures (Section 4.3): at L4, ADS detection and stopping performance dominate the PED-CP rankings, whereas for RLVW, V2X message reception remains the top-ranked RRW node and ADS stopping performance shows the highest RAW. Grounding the specific function-level ADS performance figures used here (camera/LIDAR-based detection rates, etc.) against real-world benchmarks is a priority, since the published figures are typically reported as dataset-level averages rather than broken out on a per-encounter basis.

Finally, the economic and collision-avoided quantification in Sections 4.1.1.2 and 4.1.2.2 is linear by construction: it treats V2X's effect as a reduction in crash frequency at a fixed severity composition and does not account for two plausible secondary effects: a shift in the fatality/injury/PDO mix toward less severe outcomes, or a longer-timescale reduction in conflict exposure itself (e.g., if repeated near-miss avoidance changes driver behavior over time). Both would likely increase the true benefit beyond what is reported here, making the current estimates conservative in that specific sense.

4.4.3. Future Data Collection Opportunities

The RRW/RAW results in Section 4.3 identify where the models are both most sensitive to further improvement (RRW) and most exposed to current reliability assumptions (RAW).

4.4.3.1. Scenario A: RLVW

HV and EV message-reception reliability (*HV comms failure (RX), EV comms failure (RX)*) rank highest on RRW at L0 and L4, and immediately after AEB and the red-light-running base rate at L2. The model currently applies a single nominal per-packet delivery rate, degraded by weather and LOS/NLOS conditions, rather than field-measured reception rates specific to the study area. **Field data on V2X reception and transmission reliability, particularly under high traffic congestion, is the highest-value data collection target for this scenario at L0 and L4.** Red-light-running and yield behavior (*Red Light Running (HV), Driver Fails to Stop (EV)*) also rank highly on both RRW and RAW, but the underlying $p \approx 0.27$ base rate averages over intentional and unintentional violations without distinguishing between them. Driver behavior data disaggregated by violation type (e.g., using vehicle speed as a proxy) would allow the model to estimate RLVW effectiveness for these different populations. SPaT data-integrity failure, distinct from transmission reliability, is not currently represented as its own node in the model. Field logging of actual signal state against RSU-broadcast SPaT during longer periods of operation would support adding this failure mode and would also inform the maintenance-

cost side of the Enhanced RLVW cost-benefit case. At L2, AEB is the dominant RRW node, and two data gaps limit the current estimates: AEB effectiveness for angle and crossing-path crashes at signalized intersections (the current anchor refers to front-to-rear crashes), and field evidence on whether, and how quickly L2 systems act on received RLVW warnings. **Naturalistic or test-track data on L2 responses to V2X-derived warnings would allow the L2 response path to be parameterized directly rather than borrowed from the L4 model.**

4.4.3.2. Scenario B: Pedestrian Collision Warning

Detection failure (*Driver Detection Failure at L0, ADS Detection Failure at L4*) is the top-ranked RRW node at midblock crossings at every automation level, while at intersections warned stopping performance (driver at L0, ADS at L4) and PAEB (L2) rank first (Section 4.3.2). Sensor-based detection probabilities are currently parameterized from published camera/LiDAR benchmarks rather than field-measured performance. **Perception data broken out by object distance, size, and approach speed, rather than a single aggregate detection rate, is the highest-value data collection target for this scenario, for both infrastructure-mounted and vehicle-mounted sensors, together with stopping-performance data for warned drivers and ADS at intersections.** Communication-related node (*HV comms failure (RX)*/SDSM reception) reliability is the next consistent priority, ranking among the top three RRW nodes at every automation level and crossing geometry. For L2, the main data needs are PAEB effectiveness in dark and partially occluded conditions, and onboard pedestrian detection performance for production L2 camera systems, particularly at intersections where PAEB is the top-ranked RRW node.

4.4.3.3. Common Opportunities

Insights gathered from RRW/RAW analysis reflect the level of granularity of the modeling assumptions. Function-level activation and outcome logging at the RSU and OBU (not just system-level pass/fail) is needed to estimate several of the items discussed above. Multiple tools can support reducing uncertainty of the failure rates implemented in this model, including software- and hardware-in-the-loop testing and closed-loop simulations, for instance, to more accurately determine when the *last* useful message (i.e., the lower threshold of effective time availability) may be sent from the infrastructure to the host vehicle (either as useful information for the onboard system, or directly as a warning). These same tools are also well suited to characterizing warning-timing thresholds, PRT, and braking performance under degraded conditions more broadly, since the triggering conditions for these parameters are difficult to sample efficiently through naturalistic field collection alone.

5. Stakeholder Engagement

Stakeholder engagement for V2XPRA was carried out through two channels: public-agency engagement via the FHWA-hosted Accelerating V2X Cohort Meeting, and direct outreach to private-sector companies operating in adjacent data and analytics markets. Both aimed to test whether the tool's outputs and design assumptions align with what practitioners and industry currently need.

In summary, public agencies actively pursuing V2X deployment show demonstrated demand for a tool like V2XPRA, particularly to support benefit-cost justification and leadership communication, and the RLVW and PED-CP use cases modeled in this report align with practitioner priorities. Industry engagement did not produce near-term collaboration commitments but surfaced genuine interest in the modeling approach and in future data partnerships, suggesting a path for continued engagement as the tool matures. Additional details are discussed in the following subsections.

5.1.1. Accelerating V2X Cohort Meeting

The Accelerating V2X Cohort Meeting was held June 1, 2026, hosted by the ITS Joint Program Office at USDOT, and drew approximately 97 attendees from public agencies, industry, and research organizations engaged in V2X deployment. Following a presentation of V2XPRA, a structured questionnaire was administered to gather feedback on the tool's design, use cases, and perceived value; 16 respondents completed the questionnaire. Details of the specific questions administered and the recorded responses are presented in Appendix E.

Respondents skewed heavily toward state DOTs (56%), with the remainder split among research/academic organizations, local/city agencies, and private-sector technology providers. Over 80% reported having at least a pilot V2X deployment underway, indicating engagement from organizations past the early-planning stage.

Pedestrian Collision Warning and Red-Light Violation Warning, the two scenarios modeled in this report, were rated as the highest interest use cases among those surveyed (**Figure 7.31**, Appendix E). Respondents most commonly indicated they would use a tool like V2XPRA to communicate safety benefits to leadership and elected officials, support grant applications and benefit-cost analysis, and estimate crashes avoided (**Figure 7.30**, Appendix E). The most requested additional capabilities were operations and maintenance cost assumptions, agency-specific inputs (AADT, corridor selection,

local crash data), and exportable benefit-cost/summary reports (**Figure 7.32**, Appendix E).

The most cited barrier to adopting V2X benefit-analysis tools was uncertainty about V2X benefits themselves (**Figure 7.33**, Appendix E), which reinforces the motivation for a probabilistic, uncertainty-quantified approach like V2XPRA. Respondents rated the overall value of a USDOT-supported V2X safety impact tool at 4.07 out of 5.0 ("very valuable"), and the majority expressed interest in participating in a future pilot, case study, or requirements workshop (**Figure 7.34-Figure 7.35**, Appendix E).

5.1.2. V2XPRA Industry Feedback

In addition to public-agency engagement, the V2XPRA team presented the tool directly to two companies operating in adjacent data and analytics markets: StreetLight Data and INRIX, whose products (StreetLight InSight and INRIX Safety Analytics, respectively) provide roadway exposure and historical crash-risk analytics to public agencies. In addition, the research team conducted a similar engagement activity with Google Public Sector's Transportation Industry Executive and Head of Transportation Strategy and Partnerships to discuss potential collaborations oriented towards public sector agencies. All three briefings covered the same three main topics: how V2XPRA's dashboard and risk outputs align with what each company's existing users expect and where the gaps are; whether there is organizational interest in adding a forward-looking, scenario-based safety layer on top of each company's existing data or analysis pathways; and whether each company would consider co-developing a future scaled-up iteration of the tool, licensing the V2XPRA engine, or commissioning further development, to surface V2XPRA-based results within their own platforms.

Streetlight: StreetLight described itself as a data company that continues to add connected-vehicle data sources to capture movement patterns and surrogate safety indicators such as hard-braking and acceleration events, in addition to its existing traffic volume and speed-distribution data. StreetLight viewed V2X applications as a relatively niche use case, though it expressed interest in V2XPRA's risk-mapping and prediction concept. The company noted that it has developed similar internal tools in the past but found them difficult to market, and that it is generally not aware of active V2X interest among its own clients, in part because each client operates its own data pipeline, which makes generalizing a tool across the client base difficult. StreetLight characterized its business as focused on safety insights rather than planning applications and noted interest in other safety countermeasures beyond V2X specifically.

INRIX: INRIX identified several of its data products, including intersection movement and volume, AADT, speed distributions, and lane-level directional data, as potentially useful inputs to V2XPRA, and described its typical collaboration structure as a data partnership. INRIX has separately explored risk models based on surrogate safety indicators such as hard braking but noted open questions about how to reliably link such indicators (e.g., near misses) to actual crash outcomes. INRIX also noted interest in broader fleet safety applications, such as route selection, rather than conflict-specific warnings like RLVW or PED-CP. As a software rather than hardware company, INRIX distinguished between supplying data and endorsing a standardized risk-assessment methodology, noting that the latter would require FHWA backing, and suggested that partnership opportunities may exist with parties engaged with next-generation prediction tools. INRIX indicated limited near-term interest in a V2X-specific planning tool given its position as a software provider and suggested such a tool would be better suited to markets where RSU infrastructure is already installed. Its principal open question was whether V2XPRA is intended to inform future FHWA standards for V2X application requirements or to become a separate product.

Google Public Sector: This organization is dedicated to developing tools for public agencies, enabling data hosting, compute power, and data-driven analysis for multiple sectors. The discussion evolved towards how tools such as V2XPRA would require (i) a broader analysis scope (as opposed to a V2X-dedicated analysis tool), and (ii) a stronger testing and experimentation cycle with public agencies to tailor the tool to their needs. Further discussion on model details is needed to understand potential collaboration pathways on data, compute, or hosting.

Specific methodological suggestions include:

- Move from basic benefit-cost analysis to results-based accountability methodologies, which would improve alignment with safety goals like Vision Zero.

- Shift the safety tool's conceptual framework from a V2X-specific focus to a broader model centered on overall intelligent transportation system technology, safety countermeasures, and innovation investment outcomes.

- Engage directly with the primary target audience for this tool, such as city and state capital investment planners, to understand their needs and how a tool like V2XPRA may fit into existing public agency workflows that often rely on qualitative and subjective data to assess other traditional safety countermeasure investments, noting that each state’s economic impact analysis methodology may differ.

Future development suggestions include:

- Collect input and test feedback from public agencies to understand how this type of tool can support short-to-long term planning for local/state agencies. Organizations such as AASHTO, ITS America, and ITS California were suggested as potential channels to search for tool testing and evaluation partners.

- Determine tool scaling requirements, such as model/tool access, update, and maintenance policies.

5.1.3. Remarks

The stakeholder engagement in Phase 2 focused on collecting feedback from two separate groups: public transportation agencies and private organizations identified as potential technology transfer channels.

Public agencies actively pursuing V2X deployment showed demonstrated demand for a tool like V2XPRA. Accelerating V2X Cohort Meeting respondents (n=16, 56% state DOTs) rated V2XPRA's selected applications (RLVW and PED-CP) as their highest-interest use cases, cited benefit-cost justification and leadership communication as primary intended uses, and identified uncertainty about V2X benefits as the leading adoption barrier. Respondents rated the overall tool concept 4.07/5.0 and in general expressed interest in future pilots or requirements workshops.

Engagement with StreetLight Data and INRIX did not produce near-term collaboration commitments. Both companies identified their existing data products as potentially useful inputs to a tool like V2XPRA and described data-partnership as their typical collaboration structure, but each cited limited near-term interest in a V2X-specific tool. However, engagement with Google Public Sector surfaced a different kind of interest: broadening V2XPRA's scope beyond V2X toward a general ITS/safety-countermeasure framework, with further discussion needed on collaboration pathways involving data, computing, or hosting. It was also strongly recommended to pursue direct engagement with public-agency end users (e.g., via AASHTO, ITS America, ITS California) to inform future tool development.

6. Conclusions

This report extended the V2XPRA probabilistic risk assessment framework to two infrastructure-dependent V2X safety applications, Red-Light Violation Warning and Pedestrian Collision Warning, across three levels of vehicle automation and a range of infrastructure deployment and market penetration scenarios. Applied to a 92-intersection reference deployment in Downtown Los Angeles, the results suggest that both applications produce positive safety and economic benefit, with RLVW addressing a larger volume of collisions while PED-CP delivers a higher economic return per collision avoided due to the greater severity of pedestrian-vehicle conflicts. Both applications' benefits depend on V2I deployment and connected-vehicle market penetration and are comparatively modest at Level 4 because low L4 baseline crash rates leave less absolute room for further reduction. Even so, V2X may offer an estimated additional 27–88% reduction in per-encounter crash probability for RLVW, 27–49% for intersection pedestrian collision warning, and 31–73% for midblock pedestrian collision warning at L4 (CV 25–100%). For human drivers (L0), the corresponding reductions are 29–85% for RLVW, 35–66% for intersection pedestrian collision warning, and 33–82% for midblock pedestrian collision warning. The largest relative improvements are estimated at L2, where either the driver or the partial automation can respond to a warning: 35–93% for RLVW, 45–86% for intersection pedestrian collision warning, and 33–84% for midblock pedestrian collision warning.

The importance-measure analysis in Section 4.3 identifies where the current model estimates are most sensitive to further improvement and most exposed to today's data limitations. **V2X communication reliability, red-light-running and yield behavior, and, for PED-CP, pedestrian detection performance (particularly at midblock crossings) and warned stopping performance (particularly at intersections) are the components with the largest influence on both scenarios' results; at L2, the AEB and PAEB last barriers dominate and the clearest priorities for future field data collection** (**Section 4.4.3**). Closing these gaps, particularly through field validation of communication and detection performance, is the most direct path to narrowing the uncertainty in the estimates presented here. Stakeholder engagement conducted for this project (**Section 5**) reinforces these priorities from a practitioner perspective: public agencies already pursuing V2X deployment identified RLVW and PED-CP as priority use cases, and engagement with private-sector data providers surfaced interest in future data collaboration, though not near-term integration.

On balance, **RLVW has greater potential cost-benefit given its larger addressable crash population, while PED-CP deployment at selected high-severity, high-exposure locations presents the strongest economic case despite its comparatively less mature underlying technology. Analysis suggests the greatest safety return-on-investment may come from equipping high-crash locations first and instrumenting 25% of the human-driven vehicles that use them with V2X.** Because the warning acts only at equipped locations, wide V2I coverage with partial CV penetration outperforms full CV penetration with partial V2I coverage in both scenarios, and V2X combined with partial automation (L2) yields the largest relative benefit, subject to the assumptions on the L2 response discussed in Section 4.4.2.

The V2XPRA tool developed alongside this analysis translates these risk models into an accessible, GIS-based decision-support interface, intended to support state and local agencies in evaluating V2X infrastructure investment under their own local deployment assumptions. Continued refinement of the underlying models, informed by the field data priorities identified in this report, will improve the precision of these estimates as V2X technologies move from pilot deployment toward broader adoption.

7. Supporting Materials

Appendix A. V2X Application Review

Table 7.1: V2X Application Review.

Application	Type	Messages	Emitter(s)	Receiver(s)	V2X Accelerator Site
Emergency Vehicle Preemption (EVP)	Signal Priority & Preemption	SRM, SSM, SPaT, MAP	Emergency vehicles	Signal controllers, nearby vehicles	Utah, Maricopa
Transit Signal Priority (TSP)	Signal Priority & Preemption	SRM, SSM, SPaT, MAP	Transit buses (request priority)	Signal controllers (grant/deny request)	Utah, Maricopa, Texas
Pedestrian Presence Warning (PPW)	Safety Warnings (Crash Avoidance)	PSM, TIM	Pedestrian devices, crosswalk sensors (BSM from OBUs to RSU, convert to PSM send to OBUs)	HDVs, ADS	
Road Weather Alerts (RWA)	Hazard & Environmental Alerts	TIM, BSM Part II	Infrastructure, equipped vehicles	HDVs, ADS, infrastructure	Utah, Texas
Work Zone Warnings (WZW)	Hazard & Environmental Alerts	TIM, MAP, SPaT	Work zone RSE, DOT	HDVs, ADS	Texas
Freight Signal Priority (FSP)	Signal Priority & Preemption	SRM, SSM	Freight vehicles	Signal controllers	Maricopa
Queue Warning (QUE)	Hazard & Environmental Alerts	TIM, BSM	TMCs, probe vehicles	HDVs, ADS	

Application	Type	Messages	Emitter(s)	Receiver(s)	V2X Accelerator Site
Red Light Violation Warning (RLVW)	Safety Warnings (Crash Avoidance)	BSM, SPaT, MAP	Violator vehicle, intersection RSE	HDVs, ADS	Texas
Active Emergency Vehicle Warnings (AEV)	Safety Warnings (Crash Avoidance)	BSM, TIM	Emergency vehicle	HDVs, ADS	
Curve Speed Warning (CSW)	Hazard & Environmental Alerts	TIM	RSE at curve, DOT	HDVs, ADS	Utah, Texas
Incident Alerts (INC)	Hazard & Environmental Alerts	TIM	TMCs, law enforcement	HDVs, ADS	Texas
School Zone Warning (SZW)	Safety Warnings (Crash Avoidance)	TIM	RSE, TMC	HDVs, ADS	
Mobile Accessible Pedestrian Signal (PED-SIG)	Accessibility	SPaT, MAP, PSM, TIM	Pedestrian devices, signal controller	Pedestrians, ADS	
Traffic Probe Data (TPD)	Probe & Data Sharing	BSM (Part II)	Connected vehicles	TMCs, infrastructure	
Safety Probe Data (SPD)	Probe & Data Sharing	BSM Part II	Vehicles	TMCs, researchers	
Near Miss Alerts (NMA)	Safety Warnings (Crash Avoidance)	BSM, PSM, TIM	Vehicles, infrastructure	HDVs, ADS, TMC	
Pavement Conditions Probe Data (PCP)	Probe & Data Sharing	BSM extensions	Equipped vehicles	DOTs, TMCs	

Application	Type	Messages	Emitter(s)	Receiver(s)	V2X Accelerator Site
Snowplow Preemption/Priority (SPP)	Signal Priority & Preemption	SRM, SSM	Snowplows	Signal controllers	Utah
Weather Probe Data (WPD)	Probe & Data Sharing	BSM extensions	Vehicles	DOTs, weather services	
Dilemma Zone Protection (DPHV)	Safety Warnings (Crash Avoidance)	SPaT, MAP, TIM	Signal controller	Truck drivers, ADS	
Forward Collision Warning (FCW)	Safety Warnings (Crash Avoidance)	BSM	Leading vehicle	Following HDVs, ADS	
Friction Probe Data (FPD)	Probe & Data Sharing	BSM extensions	Vehicles (ABS/traction data)	DOTs, maintenance crews	
Optimized Signal Timing (OST)	Traveler Information / Mobility	SPaT, MAP, TIM	Signal controller	HDVs, ADS	
Pedestrian Collision Warning (PCW)	Safety Warnings (Crash Avoidance)	PSM, BSM	Pedestrian devices, vehicles	HDVs, ADS	
Railroad Crossing Warning (RCW)	Safety Warnings (Crash Avoidance)	TIM, MAP	Train, crossing infra	HDVs, ADS	
School Bus Warning (SBW)	Safety Warnings (Crash Avoidance)	TIM, BSM	School bus	HDVs, ADS	
Travel Time Advisories (TTA)	Traveler Information / Mobility	TIM	TMC	HDVs, ADS	
Truck Parking Availability (TPA)	Traveler Information / Mobility	TIM	Parking facility, TMC	Truck drivers, ADS	

Application	Type	Messages	Emitter(s)	Receiver(s)	V2X Accelerator Site
Unsafe Lane Change Warning (ULCW)	Safety Warnings (Crash Avoidance)	BSM	Adjacent vehicles	HDVs, ADS	
Wrong Way Detection (WWD)	Safety Warnings (Crash Avoidance)	TIM, BSM, MAP, SPaT	RSE sensors, wrong-way vehicle (send MAP+SPaT "going wrong way" or TIM "wrong way driver alert")	HDVs, ADS, TMC	Texas
Active Construction / Maintenance Vehicle (ACM)	Hazard & Environmental Alerts	BSM, TIM	Work trucks, snowplows	HDVs, ADS, infrastructure	
Congestion Alerts (CAL)	Hazard & Environmental Alerts	TIM	TMCs	HDVs, ADS	

Appendix B. Tool User Guide

Introduction

This document describes the design and methodology behind the V2X Safety Benefit Estimation Dashboard (V2XPRA), an interactive web tool we developed to estimate the safety benefits of deploying Vehicle-to-Everything (V2X) technology in urban settings. The tool connects to a Hybrid Causal Logic (HCL) model, combining Bayesian Networks (BBN), Event Sequence Diagrams (ESD), and Fault Trees (FT), to quantify how much V2X interventions can reduce crash risk at intersections and pedestrian crossings.

The dashboard allows users to:

- Explore crash risk across 92 signalized intersections and 21 midblock crossings in a 1 sq mi study area in Downtown Los Angeles.
- Toggle between a vehicle crash scenario (red light violation) and a pedestrian crash scenario.
- Adjust deployment parameters — automation level, connected vehicle market penetration, and V2I availability — and immediately see how they affect estimated crashes and costs.
- Compare base case risk (no V2X) against intervention case risk (with V2X) in terms of crash counts and economic impact.

This project includes the following code deliverables:

- v2x-front-end-build: This enables the user to launch a local version of the V2XPRA dashboard, enabling the user to visualize and personalize the analysis based on the user toggles described in the User Inputs section of this appendix.
- v2x-front-end-source: This file contains the source code building the V2XPRA dashboard interface, including all the assets GIS-based assets required to utilize it. Note that access to HCL models and quantification engine remains in the GIRS server.

B.1. V2XPRA Overview

Study Area & Data Inventory

Study Area: Initial selection of a 1 square mile bounding box in Downtown Los Angeles, centered near (-118.259, 34.049).

Boundary	Coordinate
West	-118.267545
East	-118.250981
South	34.040860
North	34.056298

Data Inventory: All spatial data is in GeoJSON format and loads when the dashboard initializes.

Data Layer	Count	Description
Signalized Intersections	92	77 four-way, 15 three-way; each with estimated 2024 TEV
Road Segments	245	111 primary, 100 secondary, 9 tertiary, 25 residential
Midblock Crossings	21	Pedestrian crossings between intersections
Signalized Crossings (Intersections)	340	Pedestrian crossings at signalized intersections
Non-Signalized Crossings (Intersections)	28	Pedestrian crossings at unsignalized locations
Non-Signalized Intersections	24	Intersections without traffic signals

Data Layer	Count	Description
Crash Data	Variable (See Data Sources)	Historical crash records (intersection and non-intersection)

Traffic Exposure: TEV (Total Entering Volume) is pre-calculated in the dataset as "*Estimated 2024 AADT_mean*" for each signalized intersection. It represents the sum of incoming segment AADTs divided by 2. Each road segment also has its own AADT estimate with 5%–95% prediction bounds. For the one intersection missing TEV data, we use a dynamic mean fallback (~27,399 vehicles/day) computed from the other 91 valid intersections[57].

Scenarios

Scenario A — Red Light Violation Warning (RLVW):

This scenario models two-vehicle crashes at signalized intersections caused by the host vehicle (HV) running a red light. Based on received BSM and SPaT data, the RSU transmits a warning to both the HV and encountering vehicles (EV). A crash can occur when neither the HV nor EV stops before entering the intersection.

- **Driving Automation Levels:** L0, L2, L4
- **Scope:** 92 signalized intersections

Scenario B — Pedestrian Collision Warning (PED):

This scenario models vehicle-pedestrian crashes at intersections and midblock crossings where the HV fails to detect or react to a pedestrian. The RSU transmits a Cooperative Perception message to the HV based on sensor data. A crash can occur when the HV does not stop before entering the crossing area.

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- **Driving Automation Levels:** L0, L2, L4
- **Scope:** 92 signalized intersections and 21 midblock crossings

User Inputs

The dashboard has four controls that drive the quantification:

Input	Options	Function
Scenario	A (RLVW) or B (PED)	Picks which set of crash models to use
Automation Level	L0, L2, L4	Selects the intervention ESD.
CV Market Penetration	0–100% (25% steps)	Sets evidence on the CV_Market node in the Bayesian Network
V2I Availability	0–100% (25% steps)	Controls what fraction of intersections get V2I equipment. Only those intersections use the intervention model; the rest keep base risk

Model Architecture

Framework:

We use the **Hybrid Causal Logic (HCL)** framework, which ties together three model types:

- Event Sequence Diagrams (ESDs) lay out the chain of events from initial crash exposure to final outcomes (no crash, PDO, injury, fatality).
- Fault Trees (FTs) break down specific failure mechanisms — for example, whether the RSU successfully detects the vehicle, or whether the driver reacts to a warning.
- Bayesian Networks (BBNs) capture how environmental factors (weather, lighting, speeding rates) affect the underlying probabilities.

Model Mapping:

Which models get used depends on the scenario and automation level the user selects:

- **Base Models (no V2X)**

Model	Description	ESD ID
Model 1	Intersection — Vehicles [Base]	L0: [1929]; L2: [3128]; L4: [1998]
Model 2	Intersection — Pedestrians [Base]	L0: [1961]; L2: [2532]; L4: [2543]
Model 3	Segment/Midblock — Pedestrians [Base]	L0: [1958]; L2: [2533]; L4: [2535]

- **V2X Intervention Models**

Model	Description	ESD ID
Model 4	Intersection — Vehicles (Scenario A)	L0: [1919]; L2: [3129]; L4: [1951]
Model 5	Intersection — Pedestrians [V2X]	L0: [1963]; L2: [1962]; L4: [1964]
Model 6	Segment/Midblock — Pedestrians [V2X]	L0: [1965]; L2: [1966]; L4: [1967]

Each ESD is connected to FTs that represent specific failure modes for the key events represented, depending on both the scenario and the level of automation.

- **Key Fault Trees (Scenario A)**

Fault Tree	ID	What It Models
RSU Detection Failure	[1926]	Accounts for BSM/SPaT data errors, communication failures (BBN nodes), and RSU device reliability
HV Fails to Stop (L0, High Time Availability)	[1924]	Failure of the host vehicle (triggering the RLVW) to stop before entering the intersection, for warned (early warning) conditions.
HV Fails to Stop (L0, Low Time Availability)	[1992]	Failure of the host vehicle (triggering the RLVW) to stop before entering the intersection, for warned (late warning) conditions.
HV Fails to Stop (L0, No Warning)	[1988]	Failure of the host vehicle (triggering the RLVW) to stop before entering the intersection, for unwarned conditions.
EVs Fail to Stop (L0, Warned)	[1922]	Failure of any encountering vehicles to stop before entering the intersection, for warned conditions.
EVs Fail to Stop (L0, No Warning)	[1989]	Failure of any encountering vehicles to stop before entering the intersection, for unwarned conditions.
HV Fails to Stop (L2, High Time Availability)	[3131]	Failure of the host vehicle (triggering the RLVW) to stop before entering the intersection, for warned (early warning) conditions, when both the driver and the L2 system fail to respond.
HV Fails to Stop (L2, Low Time Availability)	[3132]	Failure of the host vehicle (triggering the RLVW) to stop before entering the intersection, for warned (late warning) conditions, when both the driver and the L2 system fail to respond.
HV Fails to Stop (L2, No Warning)	[3133]	Failure of the host vehicle (triggering the RLVW) to stop before entering the intersection, for unwarned conditions.
EVs Fail to Stop (L2, Warned)	[3135]	Failure of any encountering vehicles to stop before entering the intersection, for warned conditions, when both the driver and the L2 system fail to respond. Includes HV AEB response.

Fault Tree	ID	What It Models
EVs Fail to Stop (L2, No Warning)	[3136]	Failure of any encountering vehicles to stop before entering the intersection, for unwarned conditions. Includes HV AEB response.
HV Fails to Stop (L4, High Time Availability)	[1925]	Failure of the host ADS-equipped vehicle (triggering the RLVW) to stop before entering the intersection, for warned (early warning) conditions.
HV Fails to Stop (L4, Low Time Availability)	[1997]	Failure of the host ADS-equipped vehicle (triggering the RLVW) to stop before entering the intersection, for warned (late warning) conditions.
HV Fails to Stop (L4, No Warning)	[1999]	Failure of the host ADS-equipped vehicle (triggering the RLVW) to stop before entering the intersection, for unwarned conditions.
EVs Fail to Stop (L4, Warned)	[1923]	Failure of any encountering ADS-equipped vehicles to stop before entering the intersection, for warned conditions.
EVs Fail to Stop (L4, No Warning)	[1923]	Failure of any encountering ADS-equipped vehicles to stop before entering the intersection, for unwarned conditions.

- **Key Fault Trees (Scenario B)**

Conflict Type	Fault Tree	ID	What It Models
Intersection	RSU Detection Failure	[1977]	Accounts for pedestrian detection failures (intersection crossings), processing errors, communication failures (BBN nodes), and RSU device reliability
	HV Fails to Stop (L0, High Time Availability)	[1979]	Failure of the host vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (early warning) conditions.

Conflict Type	Fault Tree	ID	What It Models
	HV Fails to Stop (L2, High Time Availability)	[38173]	Failure of the host vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (early warning) conditions. Includes L2 and PAEB response.
	HV Fails to Stop (L4, High Time Availability)	[1982]	Failure of the host ADS-equipped vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (early warning) conditions.
	HV Fails to Stop (L0, Low Time Availability)	[2873]	Failure of the host vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (late warning) conditions.
	HV Fails to Stop (L2, Low Time Availability)	[38175]	Failure of the host vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (late warning) conditions. Includes L2 and PAEB response.
	HV Fails to Stop (L4, Low Time Availability)	[2874]	Failure of the host ADS-equipped vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (late warning) conditions.
	HV Fails to Stop (L0, No Warning)	[2006]	Failure of the host vehicle to stop before the pedestrian intersection crossing, for unwarned conditions.
	HV Fails to Stop (L2, No Warning)	[38175]	Failure of the host vehicle to stop before the pedestrian intersection crossing, for unwarned conditions. Includes L2 and PAEB response.
	HV Fails to Stop (L4, No Warning)	[2875]	Failure of the host ADS-equipped vehicle to stop before the pedestrian intersection crossing, for unwarned conditions.
Midblock	RSU Detection Failure	[1987]	Accounts for pedestrian detection failures (midblock crossings), processing errors, communication failures (BBN nodes), and RSU device reliability
	HV Fails to Stop (L0, High Time Availability)	[1984]	Failure of the host vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (early warning) conditions.

Conflict Type	Fault Tree	ID	What It Models
	HV Fails to Stop (L2, High Time Availability)	[38170]	Failure of the host vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (early warning) conditions. Includes L2 and PAEB response.
	HV Fails to Stop (L4, High Time Availability)	[1986]	Failure of the host ADS-equipped vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (early warning) conditions.
	HV Fails to Stop (L0, Low Time Availability)	[2883]	Failure of the host vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (late warning) conditions.
	HV Fails to Stop (L2, Low Time Availability)	[38171]	Failure of the host vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (late warning) conditions. Includes L2 and PAEB response.
	HV Fails to Stop (L4, Low Time Availability)	[2884]	Failure of the host ADS-equipped vehicle (receiving the SDSM) to stop before the pedestrian intersection crossing, for warned (late warning) conditions.
	HV Fails to Stop (L0, No Warning)	[2878]	Failure of the host vehicle to stop before the pedestrian intersection crossing, for unwarned conditions.
	HV Fails to Stop (L2, No Warning)	[38172]	Failure of the host vehicle to stop before the pedestrian intersection crossing, for unwarned conditions. Includes L2 and PAEB response.
	HV Fails to Stop (L4, No Warning)	[2882]	Failure of the host ADS-equipped vehicle to stop before the pedestrian intersection crossing, for unwarned conditions.

The BBNs are selected per scenario as shown in the following table:

Scenario	BBN ID	Description
Scenario A — Intersections	[1927]	Accounts for the Crash Exposure Model (base conditions, stopping under warned conditions), the V2X Communication Model, and the AEB recovery node (L2).
Scenario B — Midblock	[1928]	Accounts for the Crash Exposure Model (base conditions, stopping under warned conditions), infrastructure and vehicle-mounted sensor systems, and the V2X Communication Model.
Scenario B — Intersection	[1959]	Accounts for the Crash Exposure Model (base conditions, stopping under warned conditions), infrastructure and vehicle-mounted sensor systems, and the V2X Communication Model.

Base Case ESD Structure:

All base ESDs share the same branching pattern:

```
BaseCrashExposure (from BBN)
  ├── No_Crash
  └── Crash occurs
        ├── Crash_PDO → PDO_Crash
        └── Not PDO
              ├── Crash_Injury → Injury_Crash
              └── Fatality_Crash
```

The PDO/Injury/Fatality split comes from a uniform distribution fitted to 5 years of historical crash data in the study area (**Appendix C.3**).

BBN Evidence: Some BBN nodes are set from the local dataset, some are fixed for the entire study area, and one is controlled by the user:

Node	Source	Value
Intersection Type	Dataset	4-Way: 82.4%, 3-Way: 17.6%
Road Type	Dataset	Primary: 45.3%, Secondary: 40.8%, Tertiary: 3.7%, Residential: 10.2%
Weather	Fixed	Clear: 58.4%, Cloudy: 37.0%, Rain: 4.6%
Light Condition	Fixed	50% daytime, 50% nighttime
Speeding	Fixed	FARS/CRSS data
CV_Market	User input slider	P0 through P100

Quantification Methodology

Risk Metrics:

Metric	Intersection Form	Road Segment Form
Probability	POF	POF
Incident Rate	POF x TEV	POF x AADT
Financial Risk	POF x TEV x Consequence	POF x AADT x Consequence

Where:

- POF is the probability of failure, calculated as the sum of crash-related end-state probabilities from the ESD (PDO, Injury, and Fatality).
- Consequence is a weighted average cost per crash based on the severity distribution.

Calculation Procedure: When the user clicks **Calculate**, the engine runs through these steps:

Scenario A:

1. Group intersections by **type (4-way vs 3-way)**, since each type produces different BBN evidence.
2. Quantify the base case (CV Market = 0%):
    a. Patch the BBN with intersection type evidence and CV_Market = P0.
    b. Quantify the base ESD to get end-state probabilities.
    c. Extract the base POF and severity distribution.
3. Quantify the intervention case (CV Market = user's slider value):
    a. Patch the BBN with the selected CV_Market percentage
    b. Quantify the V2X intervention ESD
    c. Extract the intervention POF
4. Assign risk per intersection:
    a. V2I-enabled intersections get the intervention POF (lower risk)
    b. The rest keep the base POF
5. Aggregate and display:
    a. Sum up incident rates and financial risks across all locations
    b. Risk reduction = base total minus intervention total

Scenario B:

Scenario B runs separate quantifications for two location types: (i) intersection crossings, and (ii) midblock crossings. Intersections are grouped by **type (4-way vs 3-way)** and midblock crossings are grouped by **road type (111 primary, 100 secondary, 9 tertiary, 25 residential).**

Road segments connected to V2I-enabled intersections automatically receive the intervention POF for midblock risk. This way, deploying V2I at an intersection also benefits nearby pedestrian crossings.

API Calls:

Each full calculation involves:

- Scenario A: ~8 API calls (2 intersection types × base + intervention × patch + quantify)
- Scenario B: Up to ~24 API calls (intersection + midblock, grouped by type)

All calls go to the HCL API.

Safety Benefit Calculation

Crash Counts:

Metric	Calculation
Base crash count	POF_base x TEV, summed across all V2I-selected intersections
Intervention crash count	POF_intervention x TEV for V2I intersections, POF_base × TEV for the rest
Crashes avoided	Base total minus intervention total

We scope the comparison to V2I-selected intersections only so the base and intervention numbers are directly comparable.

Cost per Crash: These values are adapted from Benefit-Cost Analysis Guidance for Discretionary Grant Programs (2025)[58] and The Economic and Societal Impact of Motor Vehicle Crashes, 2019 (revised February 2023).

Crash Severity	Crash Cost (Comprehensive)	Congestion Cost	Total Comprehensive Cost
PDO	$6,804	$2,896	$9,700
Injury	$340,391	$3,009	$343,400
Fatality	$15,357,315	$9,585	$15,366,900

This calculation is based on the total per severity published in the Benefit-Cost Analysis Guidance for Discretionary Grant Programs (FHWA) 2024 and recreates the percentage of cost originating from congestion based on The Economic and Societal Impact of Motor Vehicle Crashes, 2019 (Revised 2023).

Economic Formulas:

The total cost for a given case is:

- $Total\ Cost = SUM(POF \times TEV \times Consequence_Crash) + SUM(POF \times TEV \times Consequence_Congestion)$

The weighted consequence per crash uses the severity distribution from the ESD:

- $Avg\ Consequence = (Fatality\% \times \$15{,}366{,}900) + (Injury\% \times \$343{,}400) + (PDO\% \times \$9{,}700)$

[58] U.S. Department of Transportation, Office of the Secretary "Benefit-Cost Analysis Guidance for Discretionary Grant Programs", December 2025 Available [online]: https://www.transportation.gov/mission/office-secretary/office-policy/transportation-policy/benefit-cost-analysis-guidance

Therefore, the savings are estimated as:

- $Estimated\ Savings\ =\ Base\ Case\ Total\ Cost\ -\ Intervention\ Case\ Total\ Cost$

Dashboard Interface

Layout:

The dashboard is a full-screen interactive map with overlay panels:

- Left sidebar: A scrollable card containing scenario selection, map layer controls, model configuration sliders, and the safety benefits panel.
- Map: MapLibre GL map centered on the DTLA study area, with multiple toggleable layers.
- Legend: A collapsible card in the bottom-right corner explaining map symbols and colors.

Map Layers:

Layer	Visual	Description
Road Segments	Colored lines	245 segments; color/width varies by AADT or model risk
Study Boundary	Dashed gray outline	1 sq mi bounding box
Signalized Intersections	Green/gray circles	92 intersections; green = V2I enabled, gray = not
Risk Circles	Gradient halos	Risk visualization around intersections (green → red)
Crash Points	Severity-colored diamonds	Fatal (dark red), serious injury (red), minor injury (orange), possible injury (yellow)
Signalized Crossings	Purple dots	340 pedestrian crossings at signalized intersections
Midblock Crossings	Teal dots	21 pedestrian crossings between intersections

Layer	Visual	Description
Non-Signalized Intersections	Indigo dots	24 unsignalized intersections (in collapsible "Additional Details")
Non-Signalized Crossings	Pink dots	28 crossings at unsignalized locations (in collapsible "Additional Details")

Crash points cluster at low zoom and expand into individual diamonds at higher zoom.

Popups:

Clicking any feature opens a popup with details:

- Signalized Intersection: Label, type, TEV, crash count breakdown, V2I status, and model-based risk metrics (after calculation)
- Road Segment: Street name, road type, AADT, length, crashes by severity, and pedestrian risk data (Scenario B)
- Crossings: Road name, location type, signalization status

Configuration Panel:

The sidebar controls are organized top-to-bottom:

1. Scenario Selection: Radio buttons for RLVW or PED, with info icons that pop out full descriptions.
2. Map Layers: Toggles for road segments, crash points, signalized intersections, signalized crossings, and midblock crossings. Non-signalized intersections and crossings are tucked under a collapsible "Additional Details" section to reduce clutter.
3. Automation Level: L0 / L2 / L4 buttons with hover tooltips explaining each SAE level.
4. V2I Availability: Slider from 0% to 100% in 25% steps. A "Regenerate" button lets the user re-randomize which intersections get V2I at the current percentage.
5. CV Market Penetration: Slider from 0% to 100% in 25% steps.

6. Calculate/Recalculate: Runs the full quantification. Turns amber if the user changes settings after a previous calculation.
7. Clear All: Resets everything back to defaults.

Safety Benefits Panel:

The results panel expands to the right of the sidebar and shows:

- Current Configuration: Which scenario, automation level, CV market %, and V2I % are in effect
- V2I Coverage: How many intersections are V2I-enabled out of the total
- Cost per Crash Table: Reference table with FHWA 2025 values
- Base Case: Crash counts by severity and total incident rate
- Intervention Case: Modified crash counts, crashes avoided, and percent risk reduction
- Economic Results: Base cost, intervention cost, and estimated savings
- Scenario B Details (collapsible): Breakdown of intersection vs. midblock contributions

Legend:

The legend shows:

- A risk gradient bar (green → red) with a description that changes by scenario
- Diamond-shaped crash severity icons matching the map markers
- The study area boundary symbol

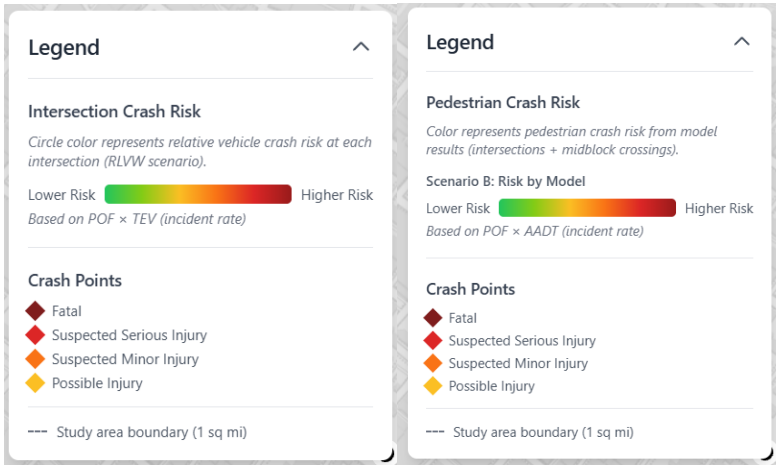


Figure 7.1: Dashboard legend for scenario (A, left) and (B, right).

B.2. GIS Data Preparation

This section describes the primary data sources used to construct the one square mile sample dataset used in this project. The refined dataset was created from a base layer of OpenStreetMap[59] geometries overlaid with historic crash and traffic data from Streetlight Data[60], as well as weather information from OpenMeteo[61] and NOAA NCEI[62] to produce the final dataset used in the project. The sources were processed into one line-type geometry dataset and several point-type geometry datasets based on distinguishing characteristics in each category (Table 7.2).

Overall, the final refined dataset based on the 1 sq. mi. of Downtown Los Angeles, CA was refined to include multiple road conditions and traffic scenarios that represent a variety of situations. The files were ultimately exported in GeoJSON format using the EPSG:32611 - WGS84 coordinate reference system for ease-of-use in creating the visualization tool for this

[59] https://www.openstreetmap.org
[60] https://www.streetlightdata.com/
[61] https://open-meteo.com/
[62] https://www.ncei.noaa.gov/

project. As previously mentioned, the overall dataset was divided into two main categories: line data and point data. The data refinement methodology for line-type data (Table 7.3) is as follows:

Table 7.2: Line data description.

Source	Download Format	Data Contents	Purpose
OpenStreetMap + Lane and road attributes (JOSM)	GeoJSON	Basic road geometries; “other_tags” and “highway” OSM attributes; intersection information	Used as the basis for road geometries, intersection definition, and key attributes
StreetLight InSight® Safety Prioritize (Crash records)	CSV; GeoJSON	Information on vehicle crashes during 2024 including location, date/time, crash type, severity, and more	Used to represent crash data in relation to the conditions and geometries of the roads and intersections in the sample area
StreetLight InSight® Planning (AADT traffic data)	CSV	Estimated 2024 AADT values and InSight® zone geometries	Used for analysis of crash likelihood and calculations of intersection vehicle movements
Open-meteo and NOAA (Environmental/weather attributes)	CSV	Uniform weather data for sample area including monthly precipitation and temperature averages, maximums and minimums	Used to increase weather data availability for crash and safety risk analysis
QGIS-derived spatial attributes	Generated during refinement	QGIS derived map geometries and identification for analysis and tool interface design; calculations for traffic movements and derived attributes for intersections and roads	Used to develop tool interface and provide information on intersections and road geometries for risk analysis

1. Boundary Definition
   - Data was clipped to the 1 sq. mi. defined by the latitude and longitude of the DTLA study area (Figure 7.2a).

2. Coordinate Reference System Standardization

   - All data were projected to match the EPSG:32611 - WGS84 coordinate reference system (Figure 7.2b).

3. Filtering Roadways and Roadway Features

   - The raw data from OSM included numerous roadways due to the myriad geometries and road types present in DTLA. Data were refined to only include those with the OSM "highway" tag whose values were primary, secondary, tertiary, and residential (Figure 7.2c).

4. StreetLight InSight® "Zone" Data Combination

   - The "zone" data from the StreetLight AADT data were overlayed on and combined with the OSM data to create a unified line data geometry set. Since AADT data are defined based on "zones" as defined by StreetLight, those data were used as the primary map geometries and naming scheme. The OSM tags and features were added on to the relevant zones in QGIS, along with derived geometric attributes, to maintain important information for later analysis and data filtering.

5. AADT Data Integration

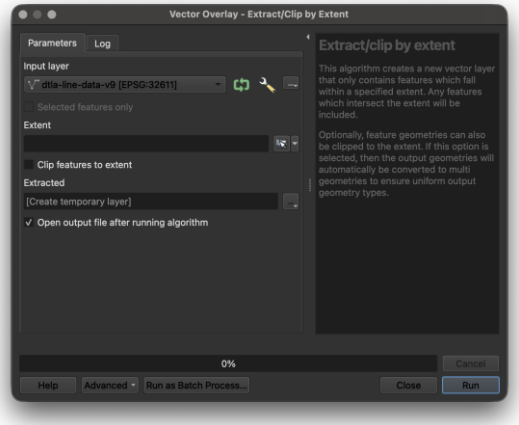
   - Given the StreetLight zone data, the 2024 AADT data was attached to the relevant line geometries (Figure 7.2e).

6. Climate Data Additional

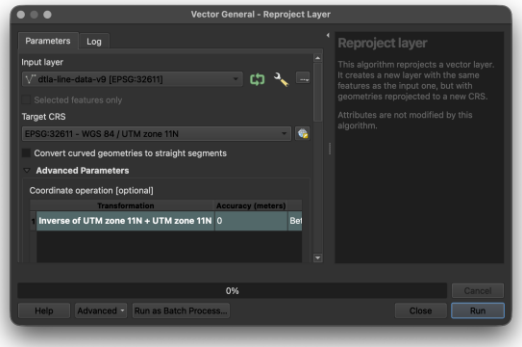
   - High-level climate data from NCEI (an organization within NOAA and the US Dept of Commerce) were added uniformly across all line data.

7. Data Validation

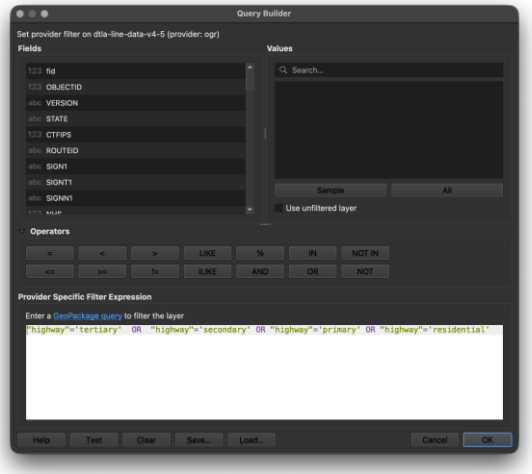
   - All geometries were validated to ensure no overlapping or duplication was present in the dataset (Figure 7.2f).



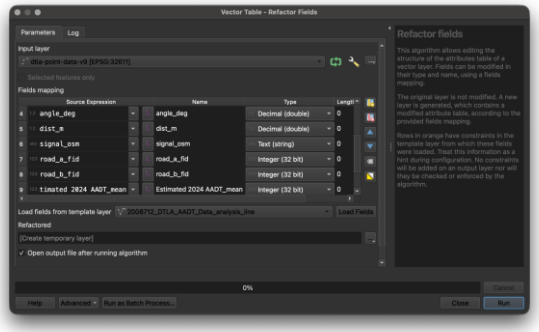
(a) Boundary definition (Extract/Clip by Extent)



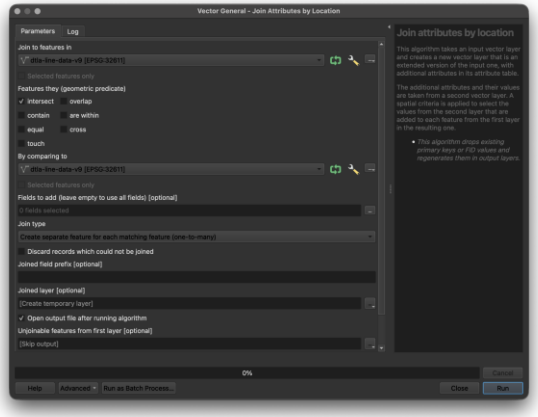
(b) CRS standardization (Reproject Layer)



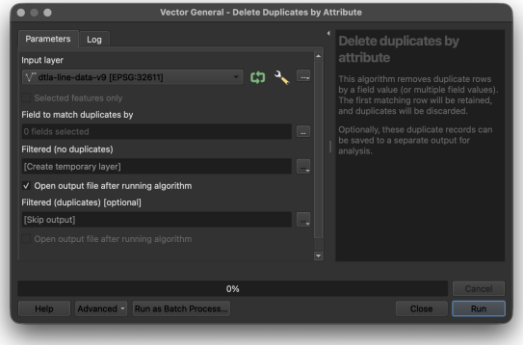
(c) Road-type filtering (Query Builder)



(d) Attribute refactoring (Refactor Fields)



e) AADT data integration (Join Attributes by Location)



(f) Data validation (Delete Duplicates by Attribute)

Figure 7.2: QGIS processing steps used to prepare the GIS dataset: (a) boundary definition, (b) coordinate reference system standardization, (c) road-type filtering, (d) attribute refactoring, (e) AADT data integration, and (f) data validation.

Table 7.3: Line Dataset Variable Descriptions

Variable	Description	Type
name	InSight® zone (i.e. road segment) name and ID	String
road_segment_id	Unique ID assigned to an individual road segment.	Text (string)
contiguous_road_id	ID linking road segments that belong to the same contiguous road geometry based on OSM data	Text (string)
intersection_ids	List of intersection IDs associated with the road segment.	Text (string) list
intersection_labels	List of intersection crossroad names associated with the road segment	Text (string) list
Estimated 2024 AADT	Estimated AADT value for 2024	Integer (32 bit)
highway	Road classification attribute from OSM	Text (string)
other_tags	Additional OSM road attributes	Text (string)
length_km	Length of the roadway segment in kilometers.	Decimal (double)
no_intersection_crossing_count	Count of non-intersection crossings associated with the road segment	Integer (32 bit)
intersection_count	Number of intersections associated with the road segment.	Integer (32 bit)
Zone Direction (degrees)	Angular orientation of zone (i.e. road segment)	Integer (32 bit)
Zone is Bi-Direction	Boolean field indicating whether the road segment is bidirectional.	Boolean
Lower 95 Percent Prediction Interval	Lower 95% Prediction Interval	Integer (32 bit)
Upper 95 Percent Prediction Interval	Upper 95% Prediction Interval	Integer (32 bit)
monthly-PRCP	Uniform study area monthly precipitation data	Integer (32 bit)
monthly-Tavg	Uniform study area monthly average temperature data	Integer (32 bit)
monthly-Tmax	Uniform study area monthly maximum temperature data	Integer (32 bit)
monthly-Tmin	Uniform study area monthly minimum temperature data	Integer (32 bit)

Filename: dtla-line-data-v9

The data refinement methodology was more involved for the point data (Table 7.4) and includes the following procedure in addition to the procedures listed above:

8. Roadway Intersection
   - QGIS-defined intersections were created where road geometries intersected and then matched to OSM-defined intersections
9. Intersection Definition
   - Intersections were split into three distinct groups: midblock, no-signal, and signal (Figure 7.2d).
10. Crossing Filtering
    - Crossing data from OSM was filtered to maintain only actual marked crossings without the extra crossing definitions included in OSM (e.g. for bike lanes, driveways, etc.)
11. Crossing Sorting
    - Crossings were sorted based on proximity to signalized intersections (i.e. 25m) and placed in their respective datasets: signal-crossing and no-signal-crossing
12. Crash Data Sorting
    - Similar to the crossings, crash data were sorted based on proximity, or lack thereof, to either a signalized intersection or non-signalized intersection.
13. Data Validation
    - All geometries were validated to ensure no overlapping or duplication was present in the dataset (Table 7.5,Table 7.6).

Table 7.4: Point Dataset Variable Descriptions.

Variable	Description	Type
intersection_id	Unique ID associated with each intersection	Text (string)
intersection_label	Formatted names of the cross roads that intersect at each intersection	Text (string)
name_a	Zone name of the first intersection road	Text (string)
name_b	Zone name of the second intersection road	Text (string)
angle_deg	Angle at which roads intersect	Decimal (double)
dist_m	Calculated value from QGIS-generated geometries	Decimal (double)
signal_osm	Intersection classification attribute from OSM	Text (string)
road_a_fid	Unique ID of the first intersection road	Integer (32 bit)
road_b_fid	Unique ID of the first intersection road	Integer (32 bit)
Estimated 2024 AADT_mean	The mean of the AADT values for roads intersecting at this point defined by the sum of all AADT values divided by two	Integer (32 bit)
intersection_type	3-way or 4-way intersection classification	Text (string)
Lower 95 Percent Prediction Interval	Lower 95% Prediction Interval mean defined by the sum of values of intersection roads divided by two	Integer (32 bit)
Upper 95 Percent Prediction Interval	Upper 95% Prediction Interval mean defined by the sum of values of intersection roads divided by two	Integer (32 bit)
is_signalized	Whether or not the intersection is signalized	Boolean

Intersections (Signalized and Non-signalized)

Filenames: dtla-point-data-v11-signal; dtla-point-data-v11-no-signal

Table 7.5: Mid-block, Signalized, and Non-Signalized Crossings.

Variable	Description	Type
osm_id	Crossing classification attribute from OSM	Text (string)
highway	Classification attribute from OSM	Text (string)
other_tags	Additional OSM crossing attributes	Text (string)
nearest_road	Zone name of the nearest road to the mid-block crossing	Text (string)
intersection_id	Intersection ID associated with the crossing	Text (string)
intersection_label	Intersection crossroad names associated with the corresponding intersection	Text (string)
is_signalized	Whether or not the corresponding intersection is signalized	Boolean

Mid-block crossings omit the "intersection_id" and "intersection_label" attributes while non-signalized and signalized crossings omit the "nearest_road" attribute

Filename: dtla-point-data-v11-midblock, dtla-point-data-v11-signal-crossing; dtla-point-data-v11-no-signal-crossing

Table 7.6: Crash Data.

Variable	Description	Type
OBJECTID	Map object ID for crash data point	Text (string)
point_x	Original longitude coordinate	Text (string)
point_y	Original latitude coordinate	Text (string)
hive_cid	Crash ID for crash data point	Text (string)
hive_date_time	Date and time of the crash	Text (string)
hive_county	County where the crash occurred	Text (string)
hive_city	City where the crash occurred	Text (string)

Variable	Description	Type
hive_collision_type	Type of collision	Text (string)
hive_crash_severity	Severity of collision	Text (string)
hive_injuries_fatal	Number of fatal injuries	Text (string)
hive_injuries_serious	Number of serious injuries	Text (string)
hive_injuries_minor	Number of minor injuries	Text (string)
hive_injuries_possible	Number of possible injuries	Text (string)
hive_b_pedestrian	Boolean indicating whether a pedestrian was involved	Text (string)
hive_b_bicycle	Boolean indicating whether a bicycle was involved	Text (string)
hive_b_road_surface	Boolean indicating whether road surface was a reported factor	Text (string)
hive_b_road_defect	Boolean indicating whether road defect(s) were present as a reported factor	Text (string)
hive_b_weather	Boolean indicating whether weather was a reported factor	Text (string)
hive_b_lighting	Boolean indicating whether lighting was a reported factor	Text (string)
hive_b_hit_run	Boolean indicating whether the crash involved a hit-and-run	Text (string)
hive_b_animal	Boolean indicating whether an animal was involved	Text (string)
hive_b_driver_impaired	Boolean indicating whether driver impairment was reported	Text (string)
hive_b_driver_speeding	Boolean indicating whether driver speeding was reported	Text (string)
hive_b_intersection	Boolean indicating whether the crash was reported as being at an intersection	Text (string)
hive_b_overturn	Boolean indicating whether the crash involved overturning	Text (string)
intersection_id	Intersection ID associated with the crossing	Text (string)
intersection_label	Intersection crossroad names associated with the corresponding intersection	Text (string)
name	Zone name of the nearest road (non-intersection crashes only)	Text (string)

Variable	Description	Type
name_a	Zone name of the first intersection road	Text (string)
name_b	Zone name of the second intersection road	Text (string)
highway	Classification attribute from OSM	Text (string)
distance	Distance from crash point to nearest matched road or point feature, in meters	Decimal (double)
feature_x	QGIS-derived projected crash x-coordinate	Decimal (double)
feature_y	QGIS-derived projected crash y-coordinate	Decimal (double)
nearest_x	QGIS-derived projected x-coordinate of nearest matched feature	Decimal (double)
nearest_y	QGIS-derived projected y-coordinate of nearest matched feature	Decimal (double)

Crashes that occurred further than 25m from an intersection omit the "intersection_id" and "intersection_label" attributes while crashes that occurred at signalized and non-signalized intersections omit the "name" attribute.

B.3. Safety Benefit Methodology

The following notes describe how we transform generic crash probabilities into location-specific crash and cost estimates (Figure 7.3).

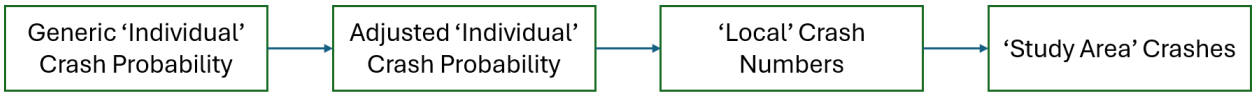


Figure 7.3: Crash Probability to Crash Estimation Pipeline.

1. The generic crash probability is estimated under average conditions (road/intersection type, weather, light) for an individual conflict, e.g., one vehicle-pedestrian conflict when V2I is available. It is reported as a function of CV%, with all other conditions held at average values. It describes how likely a crash is, not how many crashes occur.
    - Weather and road/intersection type are dependent on the location selected. In the case study, the square mile in downtown Los Angeles experiences mostly clear/cloudy weather conditions, mostly 4-way intersections (compared to 3-way), and road types are skewed towards principal and minor arterials (avoiding freeways).
2. To produce the dashboard results, we adjust the 'individual' crash probability for the local conditions at each road segment or intersection and for the selected CV%.
    - Base Case (No V2X): adjusted for local conditions only.
    - V2X Case: adjusted for local conditions and CV%.
3. 'Local' crash numbers are estimated by multiplying the adjusted 'individual' crash probability by the AADT (road segments) or TEV (total entering volume, intersections), which serve as a proxy for conflict exposure. These crash numbers are calibrated against local crash historical data.
    - Base Case (No V2X): crash numbers are estimated for ALL intersections/road segments.
    - V2X Case: crash numbers are re-estimated ONLY at the intersections/road segments equipped under the selected V2I% (sampled at random, keeping fixed seed)
    - Figure 7.4 shows a selected midblock crossing, with the base incident rate (no V2X) and intervention rate (CV=25%), where in this specific location resulted in a 19.3% reduction in crashes (on an annual basis).
4. The 'study area' crashes are the sum of the estimated crashes over all intersections/road segments.
    - Base Case (No V2X): aggregated for ALL intersections/road segments.
    - V2X Case: re-estimated crashes at equipped locations + Base Case crashes at non-equipped locations.
    - Figure 7.5 Shows the aggregated results for all intersections and road segments involved in Scenario B (accounting for all intersection and midblock pedestrian crossings).

The selected V2I% sets the baseline that results are compared against (example: V2I=25%):

- Equipped Locations: the CV=0% crash probability is replaced with the CV=25% crash probability at the **equipped road segments (V2I%)**, and crashes are summed over those segments only.
- Study Area: the CV=0% crash probability is replaced with the CV=25% crash probability at the equipped road segments (e.g., 25%) and kept at the remaining segments (e.g., 75%). Crashes are **summed over all segments**.

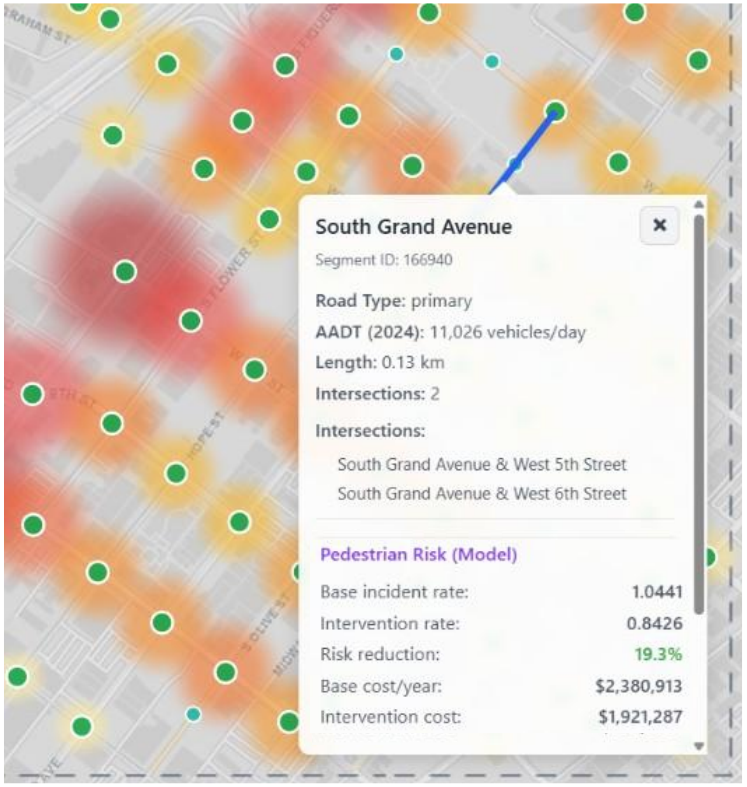


Figure 7.4: Screenshot of the V2XPRA dashboard indicating a local crash estimation at a selected road segment where a midblock crossing is located.

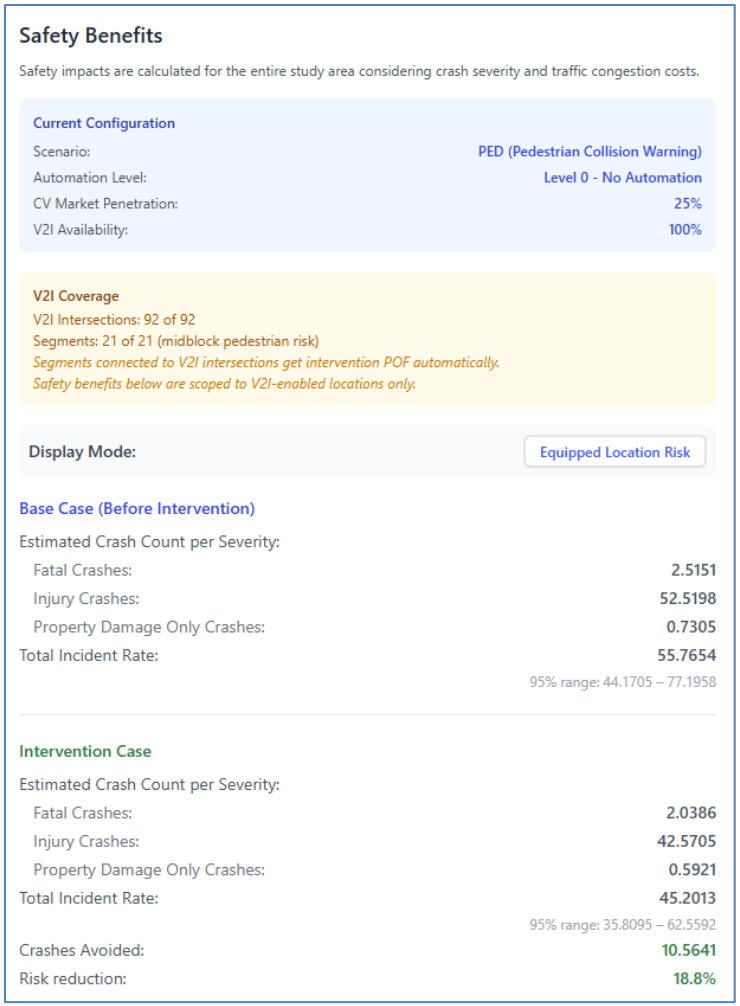


Figure 7.5: Screenshot of the V2XPRA safety benefit summary panel, showcasing the results for V2I=100% and CV=25% for Scenario B (intersection and midblock crossings).

Crashes avoided are identical in both views by design. Only the baseline (the denominator) differs, so the percent reductions differ. The two views match at V2I=100%.

- Equipped segments are selected at random, so their share of baseline crashes does not necessarily match V2I% (particularly for midblock crossing selection, as these depend on selected intersections).
- Random selection keeps the results from depending on a specific deployment priority, such as ranking locations by crash history alone. Reported results use a fixed random seed. In the dashboard, users can draw a new random selection for V2I=25% to 75% to see how results vary. Each new selection changes the crashes avoided and both percent reductions and their 5–95% ranges. At V2I=100%, all locations are equipped, so re-selection is not enabled.

Cost estimations follow the same steps: estimated crashes are converted to costs by severity and summed, so costs avoided and cost percent reductions use the same two baselines (equipped locations and study area). The crash rate reduction is modeled as a reduction in crash frequency at a fixed severity composition (based on local data for the target crashes). This is a conservative simplification that does not account for potential V2X benefits in reducing crash severity or broader crash exposure.

Absolute vs. relative reduction: The absolute reduction is the change itself (crash probability per encounter, crashes avoided per year, or dollars saved per year). The relative reduction is that change as a percentage of the corresponding no-V2X baseline. The two can rank options differently: when the baseline is already low, as for L4, a large relative reduction corresponds to a small absolute one.

Appendix C. Technical Details – Supporting Material

C.1. Scenario A Technical Details

This section presents technical details supporting the Scenario A – RLVW HCL model development. This includes industry and academic literature basis for driver (L0) and ADS (L4) failure behavior, as well as the developed HCL model details (event sequence diagrams, fault trees, and Bayesian networks).

C.1.1. Driver Warning Window and Stopping-Time Basis

This section derives the useful RLVW warning window referenced in **Section 3.1.2.2** and documents the literature basis for the driver perception-reaction time (PRT) and deceleration parameters used throughout the L0 stopping-time model.

Whether a driver can successfully stop after receiving an RLVW depends on the total critical stopping time (CST) / distance (CSD) consumed by the braking maneuver, which governs the minimum lead time at which a warning is physically actionable[63]. The critical stopping distance (x_c) can be expressed as shown in Equation (1):

$$x_c = x_{PR} + x_{BR} = v_o \cdot t_{PR} + \frac{{v_o}^2}{2a} \quad \textbf{(1)}$$

[63] J. Beeber, "An Explanation of Mats Järlström's Extended Kinematic Equation," *ITE Journal*, vol. 90, no. 3, pp. 34–38, Mar. 2020. [Online]. Available: https://redlightrobber.com/red/links_pdf/Jarlstrom-Equation-ITE-Journal.pdf

Where v_o is the approach speed, t_{PR} is the driver perception-reaction time (PRT), and a is the deceleration towards the intersection. The useful RLVW window, starting from the design detection onset of up to 10 seconds before the vehicle reaches the stop bar (T_{onset}), is shown in Equation (2):

$$t_w = T_{onset} - CST = 10 - (t_{PR} + \frac{v_o}{a}) \quad \textbf{(2)}$$

Driver PRT for braking maneuvers has been estimated to be between 0.8-1.9s depending on the driver's cognitive state[64],[65],[66]. At signalized intersections, the naturalistic PRT mean has been estimated at 1.3 s at signalized intersections[67], while the ITE signal timing design reference value is 1.57 s (85th percentile, unwarned drivers). The FHWA Lighting Handbook (2012) classifies perception-reaction time into three conditions[68]:

- Expected (~0.70 s): driver is alert and anticipating the need to brake.
- Unexpected (~1.25 s): driver encounters a common road signal such as a brake light or traffic signal.
- Surprise (~1.50 s): driver encounters an unusual circumstance.

In warning conditions, drivers can exhibit lower PRT values. For in-vehicle speech-based warnings, the mean alarm-to-brake-onset time ranged between an average of 0.87-1.14s for warnings between 2.5s-5.5[69], with a mean of 1.00s and a within-group standard deviation averaging 0.39s across warning timings 3.0–5.5s. Another study focused on driver's visual

[64] M. Bauder et al., "Influences of Vehicle Communication on Human Driving Reactions: A Simulator Study on Reaction Times and Behavior for Forensic Accident Analysis," Sensors, vol. 24, no. 14, pp. 4481–4481, July 2024, doi: 10.3390/s24144481.

[65] Y. D Wong and P. K. Goh, "Driver perception-response time for braking action during signal change interval," Road & Transport Research, vol. 9, no. 3, pp. 17–26, 2000, doi: 10.2165/00148365-200403010-00004.

[66] J. R. Setti, H. A. Rakha and I. El-Shawarby, "Analysis of Brake Perception-Reaction Times on High-Speed Signalized Intersection Approaches," *2006 IEEE Intelligent Transportation Systems Conference*, Toronto, ON, Canada, 2006, pp. 689-694, doi: 10.1109/ITSC.2006.1706822.

[67] R. Wortman and J. Matthias, "Evaluation of Driver Behavior at Signalized Intersections," Transportation Research Record, vol. 904, pp. 10-20, 1983, Available: https://onlinepubs.trb.org/Onlinepubs/trr/1983/904/904-003.pdf

[68] P. Lutkevich, D. McLean, and J. Cheung, "Vision and Fundamental Concepts," FHWA Lighting Handbook, pp. 13-27, August 2012, Available [online] at: https://highways.dot.gov/sites/fhwa.dot.gov/files/2022-09/fhwa_handbook2012.pdf

[69] X. Yan, Y. Zhang, and L. Ma, "The influence of in-vehicle speech warning timing on drivers' collision avoidance performance at signalized intersections," Transportation Research Part C: Emerging Technologies, vol. 51, pp. 231–242, Feb. 2015, doi: 10.1016/j.trc.2014.12.003.

identification of warning triggers (i.e., a red-light running vehicle) suggested that drivers warned earlier than 5s ahead of a potential crash tended to brake before identifying the RLR vehicle. The RLVW ConOps assumes PRT of 1s[70]; for the purpose of this study, the assumed value is $t_r = 1.00 \pm 0.39s$.

The RLVW ConOps additionally assumes a design deceleration value of 0.4g. The standard AASHTO value for Sight Stopping Distance (SSD) is 0.35g, with firm dry-road braking reaching 0.45g, and up to 0.7g in hard braking conditions. Under wet-weather conditions, deceleration values can decrease to around 0.25g in mild rain, up to 0.4g under hard braking conditions[71]. **Table 7.7** presents an estimation of the available RLVW cycles for two design deceleration scenarios: nominal (0.4g) and a hard-braking upper bound (0.7g). Weather-conditioned values are addressed in **Section C.1.6.1 (Crash Exposure Model).**

Table 7.7: Point estimates of useful RLVW cycles by vehicle speed approach and deceleration values (PRT=1.25s).

Approach Speed (mph)	30	35	40	45	50	55	60
Nominal (0.4g)							
Braking time (s)	3.42	3.99	4.56	5.13	5.70	6.27	6.84
CST (s)	4.67	5.24	5.81	6.38	6.95	7.52	8.09
CSD (ft)	130.2	166.5	207.1	251.7	300.6	353.6	410.9
Useful warning window (s)	5.33	4.76	4.19	3.62	3.05	2.48	1.91
Max RLVW cycles	53	47	41	36	30	24	19
Hard braking (0.7g)							
Braking time (s)	1.95	2.28	2.60	2.93	3.26	3.58	3.91

[70] Vehicle-to-Infrastructure (V2I-4) Consortium (CAMP). (2021). Red Light Violation Warning (RLVW) Application Vehicle System: Concept of Operations, Version 2.4. CAMP LLC. Available [online]: https://www.campllc.org/wp-content/uploads/sites/2896/2021/02/RLVW_ConOps_Ver_2_4_20200222.pdf?nocdn

[71] E. T. Donnel et al., "Engineering and Technical Concepts," Speed Concepts: Informational Guide, pp. 9-14, December 2009, Available [online] at: https://highways.dot.gov/safety/speed-management/speed-concepts-informational-guide/chapter-4-engineering-and-technical

Approach Speed (mph)	30	35	40	45	50	55	60
CST (s)	3.20	3.53	3.85	4.18	4.51	4.83	5.16
CSD (ft)	98.0	122.7	149.7	179.2	211.1	245.3	281.9
Useful warning window (s)	6.80	6.47	6.15	5.82	5.49	5.17	4.84
Max RLVW cycles	68	64	61	58	54	51	48

For vehicles approaching at 35-50 mph under clear conditions, t_w ranges from approximately 5.6 s (35 mph) down to 3.1 s (50 mph). Under hard braking (0.7g), $t_w$remains above 5s across this speed range. This range motivates three discrete modeling scenarios:

- High availability (t_w > 5 s): favorable speed and/or deceleration conditions. If a warning is not received nor acted upon, then the next event is assessed at the following bracket.
- Low availability (3 s < t_w < 5s): moderate speeds under nominal braking or higher speeds under high braking. If a warning is not received nor acted upon, then the next event is assessed at the following bracket.
- No availability (t_w <3s): warning not transmission or transmitted too late for driver reaction.

Simulation-based studies of RLVW effectiveness provide support for this scenario split. In general, studies of optimal warning times in crash scenarios indicate that maximum effectiveness was achieved when the controlled lead time was within the range of 5-8s[72] (t_w ~ CST). However, driver's RLR behavior is conditioned by Type II dilemma zone behavior beyond braking feasibility. This zone is defined by the equivalent distance or time representing the probability of deciding

[72] J. Wan, C. Wu, and Y. Zhang, "Effects of lead time of verbal collision warning messages on driving behavior in connected vehicle settings," Journal of Safety Research, vol. 58, pp. 89–98, Aug. 2016, doi: 10.1016/j.jsr.2016.07.003.

to stop at the onset of yellow within 10-90%[73]. Several studies have estimated its boundaries at 2.0-2.5s (lower 10%) up to 4.5-5.5s (upper 90%) from the stop line[74,75].

In addition to affecting RLR behavior, drivers receiving RLVWs within dilemma zones may show a reduced compliance rate (CST<5s in **Table 7.7**). Simulation-based studies of RLVW effectiveness across 2.5-5.5s in-advance delivery range estimated that from 2.5 s delivery approximately 57.6% of scenarios benefited from the warning, up to 87.7% at 5.5s, noting that late warnings (<3s) did not significantly change the driver's braking behavior[76]. Other studies looked at staged alert-to-warnings systems for time-to-intersection (t_w ~ CST) between 4.5-7s, reporting a 12% RLR rate despite warnings under clear conditions[77]. Regarding conflicts arising from RLRs, effectiveness of warnings issues between 2.5s-5.5s were explored, with resulting crash rates between 2.1% (5s) and 12.5% (3s)[78].

C.1.2. Level 4 ADS Perception and Reaction-Time Basis

This section documents the basis for the ADS perception-failure probability range used in **Section 3.1.2.3** and the reaction-time comparison underlying the L4 stopping-time model.

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[73] P. T. Savolainen, A. Sharma, and T. J. Gates, "Driver decision-making in the dilemma zone – Examining the influences of clearance intervals, enforcement cameras and the provision of advance warning through a panel data random parameters probit model," Accident Analysis & Prevention, vol. 96, pp. 351–360, Nov. 2016, doi: 10.1016/j.aap.2015.08.020.

[74] Y. Zhang, C. Fu, and L. Hu, "Yellow light dilemma zone researches: a review," Journal of Traffic and Transportation Engineering (English Edition), vol. 1, no. 5, pp. 338–352, Feb. 2015, doi: 10.1016/S2095-7564(15)30280-4.

[75] H. McGee et al., "Guidelines for Timing Yellow and All-Red Intervals at Signalized Intersections," NCHRP Report, vol. 731, pp. 1-93, 2012, Available [online] at: https://redlightrobber.com/red/links_pdf/nchrp-guidelines-for-timing-rpt-731.pdf

[76] X. Yan, Y. Zhang, and L. Ma, "The influence of in-vehicle speech warning timing on drivers' collision avoidance performance at signalized intersections," Transportation Research Part C: Emerging Technologies, vol. 51, pp. 231–242, Feb. 2015, doi: 10.1016/j.trc.2014.12.003.

[77] Y. Zhang, X. Yan, and X. Li, "Effect of warning message on driver's stop/go decision and red-light-running behaviors under fog condition," Accident Analysis & Prevention, vol. 150, p. 105906, Dec. 2020, doi: 10.1016/j.aap.2020.105906.

[78] Y. Zhang, X. Yan, X. Li, and J. Wu, "Changes of drivers' visual performances when approaching a signalized intersection under different collision avoidance warning conditions," Transportation Research Part F: Traffic Psychology and Behaviour, vol. 65, pp. 584–597, Mar. 2018, doi: 10.1016/j.trf.2017.12.018.

Attributing quantitative estimates to ADS failure behavior is challenging given the limited availability of standardized incident data at sufficient level of detail for this type of analysis. For instance, analysis of 5,731 California DMV disengagement records from 2022–2023 found that 86% of cases were initiated by a human driver, with predominant causes including software/hardware issues (26%), planning discrepancies (21%), and perception challenges (17%)[79]. Traffic signal misinterpretation is assumed to exist within these categories but is not reported as specific sub-statistics.

Quantitative estimates for perception-related failures draw on computer vision benchmarks for traffic light detection and state classification. For instance, YOLOv8 achieved average precision (mAP_{50}) of 97.6% on a custom dataset and 92.6% on the LISA dataset under daytime conditions, implying raw miss rates of 2.4–7.4%[80]. Under nighttime conditions, the same study reports mAP_{50} of 83.1% on the custom dataset, corresponding to a raw miss rate of 16.9%. Other studies report a field-tested YOLOv7 mAP of 93% on an AV platform under real operating conditions including partial occlusion and variable illumination[81]. An in-depth review of sensor system performance assigned camera sensors to moderate degradation severity under night and low-light conditions, with error frequencies up to 30%, consistent with the upper bound of the nighttime range above[82]. More adverse environmental factors such as rain, dense fog, low or intense light, and dust further affect perception system performance[83]. However, there are multiple factors that mitigate reported performance, including multi-sensor fusion, temporal consistency checks across multiple frames, and conservative default behaviors which reduce the per-encounter detection and tracking error rate relative to single-frame detection benchmarks[84]. Combining these sources, this model uses a working estimate for a mature L4 system operating within its designed ODD is a per-traffic signal

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[79] A. Skokan and J. Mareček, “Could Disengagement Reports Indicate Evolution of Autonomous Vehicles?,” *Vehicles*, vol. 7, no. 2, p. 32, Apr. 2025, doi: 10.3390/vehicles7020032.

[80] M. R. Z. Chowdhury, A. Seum, M. R. Talukder and F. S. Hossain, "Traffic Light Detection for Autonomous Vehicles in Diverse Environments Through Transfer Learning," *2024 27th International Conference on Computer and Information Technology (ICCIT)*, Cox's Bazar, Bangladesh, 2024, pp. 3548-3553, doi: 10.1109/ICCIT64611.2024.11022006.

[81] J. M. De Guia and M. Deveraj, “Development of Traffic Light and Road Sign Detection and Recognition Using Deep Learning,” International Journal of Advanced Computer Science and Applications, vol. 15, no. 10, 2024, doi: 10.14569/ijacsa.2024.0151095.

[82] Y. Zhang, A. Carballo, H. Yang, and K. Takeda, “Perception and sensing for autonomous vehicles under adverse weather conditions: A survey,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 196, no. 196, pp. 146–177, Feb. 2023, doi: 10.1016/j.isprsjprs.2022.12.021.

[83] Z. Chen et al., “Object detection for autonomous vehicles under adverse weather conditions,” Expert Systems with Applications, vol. 296, p. 128994, July 2025, doi: 10.1016/j.eswa.2025.128994.

[84] R. L. Rodrigues, S. J. Bhat, and K. V. Santhosh, “Prospective study on challenges faced in a perception system,” Cogent Engineering, vol. 11, no. 1, May 2024, doi: 10.1080/23311916.2024.2353498.

encounter error probability in the 0.1-1% range under normal conditions, rising to 2–10% or higher in adverse conditions or at the edges of the ODD. Additional details are described in **Section C.1.6.1 (Crash Exposure Model)**.

C.1.3. Level 2 Response and AEB Basis

The L2 sub-scenario (Section 3.1.2.4) does not introduce new driver or ADS failure models. It reuses the L0 and L4 models as follows and adds an automatic emergency braking (AEB) recovery path:

- **Reused from L0:** the unwarned red-light-running probability of the host vehicle (Table 7.15, A.4.2.2), the driver's compliance with the warning under high/low time availability (Table 7.8), and the driver perception-reaction time and deceleration parameters (Section C.1.1, Table 7.11).
- **Reused from L4:** the end-to-end reaction time from V2X message reception to brake actuation (approximately 50–100 ms) and the ADS deceleration profiles (Section C.1.2, Table 7.13), applied to the L2 response path once a warning has been received.
- **Combination:** once a warning has been received, the host or encountering vehicle fails to stop only if both the driver and the L2 response paths fail. The same early/late/no-warning ESD branching is applied (Section C.1.4).

AEB basis: AEB is added as a sequential, message-independent recovery path for the host vehicle after the driver and the L2 system have failed to stop, under warned or unwarned conditions. Consistent with the PAEB node in Scenario B, AEB is modeled at the function level, independent of the driver's braking failure probability, and is conditioned on light condition, vehicle-side LOS/NLOS, and weather.

Parameterization is anchored to PARTS (2025)[85] quasi-induced exposure (QIE) estimates, where effectiveness is defined as one minus the covariate-adjusted odds ratio of system-relevant to control crashes for equipped versus unequipped vehicles. Estimated AEB effectiveness was 44.4% for crashes at intersections, compared with 51.5% at non-intersection

[85] Partnership for Analytics Research in Traffic Safety (PARTS), "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

locations and 48.2% at other locations. These estimates refer to front-to-rear crashes; no comparable estimate is available for the angle crashes that dominate red-light violation conflicts. The intersection value is therefore adopted as a ceiling of AEB performance for Scenario A.

PARTS reports condition-specific effectiveness across all locations only: 50.6% in daylight, 40.6–43.3% in dark conditions, 50.1% in good weather (clear, cloudy), and 39.9% in rain. These values were transferred to intersections through a single scaling factor. The all-location effectiveness was estimated at 49.1% by inverse-variance pooling of the three location-specific estimates on the log-odds-ratio scale, giving an intersection factor of 0.444/0.491 = 0.904. The resulting intersection-level targets are 45.8% (daylight), 37.9% (dark, midpoint of the reported range), 45.3% (good weather), and 36.1% (rain). Light and weather effects are combined multiplicatively and assumed independent. Within each light condition, the NLOS/LOS ratio is retained from the PAEB node (Table 7.30), as no AEB-specific occlusion estimate is available. The implemented CPT is described in Section C.1.6.1 (A.4.2.3).

C.1.4. Event Sequence Diagram

The RLVW scenario is modeled as a four-leg signalized intersection in which a host vehicle approaches on a red phase. The initiating event is the vehicle entering the RLVW detection zone under conditions that meet the violation threshold. **Figure 7.6** presents the full ESD structure. The scenario unfolds through four key events:

- First, the RSU must successfully generate and transmit the RLVW required data to the approaching HV. This depends on the quality of the RSU's input data (i.e., the SPaT/MAP signal from the controller and the HV's BSM) as well as RSU hardware reliability and message transmission success.
- Second, upon receiving the warning, the HV must stop before entering the intersection. The failure model at this node differs depending on whether the vehicle is human-driven (Level 0), assisted by partial automation (Level 2), or ADS-equipped (Level 4), with distinct performance shaping factors and system reliability considerations respectively.

- Third, if the HV fails to stop, the encountering vehicle (EV) approaching on the crossing phase must avoid the conflict through braking or evasive action, again modeled separately for L0, L2, and L4. For L2, if the host vehicle fails to stop, its AEB acts as a final recovery event before the crash exposure branch (Section C.1.3).
- Finally, if neither vehicle avoids the conflict, the scenario enters the crash exposure branch, where outcomes are conditioned on severity (property damage only (PDO), injury, or fatality) calibrated to local crash data. Secondary crash risk derived from HV braking is not considered in this model.

For simplicity, even though RSU/OBU messages are continuously broadcast, warning availability is modeled under two conditions: high time availability (approximately 5 seconds to conflict) and low time availability (approximately 3 seconds to conflict), reflecting the range of practical warning lead times in deployed RLVW systems.

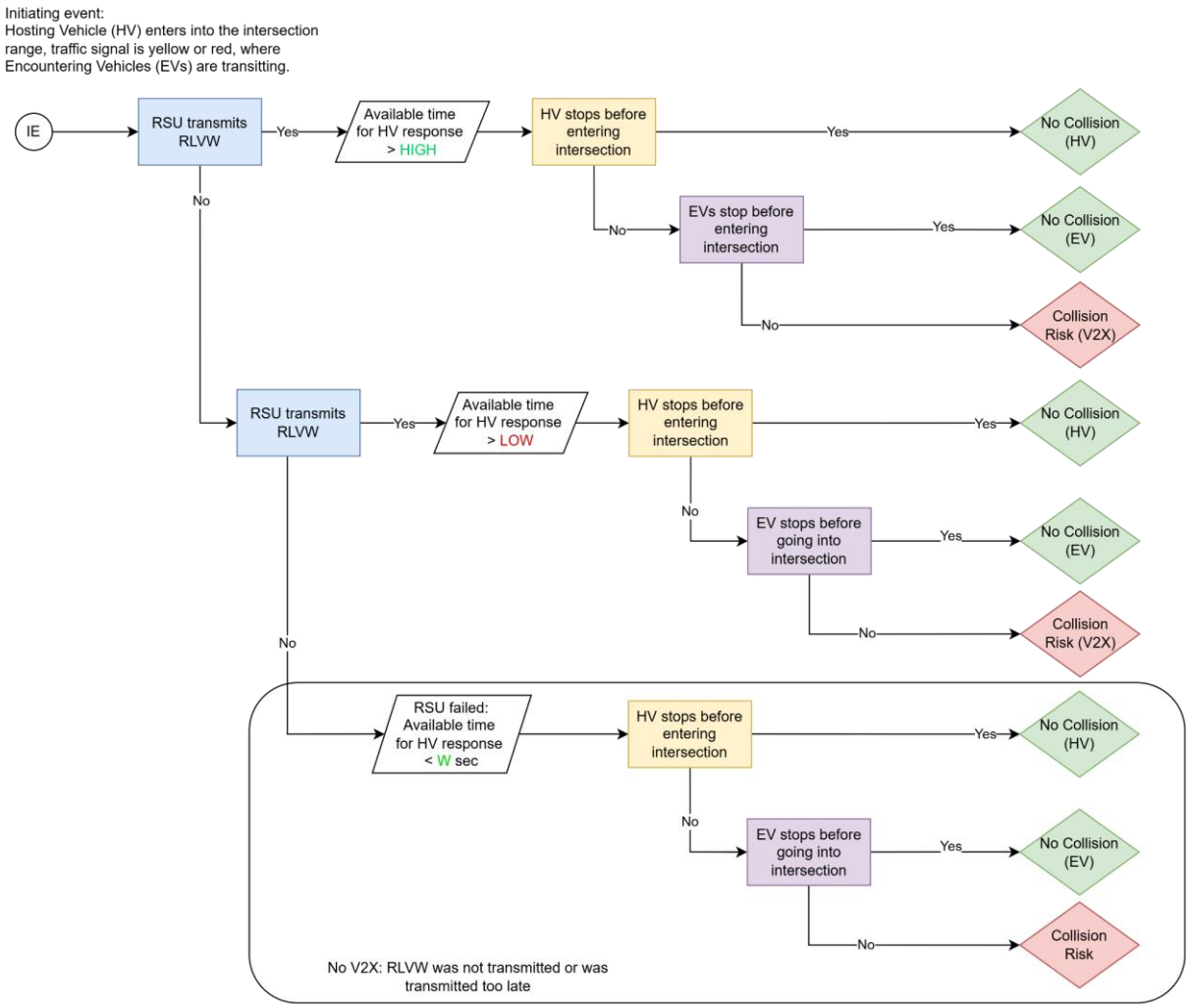

Figure 7.6: RLVW Scenario (ESD Model).

C.1.5. Fault Tree Models

C.1.5.1. A.1 RSU-RLVW Generation and Transmission Failure

This model has two branches reflecting the quality and correctness of the (i) input and (ii) output data. The model depicted in **Figure 7.7** applies to both L0-L4 scenarios.

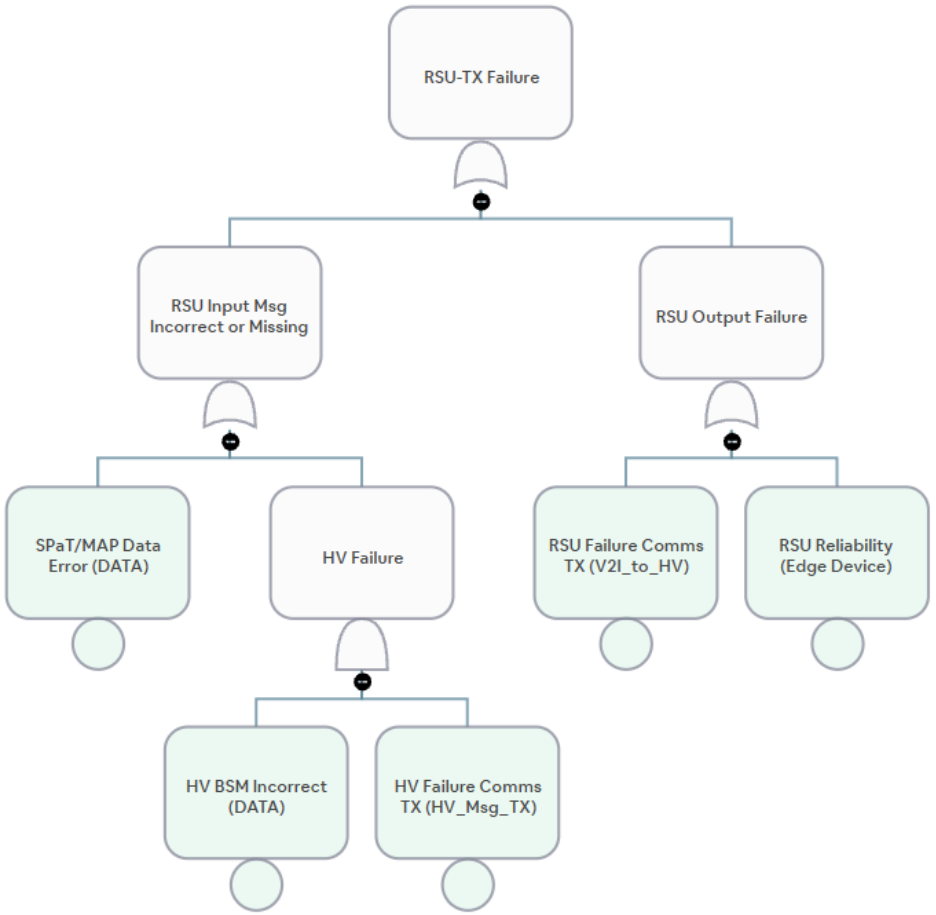

Figure 7.7: RLVW Scenario, RSU Transmission Failure (Enhanced RLVW).

A.1.1 RSU Input Data Quality (Incorrect or Missing)

This branch captures the probability that the RLVW algorithm receives incorrect or missing input data, preventing reliable warning generation. Two independent sub-branches contribute to this top event, corresponding to the primary input streams: SPaT timing and MAP content quality, and the HV-related failures: BSM GPS position accuracy and the V2I uplink reliability of the HV BSM transmission to the RSU[86].

A.1.1.1 SPaT Timing Accuracy and MAP Content Errors: SPaT timing accuracy is assessed through two main failure mechanisms: content accuracy for the encoded phase timing and broadcast periodicity. Regarding content, this is primarily determined by signal controller type. For fixed-time controllers, SPaT timing is deterministic and the dominant error source reduces to communication latency (<100 ms). For actuated controllers, the SPaT message can only provide a probabilistic estimate of phase end time, impacting RLVW functionality in the absence of an assured green phase (AGP)[87,88]. Regarding broadcasting periodicity, field measurements have shown that between 14-21% of messages exhibit inter-message intervals exceeding 110ms, depending on the broadcast mechanisms implemented[89]. RLVW implements false alarm suppression through speed-based notification thresholds and OEM-configurable escalation sensitivity, requiring a vehicle to maintain a violation-consistent trajectory across consecutive 10 Hz estimation cycles before escalating from advisory to driver-audible alert[90,91]. As such, consecutive stale SPaT messages can disrupt the required message persistence.

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[86] Crash Avoidance Metrics Partners (CAMP). (2021). Red Light Violation Warning (RLVW) Application: High-Level Requirements, Version 1.10. CAMP LLC. Available [online]: https://www.campllc.org/wp-content/uploads/sites/2896/2021/05/RLVW_High-Level_Requirements_ver_1_10_FINAL.pdf

[87] S. Ibrahim, Dileep Kalathil, R. O. Sanchez, and Pravin Varaiya, “Estimating Phase Duration for SPaT Messages,” IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 7, pp. 2668–2676, Oct. 2018, doi: 10.1109/TITS.2018.2873150.

[88] M. Arafat, M. Hadi, T. Hunsanon, and T. Wang, “Hardware-in-the-Loop Simulation for Assessing Red-Light Violation Warning Application With Semi-Actuated Signal Control in a Connected Vehicle Environment,” Transportation Research Record: Journal of the Transportation Research Board, vol. 2677, no. 5, pp. 1085–1099, Dec. 2022, doi: 10.1177/03611981221140371.

[89] Crash Avoidance Metrics Partners LLC (CAMP) Vehicle to Infrastructure 5 (V2I-5) Consortium, "Connected Intersection SPaT Accuracy Assessment Supporting Basic Red Light Violation Warning," Version 0.6, Jul. 26, 2022. [Online]. Available: https://www.campllc.org/wp-content/uploads/sites/2896/2022/08/CI-SPaT-Accuracy-Assessment-Procedure-Version-0.6-20220726-.pdf

[90] Crash Avoidance Metrics Partners LLC (CAMP) Vehicle to Infrastructure 4 (V2I-4) Consortium, "Red Light Violation Warning (RLVW) Application Vehicle System High-level System Requirements," Version 1.10, Jan. 12, 2021. [Online]. Available [online]: https://www.campllc.org/wp-content/uploads/sites/2896/2021/05/RLVW_High-Level_Requirements_ver_1_10_FINAL.pdf

[91] D. Stephens, J. L. Schroeder, and R. Klein, “Vehicle-to-infrastructure (V2I) safety applications performance requirements, vol. 3, red light violation warning (RLVW).,” Bts.gov, Aug. 2015. https://rosap.ntl.bts.gov/view/dot/32029 (accessed July 20, 2026).

Assuming the RLVW algorithm requires at least two consecutive fresh messages to sustain a warning escalation trigger, this results in an estimated SPaT-driven application failure probability of approximately 2-4.4%. In addition, assuming mature, well-maintained fixed-time deployments, MAP content errors are considered negligible (geometric positioning errors are absorbed within the localization-based errors described above)[92]. Therefore, a uniform (2%, 4.4%) distribution is modeled for SPaT/MAP data error.

A.1.1.2 BSM GPS Position Accuracy (HV Failure): Lane determination against received MAP messages is a primary contributor to RLVW accuracy. Standard GPS horizontal errors can typically reach 3-5 m (R95) under typical open-sky conditions, degrading substantially in urban environments (>15-20 m)[93,94,95]. These errors exceed the required lane-determination threshold for V2X safety applications, which the U.S. DOT defines as an R95 horizontal accuracy of 2 m or better, which approximately corresponds to half a standard lane width[96,97].

For V2X deployments, RTCM corrections (DGPS) are introduced to reduce the vehicle positioning errors to approximately 1-3 m under typical conditions and reaching <1m (R95) values under favorable open-sky conditions[98]. Empirical large-scale DGPS measurement campaigns report a 90th-percentile error of approximately 2.1 m and a 95th-percentile error of approximately 2.4 m, implying that roughly 10% of corrected position fixes exceed the 2 m lane-level threshold under

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[92] Athey Creek Consultants, LLC and Synesis Partners, LLC, "Creation of a Guidance Document for MAP Preparation (MAP Guidance Document)," Final, prepared for the Connected Vehicle Pooled Fund Study, University of Virginia Center for Transportation Studies, Charlottesville, VA, USA, Apr. 2, 2021. Available [online]: https://engineering.virginia.edu/sites/default/files/Connected-Vehicle-PFS/Resources/MAP%20Guidance%20Document%20Final%20April%202%202021.pdf

[93] P. Schwarzbach, A. Michler, P. Tauscher, and O. Michler, “An Empirical Study on V2X Enhanced Low-Cost GNSS Cooperative Positioning in Urban Environments,” Sensors, vol. 19, no. 23, p. 5201, Nov. 2019, doi: 10.3390/s19235201.

[94] H. B. Swaminathan, A. Sommer, A. Becker, and M. Atzmueller, “Performance Evaluation of GNSS Position Augmentation Methods for Autonomous Vehicles in Urban Environments,” Sensors, vol. 22, no. 21, p. 8419, Nov. 2022, doi: 10.3390/s22218419.

[95] S. Stefanov, V. Markova and M. Markov, "Evaluating Global Navigation Satellite System (GNSS) Performance for Autonomous Vehicle Navigation in Urban Environments," *2025 6th International Conference on Communications, Information, Electronic and Energy Systems (CIEES)*, Ruse, Bulgaria, 2025, pp. 1-6, doi: 10.1109/CIEES66347.2025.11300010.

[96] T. Williams, P. Alves, G. Lachapelle, and C. Basnayake, “Evaluation of GPS-based methods of relative positioning for automotive safety applications,” Transportation Research Part C: Emerging Technologies, vol. 23, pp. 98–108, Nov. 2011, doi: 10.1016/j.trc.2011.08.011.

[97] D. Stephens, J. L. Schroeder, and R. Klein, "Vehicle-to-Infrastructure (V2I) Safety Applications: Performance Requirements," Battelle Memorial Institute for U.S. Department of Transportation, Intelligent Transportation Systems Joint Program Office, Washington, DC, USA, Rep. FHWA-JPO-16-248, Aug. 2015. Vol. 1, Introduction and Common Requirements [Online]. Available: https://rosap.ntl.bts.gov/view/dot/3592; Vol. 3, Red Light Violation Warning (RLVW) [Online]. Available: https://rosap.ntl.bts.gov/view/dot/32029

[98] M. Specht, “Consistency analysis of global positioning system position errors with typical statistical distributions,” Journal of Navigation, pp. 1–18, June 2021, doi: 10.1017/s0373463321000485.

representative conditions[99]. Therefore, treating the failure mode as a binary state-switching event, a 5% to 10% probability of localization-driven application failure per intersection approach is modeled using a uniform distribution (with boundaries matching the 5th and 95th percentiles).

A.1.1.3 Connectivity (V2I HV-to-RSU path): This represents the failure of BSM transmission from vehicle-to-infrastructure node as a factor contributing to RLVW calculation errors on the infrastructure side. Details on this portion of the model are discussed in **Section C.1.6.2 (V2X Communication Model)**. This failure mode is only relevant for RSU-generated warnings.

A.1.2 RSU Output Failures

This branch captures the probability that the message content required to generate the RLVW is not transmitted correctly. Two independent sub-branches contribute to this top event, corresponding to the V2I RSU-to-HV path and the RSU device reliability.

A.1.2.1 Connectivity (V2I RSU-to-HV path): This represents the failure of the SPaT/MAP (and optionally, the RSU-generated RLVW) transmission from the infrastructure-to-vehicle node as a factor contributing to the vehicle not (i) calculating local RLVWs or (ii) receiving RSU-generated RLVWs. Details on this portion of the model are discussed in **Section C.1.6.2 (V2X Communication Model)**.

A.1.2.2 Device Failure (Failure Model): This is a generic failure model re-used in multiple instances of the model. Both RSU and OBU hardware failures are modeled as on-demand failure events, consistent with the discrete-demand nature of the RLVW application at each intersection approach. Thus, a Probability of Failure on Demand (PFD) formulation is adopted in place of a per-hour failure rate. The reference safety integrity target for this device class is drawn from ISO 26262[100] and

[99] C. Specht, “Maritime DGPS System Positioning Accuracy as a Function of the HDOP in the Context of Hydrographic Survey Performance,” Remote Sensing, vol. 15, no. 1, p. 10, Dec. 2022, doi: 10.3390/rs15010010.

[100] International Organization for Standardization, "Road vehicles — Functional safety," Geneva, Switzerland, ISO 26262:2018, 2018. [Online]. Available: https://www.iso.org/publication/PUB200262.html

IEC 61508[101] automotive and safety-instrumented system practice, where a Probabilistic Metric for Hardware Failures (PMHF) of 10^{-7} per hour is specified for ASIL B/SIL 2 targets[102]. At an assumed operational demand rate of one intersection approach per hour, this yields an equivalent PFD of 1×10^{-6} per demand. A lognormal distribution with median $M_{50} = 1 \times 10^{-6}$ and Error Factor $EF = 5$ (σ_{ln} = 0.98) is used, consistent with standard PRA practice for safety-instrumented systems[103].

C.1.5.2. A.2. Host Vehicle Failure to Stop

This model represents the probability of a vehicle failing to stop before the intersection stop bar, with separate contributions from warned and non-warned actors (drivers or ADS) given available time and road conditions. Warned actors may fail to stop at the intersection if (i) they do not comply with the RLVW or (ii) the resulting time to brake after RLVW is received is unfeasible. Non-warned actors may fail to stop at the intersection if (i) they continue on the RLR trajectory after yellow phase onset or (ii) they independently determine to stop, but the resulting time to brake time is unfeasible. The implemented models for L0 and L4 are depicted in **Figure 7.8** and in **Figure 7.9**, respectively. The L2 model, which combines both response paths, adds the AEB recovery event. Crash calibration values are used to ensure base case (no V2X) replicate existing crash statistics (refer to **Appendix C.3**).

A.2.1 Message-related failures

This branch captures failure modes through which the RLVW fails to produce a stop response in the driver, including not receiving or not responding to it. It is structured as an OR gate over three contributing events:

A.2.1.1 V2I communication failure (V2I HV-to-RSU path). The V2I link from RSU to HV may fail to deliver the SPaT-based warning message. This node is fed by the BBN, which conditions packet delivery probability on Weather and LOS/NLOS

[101] International Electrotechnical Commission, "Functional safety of electrical/electronic/programmable electronic safety-related systems — Part 1: General requirements," Geneva, Switzerland, IEC 61508-1:2010, Ed. 2.0, Apr. 2010. [Online]. Available: https://webstore.iec.ch/en/publication/5515

[102] O. Ballan, P. Maillard, J. Arver, C. Smith, R. Petersson, A. Griessing, and F. Venini, "Evaluation of ISO 26262 and IEC 61508 metrics for transient faults of a multi-processor system-on-chip through radiation testing," *Microelectron. Rel.*, vol. 107, art. no. 113601, Apr. 2020, doi: 10.1016/j.microrel.2020.113601.

[103] P. Britton, M. Al Hassan, and R. Ring, "Lognormal Uncertainty Estimation for Failure Rates," presented at the RAM X Training Summit, Huntsville, AL, USA, Nov. 8–9, 2017, NASA/NTRS document 20170012473. [Online]. Available: https://ntrs.nasa.gov/api/citations/20170012473/downloads/20170012473.pdf

geometry (see **Section C.1.6.2, V2X Communication Model**). Nominal baseline $PDR \approx 0.97 - 0.99$; degraded under congestion or NLOS conditions. This model applies to both L0-L4 scenarios.

A.2.1.2 HV ignores warning:

- **L0 Scenario:** This probability is conditioned on the available stopping time relative to CST (as derived in **Section C.1.1**) and is the dominant failure mode in the message branch at nominal communication reliability. Two parameter values are used, corresponding to the high- and low-availability branches of the ESD in **Table 7.8** below.

- **L2 Scenario:** Warning compliance remains a driver decision and follows the L0 values in Table 7.8. Once the warning is not ignored, braking can be initiated by either the driver or the L2 system (Section C.1.3).

- **L4 Scenario:** In the case of an ADS-equipped vehicle, the probability of not acting upon received RLVW information is assumed to be related to software processing issues of the ADS stack. Latency and content quality issues are captured by other events in this model. Few quantitative references exist for this failure mode. A related field-based study reported that a LLM-based signal phase detection accuracy of 98.1% was achieved from over 110,000 SPaT messages, implying a misclassification or non-response rate of approximately 1.9% at the parsing layer[104]. A potential order of magnitude estimation may be parameterized as Uniform (0.005, 0.035), with a point estimate of 0.020. However, due to limited generalizability, this failure mode was not implemented in the final model.

Table 7.8: Driver Ignores Warning (HV) values.

Parameter	P(driver fails | warned) ~ Uniform	Reference
P(failure to comply with RLVW | high time availability $t_w > 5s$)	0.08-0.15	Dilemma zone 90th pct (NCHRP 731); Arafat et al. (2023) best-case residual; Zhang et al. (2021) lower bound.

[104] K. Wu et al., "V2X-LLM: Enhancing V2X Integration and Understanding in Connected Vehicle Corridors," arXiv:2503.02239 [cs], Mar. 2025. [Online]. Available: https://arxiv.org/abs/2503.02239

Parameter	P(driver fails | warned) ~ Uniform	Reference
P(failure to comply with RLVW | low time availability $3s < t_w < 5s$)	0.25-0.42	Yan et al. (2015) at 2.5 s delivery; dilemma zone transition boundary (Chang et al.; NCHRP 731).

A.2.1.3 OBU device reliability (Failure Model): The onboard unit may fail to process or display the received message due to hardware or software faults. This is modeled as a lognormal reliability distribution with ASIL B/C PMHF targets (below 100 FIT), consistent with IEC 61508 / ISO 26262 requirements for safety-relevant onboard electronics (see **C.1.5.1, Device Failure Model**). This model applies to both L0-L4 scenarios.

A.2.2 Stopping-related failures

This represents failures of the vehicle not stopping before entering the intersection, depending on whether (i) the message was received, but there is not enough time to stop based on the driving conditions or (ii) the message was not received (i.e., base probability of running the red light). Different fault tree structures are considered for L0 (**Figure 7.8**) and L4 (**Figure 7.9**) scenarios. The L2 structure combines both response paths, adding the AEB recovery event.

A.2.2.1 Base red-light running (non-V2X):

- **L0 Scenario:** The unconditional probability that a driver runs a red light, absent any warning intervention, estimated at $p \approx 0.27$ from intersection-level RLR statistics (NHTSA CRSS/FARS). This value represents the population-level rate of signal non-compliance and serves as the baseline against which RLVW safety benefit is quantified. Detailed parameterization as a function of weather conditions is given in **Section C.1.6.1 (Crash Exposure Model).**

- **L4 scenario:** The unconditional probability that an ADS-equipped vehicle runs a red light is assumed to be primarily related to the vehicle's perception module rather than planning or control-related. Therefore, the main driver for RLR behavior is rooted in camera-based detections and traffic signal misclassification. Detailed parameterization as a function of light conditions is given in **Section C.1.6.1 (Crash Exposure Model).**

- **L2 Scenario:** The unwarned red-light-running probability depends only on the human driver and follows the L0 parameterization (Section C.1.6.1).

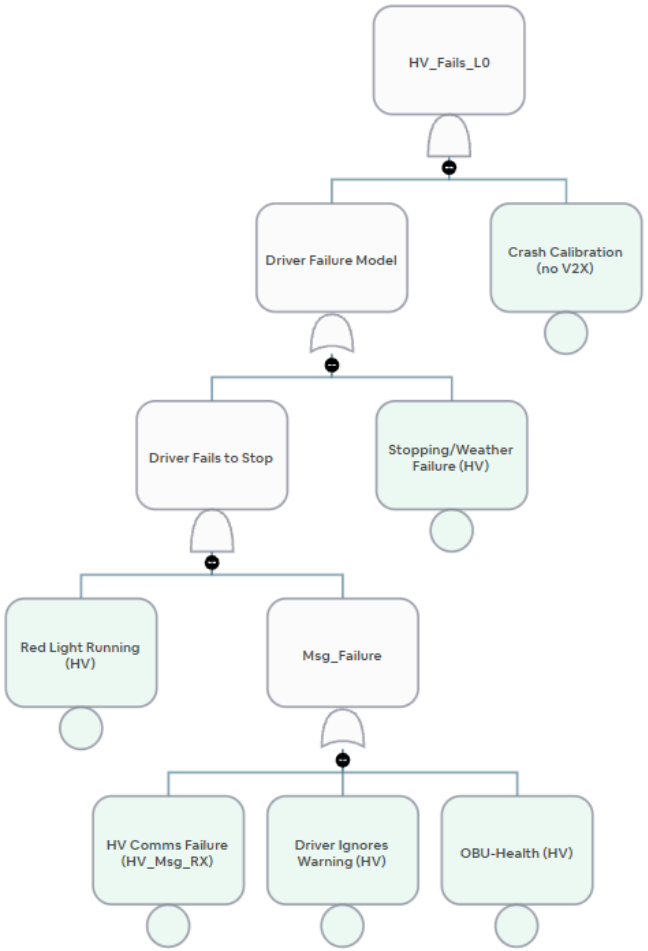

Figure 7.8: RLVW Scenario, Host Vehicle L0 Failure (V2X Enabled).

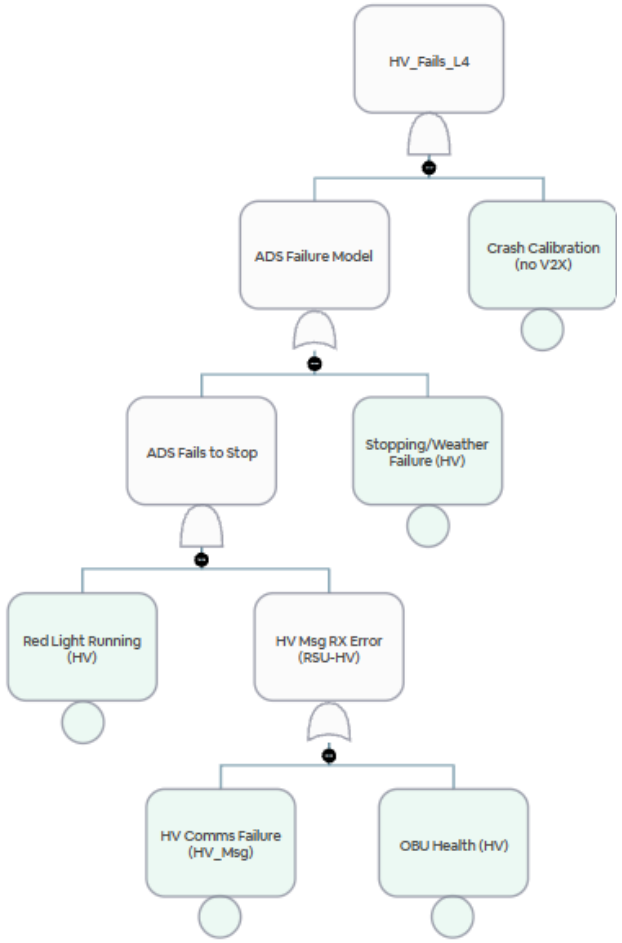

Figure 7.9: RLVW Scenario, Host Vehicle L4 Failure (V2X Enabled).

A.2.2.2 Insufficient stopping time given road conditions (Stopping/Weather Failure):

- **L0 Scenario:** Even a driver intending to stop may be physically unable to do so if the available deceleration is insufficient given approach speed and road surface conditions. This node is derived from the stopping feasibility (**Section 3.1.2.2**) conditioned on weather-dependent deceleration and is propagated through the BBN as a function of weather state (clear, cloudy, rain), vehicle approach speed, and warning timing.
- **L2 Scenario:** Both response paths are evaluated with the same structure: the driver path uses the L0 reaction-time and deceleration assumptions, and the L2 path uses the L4 assumptions. Insufficient stopping time results in a failure only if both paths fail. If the host vehicle fails to stop, AEB acts as a final recovery event (A.4.2.3).
- **L4 Scenario:** This node replicates the same structure as for the L0 Scenario, with updated assumptions regarding reaction and braking times.

When there is no V2X available ($t_w < 3s$), it is assumed that the only failure modes applicable are A.2.2.1 (*Base red-light running (non-V2X))* and A.2.2.2 (*Insufficient stopping time given road conditions (Stopping/Weather Failure)*). Further, the HV's stopping probability is governed by the high-time availability values. Detailed parameterization is given in **Section C.1.6.1 (Crash Exposure Model)**.

C.1.5.3. A.3. Encountering Vehicles Failure to Stop

This portion of the model accounts for the probability that one or more EVs entering the intersection on a conflicting approach fail to stop when an HV is executing a red-light violation. Three approach families are represented, corresponding to the crash geometry groupings shown in **Figure 7.10**[105]: perpendicular approaches (AD), diagonal approaches (BCE), and opposing turn approaches (FGH). For each approach family, a parallel sub-tree is instantiated with the same leaf structure; the top-level gate evaluates to failure when at least one approach branch fails. Crash calibration values are used to ensure base case (no V2X) replicate existing crash statistics (refer to **Appendix C.3**).

Each EV fault tree is a simplified version of the HV model, given that EVs are operating on a green phase, thus, their failure mode is reactive: failing to respond to an unexpected incursion by the HV. Message-related failures follow a similar structure

[105] Zhang Y, Yan X, Li X, Wu J, Dixit VV. Red-Light-Running Crashes' Classification, Comparison, and Risk Analysis Based on General Estimates System (GES) Crash Database. Int J Environ Res Public Health. 2018 Jun 19;15(6):1290. doi: 10.3390/ijerph15061290. PMID: 29921809; PMCID: PMC6025625.

than the HVs, while stopping probabilities are simplified to represent high-time availability scenarios. The complete model, accounting for all approaches, is presented in **Figure 7.11** for L0 and **Figure 7.12** for L4.

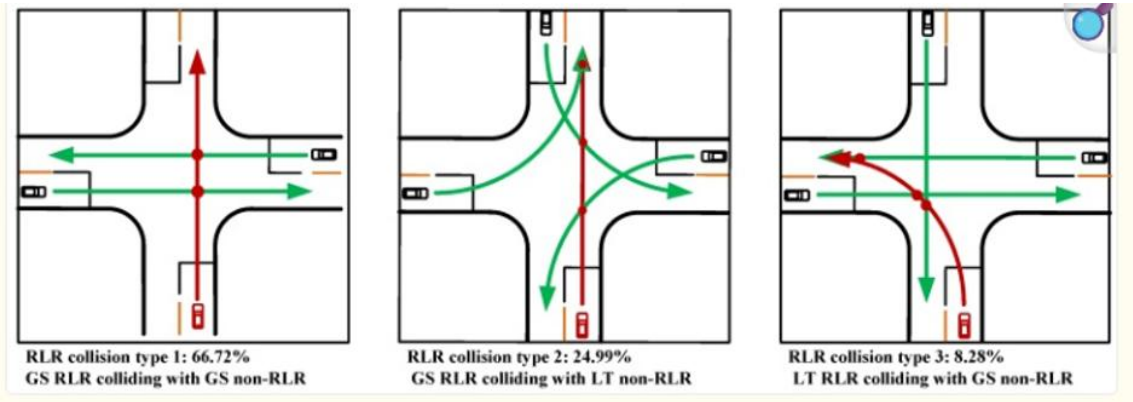

Figure 7.10: RLR Collision Families.

A.3.1 Message-related failures

This branch captures failure modes through which the RSU-based RLVW fails to produce a stop response in the EVs, including not receiving or not responding to it. It is structured as an OR gate over three contributing events:

A.3.1.1 V2I communication failure (V2I RSU-to-EV path). The V2I message transmission is subject to the same weather- and LOS-conditioned PDR as the HV path. Additionally, the probability of message reception is conditioned on whether the EV is a Connected Vehicle (CV%). This node is fed by the BBN (see **Section C.1.6.2 V2X Communication Model**).

A.3.1.2 OBU device reliability (Failure Model): This reuses the same failure model described for HV OBU failures (A.2.1.3).

A.3.1.3 EV drivers ignore warnings (L0/L2):

- **L0 Scenario:** This probability is conditioned on the available stopping time relative to CST (as derived in **Section C.1.1**) and adopts P(failure to comply with RLVW | high time availability $t_w > 5s$) described in **Table 7.8** given that EVs face an unexpected alert instead of dilemma-zone related stop-or-go decision.

- **L2 Scenario:** Encountering-vehicle drivers may disregard the warning with the same probability as in the L0 scenario; once the warning is not ignored, either the driver or the L2 system can respond.

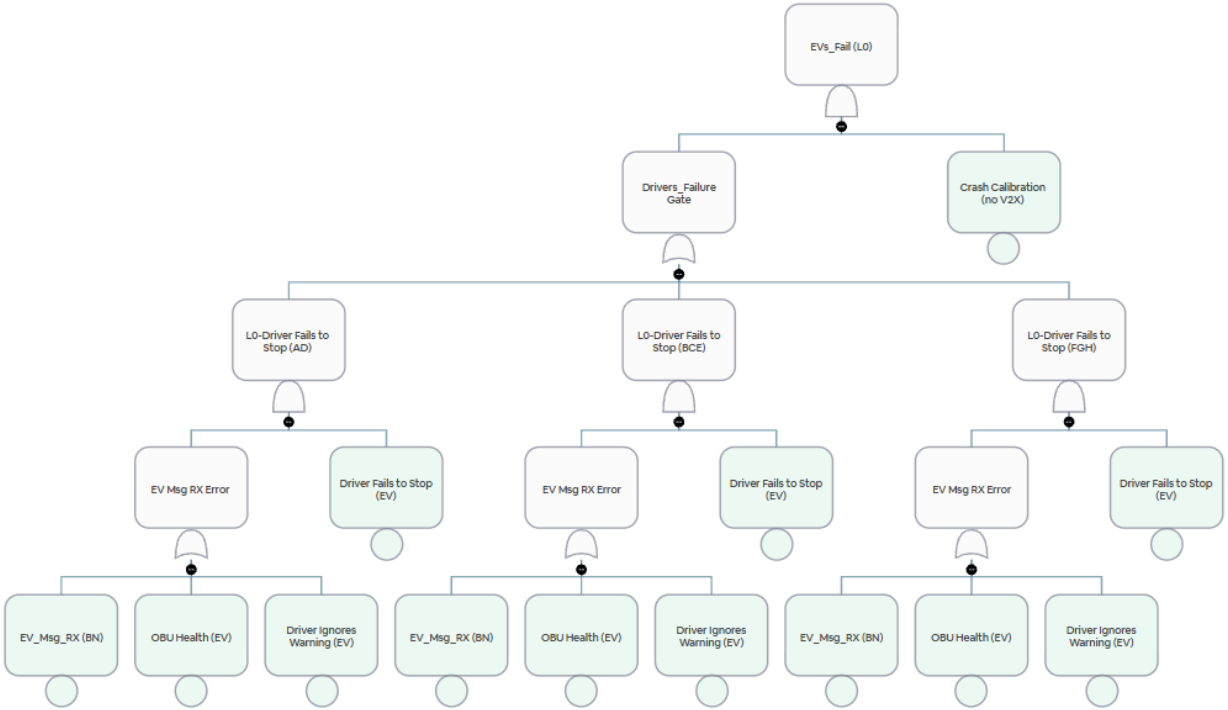

Figure 7.11: RLVW Scenario, Encountering Vehicles L0 Failure (V2X Enabled).

A.3.2 Stopping-related failures

A.3.2.1 Insufficient stopping time (Failure Model):

- **L0 Scenario:** Even an EV driver who independently detects an RLR threat or responds to the warning may be unable to stop if the available lead time is shorter than the EV's own CST. From **Section C.1.1**, this is modeled as a uniform (0.021-0.125) and treated as a conservative upper bound on EV stopping failure given warning receipt, because insufficient stopping time does not deterministically produce a collision[106].
- **L2 Scenario:** The EV stopping failure requires both the driver path (L0 values) and the L2 path (L4 values) to fail.
- **L4 Scenario:** Following the same structure, this event draws from empirical studies on Level 4 ADS crash reduction impacts[107]. As discussed in Appendix C.3, the area-specific estimation for Los Angeles, vehicle-to-vehicle crashes at intersections are 85% (5%,100%) lower with respect to human drivers. This event then addresses the estimated 15% of unavoidable crashes, to construct a working uniform distribution (0.006-0.002) compared to the human baseline in L0 Scenarios.

When there is no V2X available ($t_w < 3s$), it is assumed that the only failure mode applicable is A.3.2.1 (*Insufficient stopping time*). Further, the EV's stopping probability is governed by the high-time availability values.

[106] Y. Zhang, X. Yan, X. Li, and J. Wu, "Changes of drivers' visual performances when approaching a signalized intersection under different collision avoidance warning conditions," Transportation Research Part F: Traffic Psychology and Behaviour, vol. 65, pp. 584–597, Aug. 2019, doi: 10.1016/j.trf.2017.12.018.

[107] K. D. Kusano, J. M. Scanlon, Y. H. Chen, T. L. McMurry, T. Gode, and T. Victor, "Comparison of Waymo Rider-Only crash rates by crash type to human benchmarks at 56.7 million miles," Traffic Injury Prevention, vol. 26, no. sup1, May 2025, doi: 10.1080/15389588.2025.2499887.

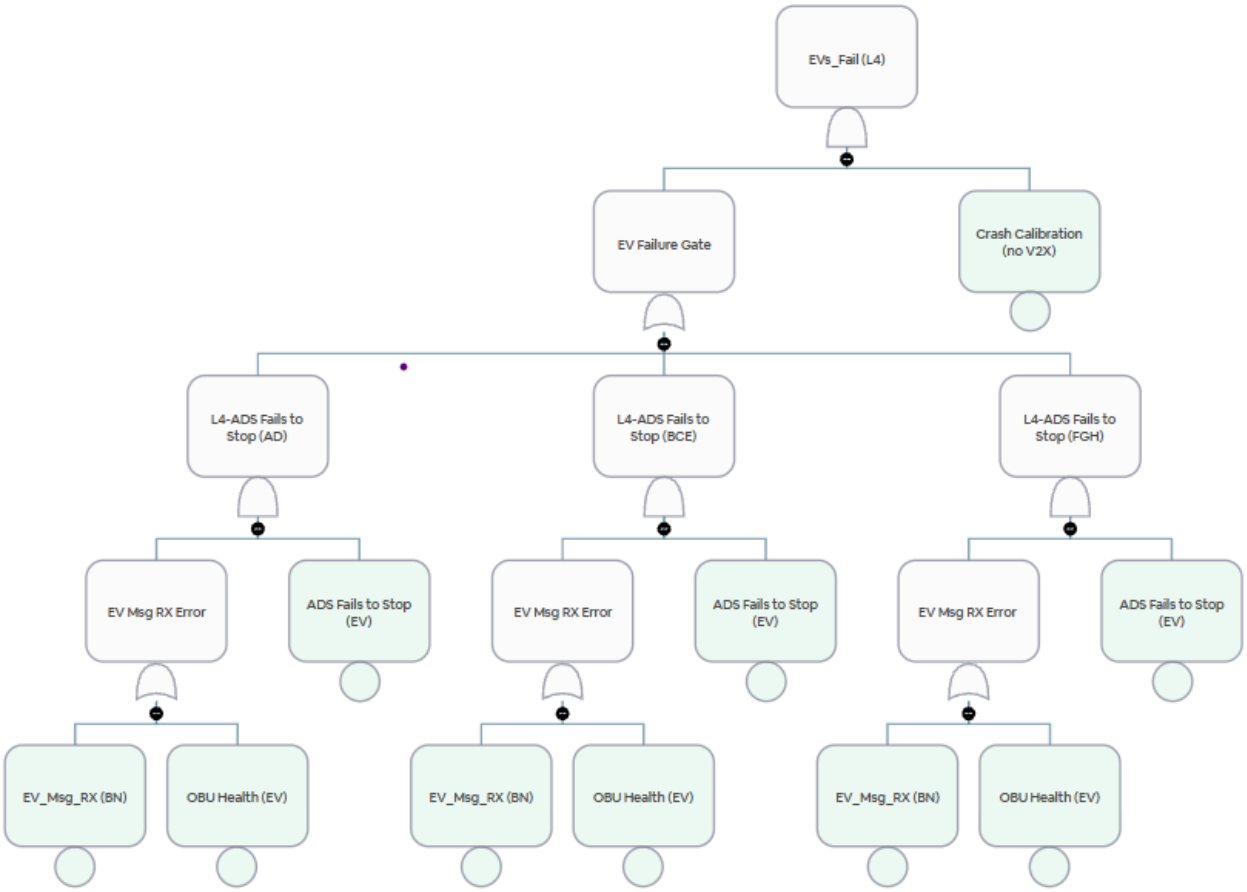

Figure 7.12: RLVW Scenario, Encountering Vehicles L4 Failure (V2X Enabled).

C.1.6. Bayesian Network Model

The BBN model serves multiple purposes. This establishes the impact of different factors on the baseline crash probabilities and failures of basic events in fault tree models. Nodes are classified as those with fixed, predetermined values depending

on where the scenario is taking place (weather, light conditions, speeding, and line-of-sight effects, and in this case, the intersection type), those depending on technology choices (in this case, the CV market penetration rate), and those which represent basic event failure probabilities. The implemented graph is presented in **Figure 7.13**.

C.1.6.1. A.4. Crash Exposure Model

The nodes in this section characterize the conditional probability of crash exposure resulting from a red-light running event as a function of environmental and roadway conditions. Parameters are derived from FARS/CRSS crash records and are intended to represent contributing factor distributions in police-reported crashes; values are therefore area-dependent and are presented here for the Downtown Los Angeles (DTLA) reference area. These parameters affect the magnitude of modeled crash exposure but do not impact structural modeling choices in the BBN. Further details on data extraction and area-specific calibration are provided in **Appendix C.3**.

A.4.1. Base Crash Exposure

Priors to the base crash exposure for scenario A have parent nodes for weather, light conditions, speeding, and intersection type. These priors are presented in **Table 7.9**.

A.4.1.1 Weather: This is a shared parent node serving three downstream components: (i) the base crash probability at the intersection, the conditional stopping probabilities when warned under (ii) high/low warning time availability (A.4.2.1), and (iii) the conditional stopping probabilities in non-warning conditions for L0/L2 Scenarios. It is also a parent node to the AEB (L2) node (A.4.2.3). Prior probabilities are derived from OpenWeatherMap historical data for the DTLA area on an average annual basis.

A.4.1.2 Light conditions: This is a fixed node at 50%-50% chance of day-night conditions. It is a parent node to the conditional stopping probabilities in non-warning conditions for L4 Scenarios (See **C.1.6.1**). It is also a parent node to the AEB (L2) node (A.4.2.3).

A.4.1.3 Speeding: The speeding indicator is a fixed binary node with priors derived from FARS crash records for the modeled area (See **Appendix C.3**).

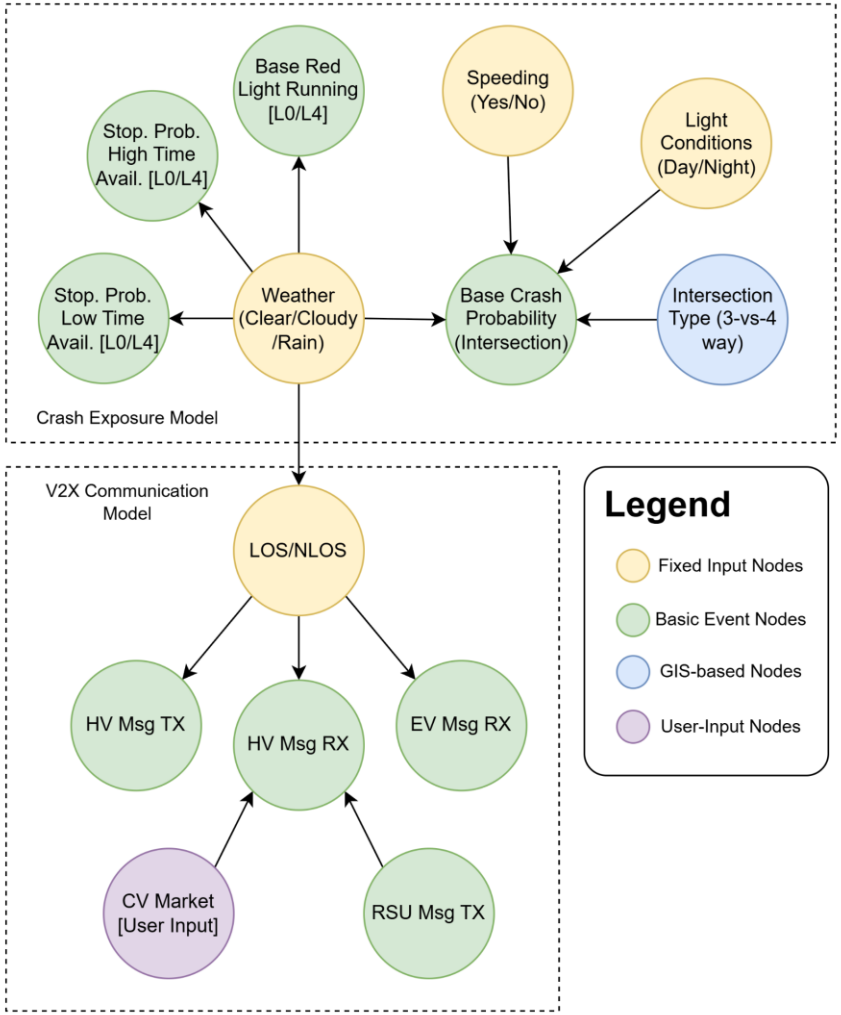

Figure 7.13: BBN Structure for Scenario A - RLVW.

A.4.1.4 Intersection Type: Intersection type is simplified to 4-way versus 3-way, with the latter category encompassing T- and Y-intersections. The priors are derived from GIS data for the DTLA area (See **Appendix C.3**).

Table 7.9: Parent nodes to Base Crash Probability for Scenario A.

Node	States	Prior Values P(State)
Weather	Clear	0.5842
	Cloudy	0.3698
	Rain	0.0460
Light Condition	Daytime	0.5000
	Nighttime	0.5000
Speeding	Speeding	0.4724
	Not Speeding	0.5276
Intersection Type	4-Way	0.8241
	3-Way	0.1758

A.4.1.5 Base Crash Probability: This node represents the conditional probability of a crash given a vehicle encounter under the specified conditions, i.e., $P(crash\ exposure \mid conditions)$. Values presented in **Table 7.10** are derived from five years of FARS data (2019–2023) filtered to two-vehicle, non-interstate, urban arterial intersection crashes in Los Angeles City, excluding pedestrian, pedal cyclist, work zone, and special jurisdiction records. Note that the selected sample is sparse for several weather conditions, which reflects the composition of the underlying crash record for this specific filtered scenario population. Full filter specifications and crash model calibrations for L0-L4 Scenarios are provided in **Appendix C.3**.

Table 7.10: Base Crash Probability for Scenario A.

Weather	Speeding	Intersection Type	Light Condition	P(No Crash Exposure)	P(Crash Exposure)
clear	speeding	4 way	daylight	8.65E-01	1.35E-01
clear	speeding	4 way	nighttime	9.57E-01	4.29E-02
clear	speeding	3 way	daylight	7.73E-01	2.27E-01
clear	speeding	3 way	nighttime	9.45E-01	5.52E-02
clear	no speeding	4 way	nighttime	9.90E-01	1.00E-02
clear	no speeding	3 way	nighttime	9.90E-01	1.00E-02
rain	speeding	4 way	daylight	9.94E-01	6.13E-03
rain	speeding	4 way	nighttime	9.94E-01	6.13E-03
rain	speeding	3 way	daylight	9.88E-01	1.23E-02
rain	no speeding	4 way	daylight	8.34E-01	1.66E-01
rain	no speeding	4 way	nighttime	9.51E-01	4.91E-02
rain	no speeding	3 way	daylight	7.91E-01	2.09E-01
rain	no speeding	3 way	nighttime	9.63E-01	3.68E-02
cloudy	no speeding	4 way	daylight	9.94E-01	6.13E-03
cloudy	no speeding	4 way	nighttime	9.94E-01	6.13E-03
cloudy	no speeding	3 way	daylight	9.82E-01	1.84E-02
cloudy	no speeding	3 way	nighttime	9.94E-01	6.13E-03

* Combinations not represented reflect insufficient cell counts in the filtered FARS sample. Not interpreted as a zero-risk condition. See Appendix C.3.

A.4.2 Vehicle Failure Nodes

These nodes alter base events probabilities discussed in **Section C.1.5** regarding driver-, L2-, and ADS-related failure events.

A.4.2.1 Stopping under warned conditions (Stop. Prob. High/Low Time)

L0 Scenarios

A simple model was developed to derive the stopping probability of a warned driver under various warning and weather conditions. This model quantifies the conditional probability that a warned driver can physically complete a full stop before entering the intersection, represented as P(vehicle stops in time | weather condition, initial speed, available time window). This applies to Level 0 host vehicles and to the driver response path of Level 2 host vehicles in a dilemma-zone RLVW. Deliberate red-light runners (constant speed or acceleration) are excluded from this portion of the model. This is a simplified approach, acknowledging that complex two- and three-piecewise models are more representative of vehicle deceleration models.[108]

The vehicle successfully stops if: $T_{stop} = t_r + V/a \leq T_{avail}$, where t_r is driver reaction time, V is initial speed, a is deceleration, and T_{avail} is the time remaining after the warning was delivered since the offset at 10s. The model assumes constant deceleration from warning reception to full stop. Transient brake application dynamics (e.g., jerk) are not modeled. The vehicle is assumed to be traveling at constant speed at the moment the warning is received to estimate the upper bound of the total braking time required to the stop bar. As discussed in **Section C.1.1** and **C.1.5** (A.*2.2.2 Insufficient stopping time given road conditions*), the ESD takes into account three branches: a high ($T_{avail} > 5s$), low ($3s < T_{avail} < 5s$), and no additional time availability provided by the warnings ($T_{avail} < 3s$).

[108] G. Markkula, J. Engström, J. Lodin, J. Bärgman, and T. Victor, "A farewell to brake reaction times? Kinematics-dependent brake response in naturalistic rear-end emergencies," Accident; analysis and prevention, vol. 95, no. Pt A, pp. 209–26, Oct. 2016, doi: 10.1016/j.aap.2016.07.007.

Values for reaction times and vehicle deceleration were considered under clear, cloudy and rainy conditions. For simplicity, a standard value for driver PRT of $t_r = 1.00 \pm 0.39s$ is considered across all weather conditions[109] and only clear and rain values for deceleration were implemented, while cloudy conditions absorb clear condition results. This design choice reflects the study area and is an assumption that must be revisited while studying other areas with more adverse weather conditions.

Three vehicle deceleration values were considered to represent plausible braking behavior for a warned driver intending to stop under clear and mild rain weather conditions. These values presented in **Table 7.11** are modeled as truncated normal distributions $a \sim N(\mu, \sigma^2) \in \pm 3\sigma$. Low/Mid values span the AASHTO comfortable braking design band (0.35-0.45g) at $\pm 2\sigma$, while rain-related values are derived from the ratio of dry/wet friction coefficients ($f_{dry,asphalt} = 0.9, f_{wet,asphalt} = 0.7$)[110], and higher variability is assigned to high-effort braking conditions.

Table 7.11: Deceleration values per weather condition (L0).

Weather	Clear	Rain
Low	N(0.36g, 0.025g²)	N(0.28g, 0.025g²)
Mid	N(0.45g, 0.025g²)	N(0.35g, 0.025g²)
High	N(0.70g, 0.050g²)	N(0.54g, 0.055g²)

The probability of a driver stopping under weather, approach speed, and warned conditions are estimated from the joint distribution of T_{stop}through a Monte Carlo simulation ($N = 100{,}000$). This simulation assumes independence between driver PRT and vehicle deceleration, and truncated normal distributions for both random variables, with restricted values for driver PRT ($t_r > 0$) and vehicle deceleration values ($a \pm 3\sigma$). Thus, P(stop) is modeled as shown in Equations (3) and (4):

[109] Reaction time parameters are derived from Yan et al. (2015): the alarm-to-brake-onset time across warning timings 3.0–5.5 s gives a mean of 1.00 s and a within-group standard deviation averaging 0.39 s. See Section 3.1.2 for more details.

[110] S. A. Elsagheer Mohamed, K. A. Alshalfan, M. A. Al-Hagery, and M. T. Ben Othman, "Safe Driving Distance and Speed for Collision Avoidance in Connected Vehicles," *Sensors*, vol. 22, no. 18, art. no. 7051, Sep. 2022, doi: 10.3390/s22187051.

$$T_stop \approx N(\mu_{t_r} + V/\mu_a,\ {\sigma_{t_r}}^2 + (V \cdot \sigma_a/{\mu_a}^2)^2) \quad \textbf{(3)}$$

$$P(stop|t_r, a, V, T_{avail}) = \Phi((T_{avail} - \mu_{t_r} - V/\mu_a) / \sqrt{({\sigma_{t_r}}^2 + (V \cdot \sigma_a/{\mu_a}^2)^2)}) \quad \textbf{(4)}$$

Representative conditions for each ESD time-availability branch were selected for the BBN node states, as shown in **Table 7.12**.

Table 7.12: Representative stopping probability values for BBN nodes (L0).

Node	Vehicle Approach Speed	Deceleration Scenario	Representative Time Available	Clear / Cloudy	Rain
Stop. Prob. (High Time)	40mph	Mid	6.5s	0.999	0.706
Stop. Prob. (Low Time)	35mph	High	4s	0.956	0.538

Figure 7.14 presents a summary of the obtained stopping probabilities for $T_{avail} = 6.5s$ for the high time availability scenario and $T_{avail} = 4.0s$ for the low time availability scenario, respectively. **Figure 7.15** presents the cumulative probability distribution curve at different approach speeds as a function of T_{avail}, highlighting the anchors selected for the BBN nodes.

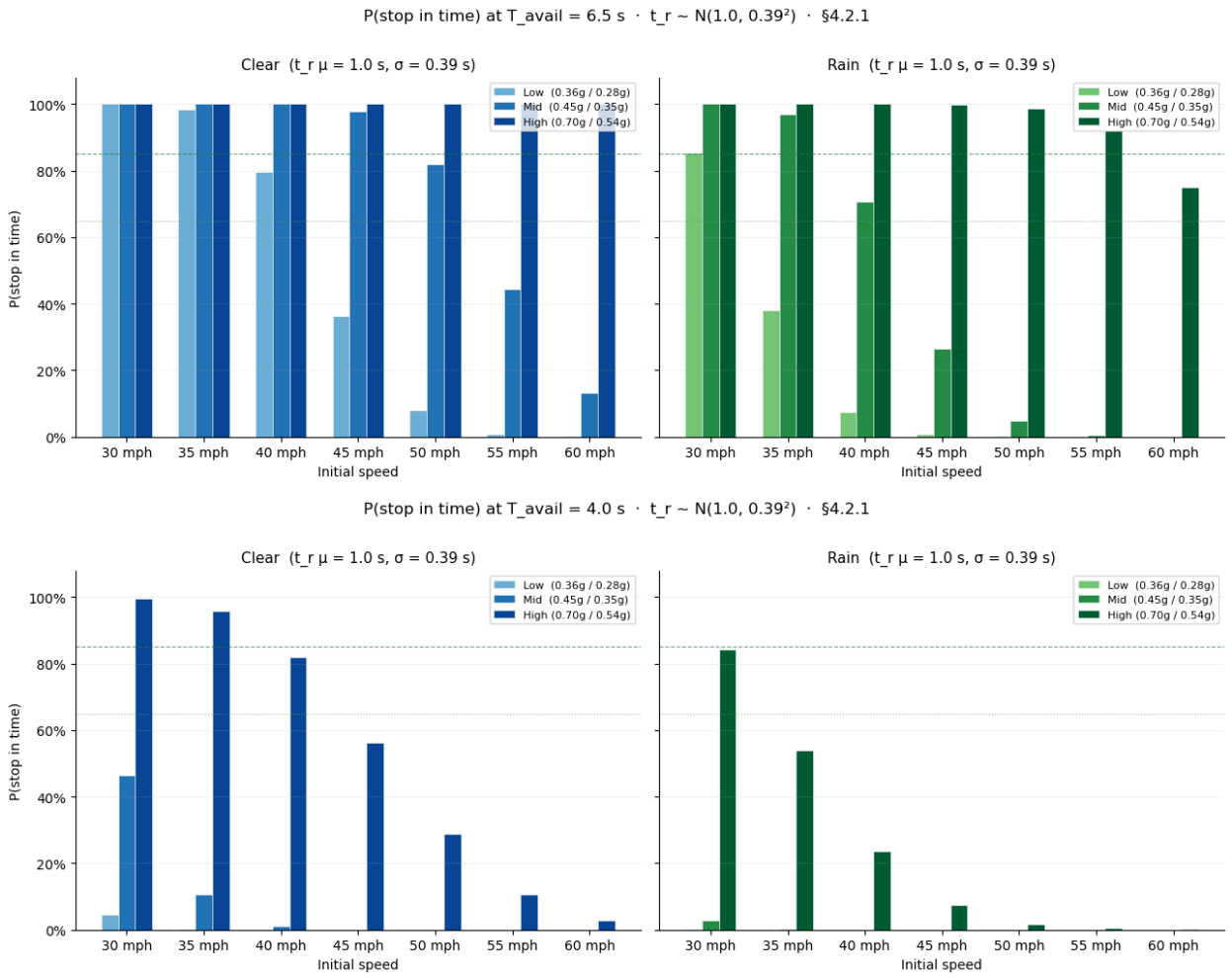

Figure 7.14: Stopping probability at 4-6.5 second warnings (RLVW, L0).

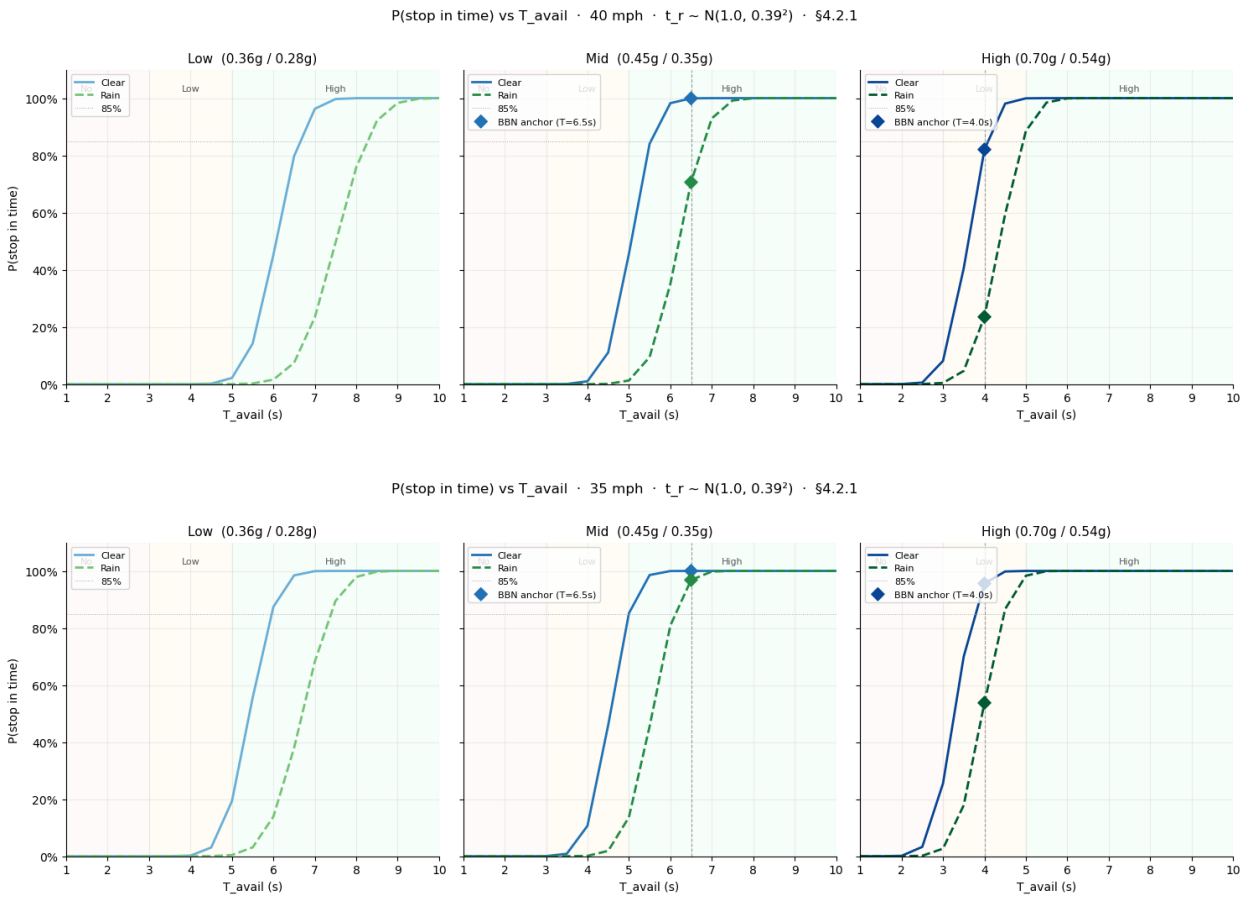

Figure 7.15: Cumulative probability functions at 35-40mph (RLVW, L0).

L4 Scenarios

The described physics-based stopping model is retained for the L4 ADS, with two modifications. First, reaction time is updated to $t_r \sim N(0.10, 0.02^2)\ s$, reflecting end-to-end ADS latency from V2X message receipt through brake actuation of approximately 50-100 ms, with $\sigma = 0.02\ s$ capturing variability in message processing and perception pipeline timing. The same L4 parameters are used for the L2 response path once a warning has been received (Section C.1.3).

Second, deceleration distributions are updated to reflect ADS-specific braking behavior (**Table 7.13**). Under routine conditions (e.g., approaching a red light, stop sign, or yield), ADS are expected to target lower deceleration values in the range of $1.5 - 2.5\ m/s^2$ $(0.15g - 0.25g)$ to minimize passenger discomfort[111,112]. Conflict-driven stoppages, on the other hand, suggest values within the $0.30 - 0.40g$ $(3.0 - 3.9\ m/s^2)$ range for assertive planned braking in response to a V2X warning or signal state change with limited time availability[113]. For emergency braking scenarios, the high-end values used for reference correspond to maximum achievable deceleration under full AEB authority, empirically observed at approximately $0.64g$[114,115], as well as the higher end reported in Wang et. al, 2023.

The same scaling for rain conditions as for L0 scenarios is applied. For L4 systems, the friction penalty additionally reflects the deliberate reduction in commanded deceleration targets applied by ADS motion planners under detected low-friction conditions to preserve a safety margin against wheel slip and loss of directional control Representative conditions for each ESD time-availability branch were selected for the BBN node states, as shown in Table 7.14.

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[111] S. Carlowitz et al., “Balancing comfort and efficiency: Optimal deceleration rates at crosswalks and intersections in automated driving,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 116, p. 103289, Oct. 2025, doi: 10.1016/j.trf.2025.06.029.

[112] Y. Rahmati, A. Samimi Abianeh, Mahmood Tabesh, and Alireza Talebpour, “Toward Human-Centered Design of Automated Vehicles: A Naturalistic Brake Policy,” Frontiers in Future Transportation, vol. 2, June 2021, doi: 10.3389/ffutr.2021.683223.

[113] Y. Wang, H. Farah, R. Yu, S. Qiu, and Bart van Arem, “Characterizing Behavioral Differences of Autonomous Vehicles and Human-Driven Vehicles at Signalized Intersections Based on Waymo Open Dataset,” Transportation Research Record, vol. 2677, no. 11, pp. 324–337, May 2023, doi: 10.1177/03611981231165783.

[114] A. Skokan, “Field Testing of ADAS Technologies in Naturalistic Driving Conditions,” Vehicles, vol. 7, no. 4, p. 135, Nov. 2025, doi: 10.3390/vehicles7040135.

[115] V. V. Petin, A. V. Keller, S. S. Shadrin, D. A. Makarova, and Y. M. Furletov, “Experimental Investigation and Performance Evaluation of Automated Emergency Braking (AEB) Systems Under Actual Driving Conditions,” Vehicles, vol. 7, no. 4, p. 152, Dec. 2025, doi: 10.3390/vehicles7040152.

Table 7.13: Deceleration values per weather condition (L4).

Weather	Clear	Rain
Low	$N(0.20g, 0.010g^2)$	$N(0.16g, 0.010g^2)$
Mid	$N(0.40g, 0.015g^2)$	$N(0.31g, 0.015g^2)$
High	$N(0.64g, 0.030g^2)$	$N(0.50g, 0.030g^2)$

Table 7.14: Representative stopping probability values for BBN nodes (L4).

Node	Vehicle Approach Speed	Deceleration Scenario	Representative Time Available	Clear / Cloudy	Rain
Stop. Prob. (High Time)	40mph	Mid	6.5s	0.99	0.96
Stop. Prob. (Low Time)	35mph	High	4s	0.99	0.99

Figure 7.16 presents a summary of the obtained stopping probabilities for $T_{avail} = 6.5s$ for the high time availability scenario and $T_{avail} = 4.0s$ for the low time availability scenario, respectively. **Figure 7.17** presents the cumulative probability distribution curve at different approach speeds as a function of T_{avail}, highlighting the anchors selected for the BBN nodes.

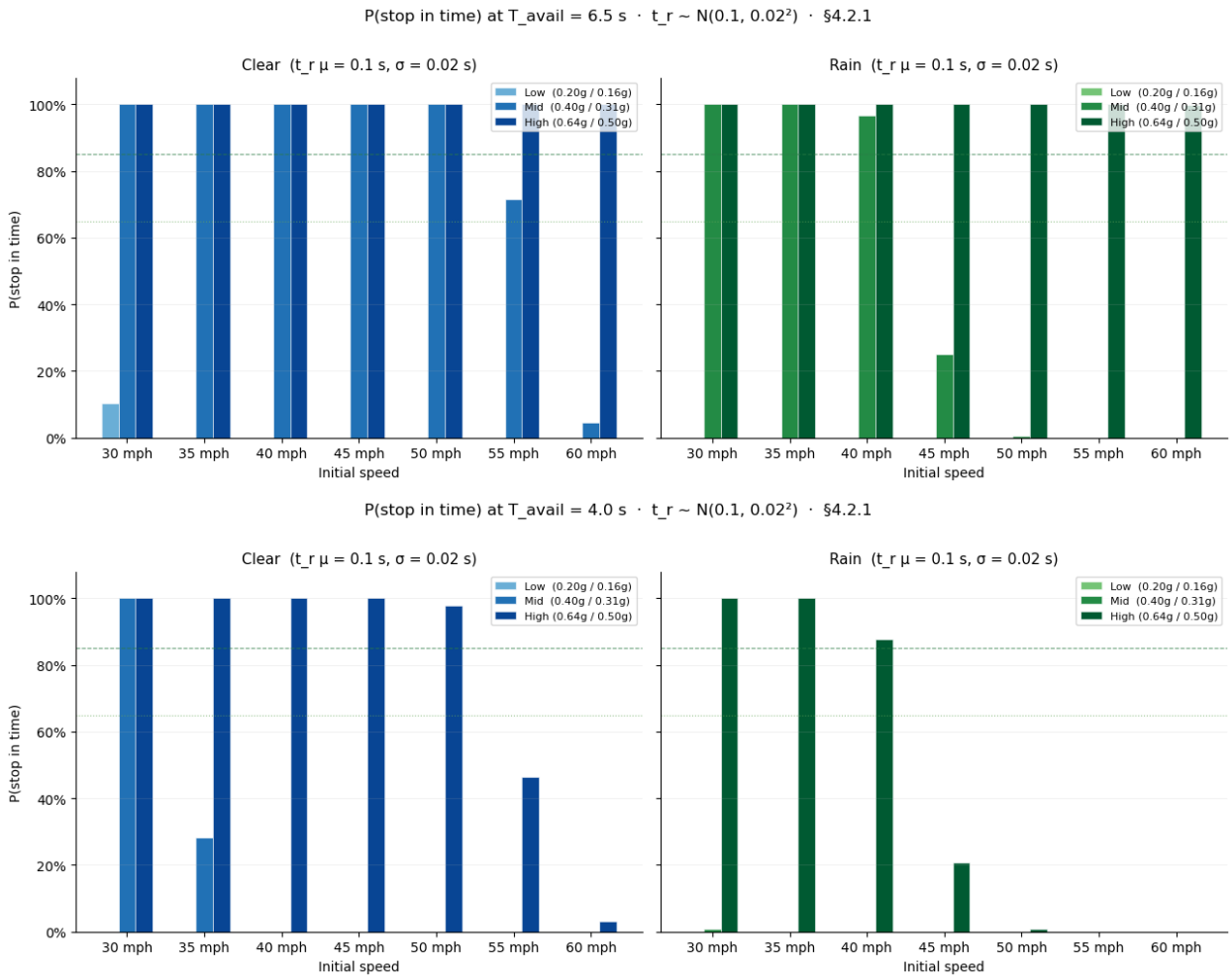

Figure 7.16: Stopping probability at 4-6.5 second warnings (RLVW, L4).

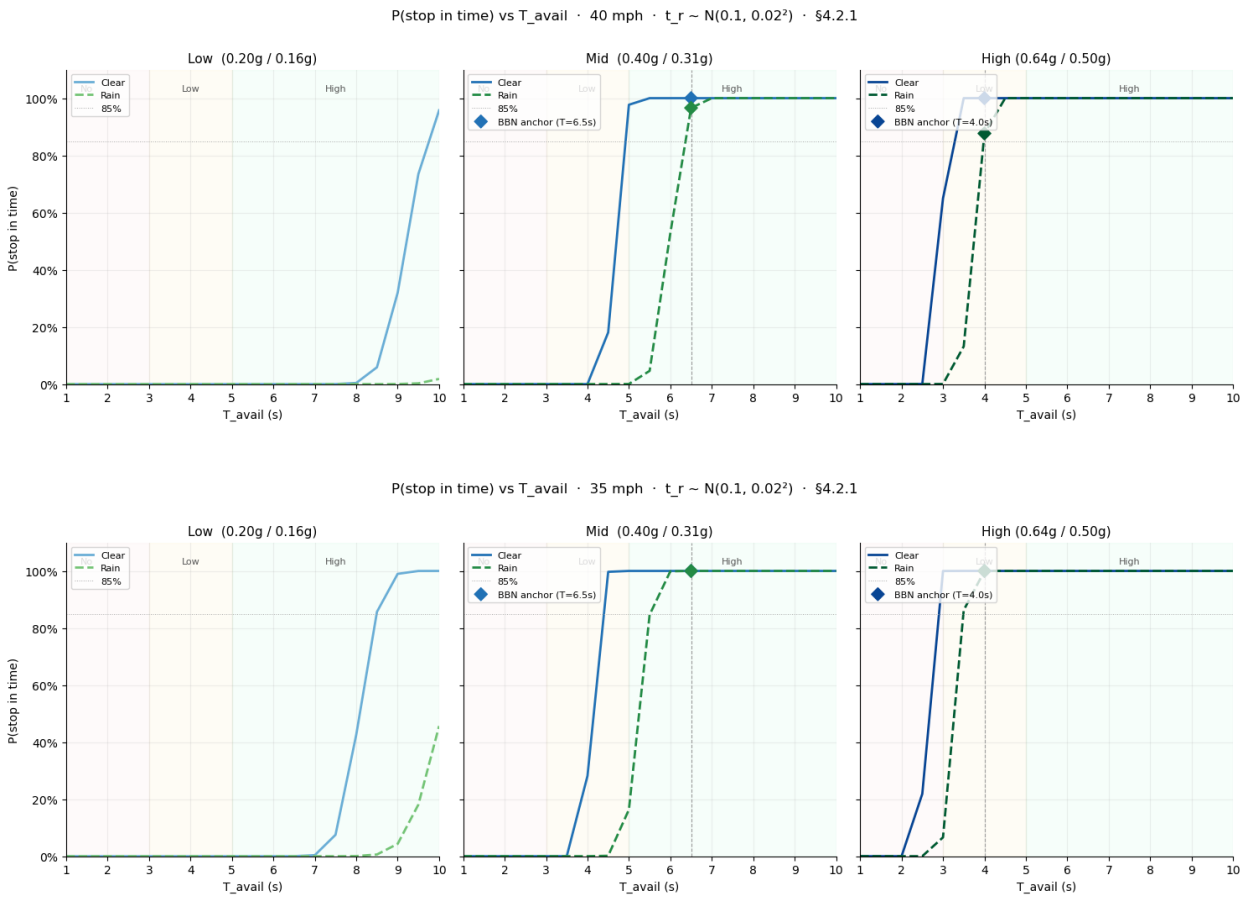

Figure 7.17: Cumulative probability functions at 35-40mph (RLVW, L4).

A.4.2.2 Stopping under unwarned conditions (Base Red Light Running)

L0 Scenarios:

This node represents the probability of an unwarned RLR driver as a function of weather conditions. Separate studies have reported a dilemma zone boundary shift farther from the stop bar in rain (approx. 0.2s) and increases in PRT (median 0.74s to 0.80s)[116]. The combined effect implies that naturalistic RLR behavior may decrease under rainy conditions, even under lower deceleration[117].

For instance, a field study showed a reduction from 14% to 2% in light rain and 1% under moderate rain[118]. Cloudy weather conditions are treated as an intermediate state between clear and rainy conditions: reduced visibility relative to clear but no dilemma zone boundary shift reported in literature. Considering the overall RLR probability has been estimated at $P(RLR) = 0.27$, this value has been reconstructed to reflect the impact of weather conditions, as shown in **Table 7.15**.

Table 7.15: RLR vs Weather (L0 Scenarios).

Weather	P(runs red)	P(stops)
Clear	0.291	0.709
Cloudy	0.268	0.732
Rain	0.038	0.962

[116] H. Li, H. Rakha, and I. El-Shawarby, “Designing Yellow Intervals for Rainy and Wet Roadway Conditions,” International Journal of Transportation Science and Technology, vol. 1, no. 2, pp. 171–189, Nov. 2016, doi: 10.1260/2046-0430.1.2.171.

[117] H. Perrin, P. T. Martin, and B. G. Hansen, “Modifying Signal Timing During Inclement Weather,” Transportation Research Record Journal of the Transportation Research Board, vol. 1748, no. 1, pp. 66–71, Jan. 2001, doi: 10.3141/1748-08.

[118] J. Oyaro and J. Ben-Edigbe, “Influence of Rainfall on the Probability of Red-Light Running at Signalised Intersections,” Lecture Notes in Civil Engineering, pp. 379–392, 2022, doi: 10.1007/978-981-19-1065-4_31.

For L2 Scenarios, the unwarned red-light-running probability follows the L0 values in Table 7.15.

L4 Scenarios:

This node represents the probability of an unwarned RLR ADS-equipped vehicle as a function of light conditions. As described in **Section 3.1.2.3**, this failure mode is dominated by vision-based systems, independent of the local sensor fusion configuration of the vehicle. The implemented CPT is presented in **Table 7.16**.

Table 7.16: RLR vs Light Conditions (L4 Scenarios).

Light Conditions	P(runs_red)	P(stops)	Model	Reference
Daytime	0.005	0.995	P(failure) ~ Uniform(0.001, 0.01)	Chowdhury 2024; De Guia 2024.
Nighttime	0.020	0.98	P(failure) ~Uniform(0.005, 0.035)	Chowdhury 2024 (night mAP_{50} = 83.1%)

A.4.2.3 Stopping failure recovery path (L2)

L2 Scenario (AEB):

This node represents the L2 AEB outcome after the driver and the L2 system have failed to stop the host vehicle (under warned or unwarned conditions). As described in Section C.1.3, AEB is modeled as a sequential, function-level recovery path conditioned on light condition, vehicle-side LOS/NLOS (LOS 0.7, NLOS 0.3), and weather. The CPT is scaled to reproduce the PARTS-derived intersection targets under the crash-exposure mix implied by the PARTS estimates (approximately 83% daylight and 90% good weather). Under the DTLA priors used in this model (50% nighttime, 4.6% rain), the node marginalizes to 42.3%, below the 44.4% headline value due to the higher nighttime exposure. The implemented CPT is presented in Table 7.17.

Table 7.17: AEB Conflict Probability (L2 Scenarios).

Light Condition	LOS Condition	Weather	P(conflict)*
Daytime	LOS	Clear/Cloudy	3.55E-01
Daytime	LOS	Rain	4.86E-01
Daytime	NLOS	Clear/Cloudy	9.49E-01
Daytime	NLOS	Rain	9.59E-01
Nighttime	LOS	Clear/Cloudy	4.63E-01
Nighttime	LOS	Rain	5.73E-01
Nighttime	NLOS	Clear/Cloudy	9.62E-01
Nighttime	NLOS	Rain	9.69E-01

*Derived from PARTS (2025)[119]; NLOS/LOS ratios from Table 7.30.

C.1.6.2. A.5. V2X Communication Model

The V2X communication model characterizes the probability of successful message exchange between RSUs and vehicle OBUs as a function of intersection geometry, weather conditions, and market penetration. The model is structured in two components: a link quality node (A.5.1) that represents the probability of effective LOS between the RSU and vehicle as a function of weather, and a conditional message transmission/reception model (A.5.2) that assigns delivery probabilities given the effective link state. This portion of the model is applied to both L0-L4 Scenarios.

A.5.1 Line of Sight Conditions

[119] Partnership for Analytics Research in Traffic Safety (PARTS), "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

The LOS/NLOS is a simplified binary node that represents the effective link quality sufficient for message delivery between the RSU and a target vehicle (either the host vehicle or an encountering vehicle), as influenced by intersection geometry and weather conditions.

At urban intersections, the dominant determinant of effective link quality is building occlusion along approach legs. Baseline geometric LOS probabilities at urban intersections at ranges of 100–200 m is approximately 0.55–0.70 depending on building density[120,121]. Consistent with empirical V2X intersection propagation literature, a baseline geometric LOS probability of $P(effective\ LOS) = 0.60$ is assumed for clear and cloudy conditions, reflecting moderate urban building density representative of arterial intersections.

At 5.9 GHz, ITU-R P.838 gives specific attenuation of approximately 0.01 dB/km for light rain (2.5 mm/hr) and 0.05 dB/km for moderate rain (12.5 mm/hr)[122]. At an intersection approach distance of 200 m, total path attenuation due to rainfall absorption is negligible[123]. This is consistent with the IEEE 802.16cc rain attenuation model, which finds signal loss below 10% for rainfall rates up to approximately 55 mm/hr at 6 GHz. However, a conservative 5-percentage-point reduction in P(effective LOS) is applied under rain conditions, representing an upper bound on secondary effects (including multipath scattering from precipitation). The resulting CPT for the LOS node is shown in **Table 7.18.**

Table 7.18: LOS vs Weather (Scenario A).

Weather	P(effective LOS)	P(effective NLOS)
Clear	0.60	0.40

[120] T. Mangel, O. Klemp, and H. Hartenstein, “5.9 GHz inter-vehicle communication at intersections: a validated non-line-of-sight path-loss and fading model,” EURASIP Journal on Wireless Communications and Networking, vol. 2011, no. 1, Nov. 2011, doi: 10.1186/1687-1499-2011-182.

[121] A. Al-Hourani, "On the Probability of Line-of-Sight in Urban Environments," in *IEEE Wireless Communications Letters*, vol. 9, no. 8, pp. 1178-1181, Aug. 2020, doi: 10.1109/LWC.2020.2984497.

[122] *Specific Attenuation Model for Rain for Use in Prediction Methods*, Recommendation ITU-R P.838-3, International Telecommunication Union, Geneva, Switzerland, Mar. 2005.

[123] R. Bharathiraja and M. A. Bhagyaveni, "Investigating Rain Attenuation and Doppler Effects in 5G-Based V2V and V2I Communication," *2023 Second International Conference on Advances in Computational Intelligence and Communication (ICACIC)*, Puducherry, India, 2023, pp. 1-5, doi: 10.1109/ICACIC59454.2023.10435124.

Weather	P(effective LOS)	P(effective NLOS)
Cloudy	0.60	0.40
Rain	0.55	0.45

A.5.2 V2X Communication Models

Message delivery reliability for RSU-to-OBU transmissions is modeled using a simplified binary success/failure structure conditioned on effective link quality (LOS or NLOS). At intersection approach distances below 250 m, empirical field evaluations of both DSRC and C-V2X systems have demonstrated that packet error rates remain at or below the 10% reliability threshold across LOS and NLOS urban conditions well beyond this range [124]. These findings are consistent with the 5GAA V2X Functional and Performance Test Report (2019), which documents similar range reliability under standardized test conditions[125].

On this basis, a nominal transmission success probability of $P(MsgTX \mid LOS) = 0.97$ is assumed for LOS conditions, representing a conservative floor relative to available field evidence. This nominal LOS value is expected to degrade under channel congestion from high vehicular density[126,127]. V2I simulation studies indicate that PDR decreases under higher traffic intensities, with DSRC maintaining PDR above 96% across all investigated urban scenarios, while LTE-based modes

[124] Z. Zhong, L. Cordova, M. Halverson, and B. Leonard, "Field Tests on DSRC and C-V2X Range of Reception on Utah Roadways," Panasonic Corp. of North America for Utah Dept. of Transportation, Salt Lake City, UT, USA, Apr. 23, 2021. [Online]. Available: https://transportationtechnology.utah.gov/wp-content/uploads/2023/01/UDOT.Range-of-Reception-DSRC-C-V2X-Report-FINAL-2.pdf

[125] 5G Automotive Association, "V2X Functional and Performance Test Report; Test Procedures and Results," 5GAA, Munich, Germany, Tech. Rep. P-190033, Apr. 2019

[126] M. Gonzalez-Martin, M. Sepulcre, R. Molina-Masegosa, and J. Gozalvez, “Analytical Models of the Performance of C-V2X Mode 4 Vehicular Communications,” IEEE Transactions on Vehicular Technology, vol. 68, no. 2, pp. 1155–1166, Dec. 2018, doi: 10.1109/tvt.2018.2888704.

[127] T. Hirai and T. Murase, “Performance Evaluations of PC5-based Cellular-V2X Mode 4 for Feasibility Analysis of Driver Assistance Systems with Crash Warning,” Sensors, vol. 20, no. 10, pp. 2950–2950, May 2020, doi: 10.3390/s20102950.

degrade more severely under congestion[128]. The intersection traffic densities assumed in the RLVW scenario are consistent with the low-to-moderate density range in these studies.

For NLOS conditions, a conservative lower bound of $P(MsgTX \mid NLOS) = 0.90$ is assumed. NLOS induced by a truck-sized blocker reduces LTE-V2X effective communication range, with PDR near 90% preserved at distances around 200m-250m[129,130], supporting the assumed $P(MsgTX \mid NLOS)$ value. It should be noted that in real urban C-V2X V2I deployments, building proximity has been identified as a significant secondary degradation factor independent of RSU distance; aggregate PDR values as low as 0.61 have been reported over full approach ranges up to 600m in dense urban arterial environments[131,132,133].

The following conditional probability tables are implemented to characterize the modeled RLVW scenario. Transmission-related event probabilities are provided in **Table** 7.19, while reception-related event probabilities are provided in **Table 7.20**, as a function of the CV market penetration. For EV-related probabilities, CV market penetration rate is applied as a multiplier to the per-vehicle delivery probability.

Table 7.19: Communication Failure Probabilities (No TX) for RSU and host vehicle.

[128] T. Petrov, L. Sevcik, P. Pocta, and M. Dado, “A Performance Benchmark for Dedicated Short-Range Communications and LTE-Based Cellular-V2X in the Context of Vehicle-to-Infrastructure Communication and Urban Scenarios,” Sensors, vol. 21, no. 15, p. 5095, July 2021, doi: 10.3390/s21155095.

[129] E. Moradi-Pari, D. Tian, M. Bahramgiri, S. Rajab, and S. Bai, "DSRC Versus LTE-V2X: Empirical Performance Analysis of Direct Vehicular Communication Technologies," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 5, pp. 4889–4903, May 2023, doi: 10.1109/TITS.2023.3247339.

[130] Crash Avoidance Metrics Partners LLC (CAMP) C-V2X Consortium, "C-V2X Performance Assessment Project," Dec. 5, 2019. [Online]. Available: https://pronto-core-cdn.prontomarketing.com/2/wp-content/uploads/sites/2896/2020/02/CAMP-CV2X_SAE_01152020_v2.pdf

[131] M. Boban and P. M. d'Orey, "Exploring the Practical Limits of Cooperative Awareness in Vehicular Communications," *arXiv:1503.06590 [cs.NI]*, Mar. 2016. [Online]. Available: https://arxiv.org/abs/1503.06590

[132] S. Guo, D. N. Aloi, J. Li, and H. Zhao, "Physical Layer Evaluation on IEEE 802.11p With Different Configurations in NLOS Scenarios for V2V Communications," *IEEE Access*, vol. 13, pp. 44428–44444, 2025, doi: 10.1109/ACCESS.2025.3548881.

[133] P. Li, K. Wu, Y. Cheng, S. T. Parker and D. A. Noyce, "How Does C-V2X Perform in Urban Environments? Results From Real-World Experiments on Urban Arterials," in *IEEE Transactions on Intelligent Vehicles*, vol. 9, no. 1, pp. 2520-2530, Jan. 2024, doi: 10.1109/TIV.2023.3326735.

Event	Node	*State LOS/NLOS*	*CV %*	TX	No TX
RSU Message Transmission*	RSU_Msg_TX			0.97	0.03
Host Vehicle Transmission	HV_Msg_TX	*LOS*	*P0*	0.00	1.00
		LOS	*P25*	0.24	0.76
		LOS	*P50*	0.49	0.52
		LOS	*P75*	0.73	0.27
		LOS	*P100*	0.97	0.03
		NLOS	*P0*	0.00	1.00
		NLOS	*P25*	0.23	0.78
		NLOS	*P50*	0.45	0.55
		NLOS	*P75*	0.68	0.33
		NLOS	*P100*	0.90	0.10

* Note that RSU Message Transmission is treated as unconditional while LOS/NLOS and weather effects are collected in the LOS/NLOS node.

Table 7.20: Communication Failure Probabilities (No RX) for host and encountering vehicles as a function of CV market penetration rate.

Host & Encountering Vehicles Reception	LOS/NLOS State	RSU Message Transmission	RX	No RX
P0	LOS	TX	0.00	1.00
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.00	1.00
	NLOS	No_TX	0.00	1.00
P25	LOS	TX	0.24	0.76
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.23	0.78
	NLOS	No_TX	0.00	1.00
P50	LOS	TX	0.49	0.52
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.45	0.55
	NLOS	No_TX	0.00	1.00
P75	LOS	TX	0.73	0.27
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.68	0.33
	NLOS	No_TX	0.00	1.00
P100	LOS	TX	0.97	0.03
	LOS	No_TX	0.00	1.00

Host & Encountering Vehicles Reception	LOS/NLOS State	RSU Message Transmission	RX	No RX
	NLOS	TX	0.90	0.10
	NLOS	No_TX	0.00	1.00

C.2. Scenario B Technical Details

This section presents technical details supporting the Scenario B – CP-PED HCL model development. This includes industry and academic literature basis for driver (L0) and ADS (L4) failure behavior, as well as the developed HCL model details (event sequence diagrams, fault trees, and Bayesian networks).

C.2.1. Driver Warning-Timing Basis

Collision-warning research broadly converges on a time-to-collision (TTC) threshold near 5 seconds for forward, lateral, and rear-end conflicts[134,135,136,137]. Extensive analysis has documented how poorly timed warnings can undermine a driver's response[138,139], as well as the impact on unreliable warnings[140]. Early warnings may be ignored or interpreted as a false

[134] X. Yan, Y. Zhang, and L. Ma, "The influence of in-vehicle speech warning timing on drivers' collision avoidance performance at signalized intersections," Transp. Res. Part C Emerg. Technol., vol. 51, pp. 231–242, Feb. 2015, doi: 10.1016/J.TRC.2014.12.003.

[135] J. J. Scott and R. Gray, "A comparison of tactile, visual, and auditory warnings for rear-end collision prevention in simulated driving," Hum. Factors, vol. 50, no. 2, pp. 264–275, Apr. 2008, doi: 10.1518/001872008X250674

[136] Mostafa H. Tawfeek and Karim El-Basyouny. 2018. A perceptual forward collision warning model using naturalistic driving data. Canadian Journal of Civil Engineering. 45(10): 899-907. https://doi.org/10.1139/cjce-2017-0592

[137] W. Zhao, S. Gong, D. Zhao, F. Liu, N. N. Sze, and H. Huang, "Effects of collision warning characteristics on driving behaviors and safety in connected vehicle environments," Accident Analysis & Prevention, vol. 186, p. 107053, Apr. 2023, doi: 10.1016/j.aap.2023.107053.

[138] F. Hajiseyedjavadi, T. Zhang, R. Agrawal, M. Knodler, D. Fisher, and S. Samuel, "Effectiveness of visual warnings on young drivers hazard anticipation and hazard mitigation abilities," Accident Analysis & Prevention, vol. 116, pp. 41–52, Dec. 2017, doi: 10.1016/j.aap.2017.11.037.

[139] J. D Lee, D. V. McGehee, T. L. Brown, and M. L. Reyes, "Collision warning timing, driver distraction, and driver response to imminent rear-end crashes in a high-fidelity driving simulator," Human factors, vol. 44, no. 2, pp. 314–34, 2002, doi: 10.1518/0018720024497844.

[140] M. Vollrath and J. Morawietz, "Only an unreliable warning system is a good system – but which errors help?," Transportation Research Part F: Traffic Psychology and Behaviour, vol. 117, p. 103446, Nov. 2025, doi: 10.1016/j.trf.2025.103446.

alarm by the drivers while late alerts may disrupt a concurrent vehicle maneuver[141]. An early study assessing the impact of driver warning timings in connected environments studied warning delivery times between 0-60s to conflict for multiple crash scenarios. In general, early warnings resulted in fewer crashes than late warnings did, and a lead time ranging from 4.5 to 10 s brought the greatest safety benefit (see **Figure 7.18**)[142].

For pedestrian-specific hazards, two independent driving-simulator studies converge on 4s as the minimum warning lead time producing a measurable protective effect. Hajiseyedjavadi et al. (2018) tested head-up-display alerts delivered 2, 3, or 4s before a latent pedestrian threat and found that only the 3-4s conditions produced a significant reduction in approach speed[143].

Miao & Yan (2021)[144] tested warning release times between 2.5-4.5s against pedestrian-vehicle crash rate and concluded that 4s provided the highest reduction in crash rates (6.25%), additionally reporting that earlier warnings produced measurably lower peak deceleration which are also linked to reducing secondary crashes[145]. Large et al. (2018)[146] varied both the urgency (TTC) and modality of pedestrian alert warnings and found acceptance was lowest at the shortest (2.0-s) TTC, with combined audio-visual warnings producing greater driver confidence than audio alone; also noting that driver PRT also improved as TTC increased toward four and five seconds.

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[141] J. D. Lee, D. V. McGehee, T. L. Brown, and M. L. Reyes, "Collision warning timing, driver distraction, and driver response to imminent rear-end crashes in a high-fidelity driving simulator," Human Factors, vol. 44, no. 2, pp. 314–334, Jun. 2002, doi: 10.1518/0018720024497844. [Online]. Available: https://doi.org/10.1518/0018720024497844

[142] J. Wan, C. Wu, and Y. Zhang, “Effects of lead time of verbal collision warning messages on driving behavior in connected vehicle settings,” Journal of Safety Research, vol. 58, pp. 89–98, Sept. 2016, doi: 10.1016/j.jsr.2016.07.003.

[143] F. Hajiseyedjavadi, T. Zhang, R. Agrawal, M. Knodler, D. Fisher, and S. Samuel, “Effectiveness of visual warnings on young drivers hazard anticipation and hazard mitigation abilities,” Accident Analysis & Prevention, vol. 116, pp. 41–52, Dec. 2017, doi: 10.1016/j.aap.2017.11.037.

[144] Y. Miao and X. Yan, “The Impacts of Warning Release Time and Speed Limit on Driving Behaviour and Pedestrian-Vehicle Collision Rate on Side-parking Road,” IOP Conference Series: Earth and Environmental Science, vol. 638, no. 1, p. 012034, Feb. 2021, doi: 10.1088/1755-1315/638/1/012034.

[145] F. Naujoks and A. Neukum, “Specificity and timing of advisory warnings based on cooperative perception,” Mensch & Computer 2014 - Workshopband, pp. 229–238, Aug. 2014, doi: 10.1524/9783110344509.229.

[146] D. R. Large et al., “Investigating the effect of urgency and modality of pedestrian alert warnings on driver acceptance and performance,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 60, pp. 11–24, Oct. 2018, doi: 10.1016/j.trf.2018.09.028.

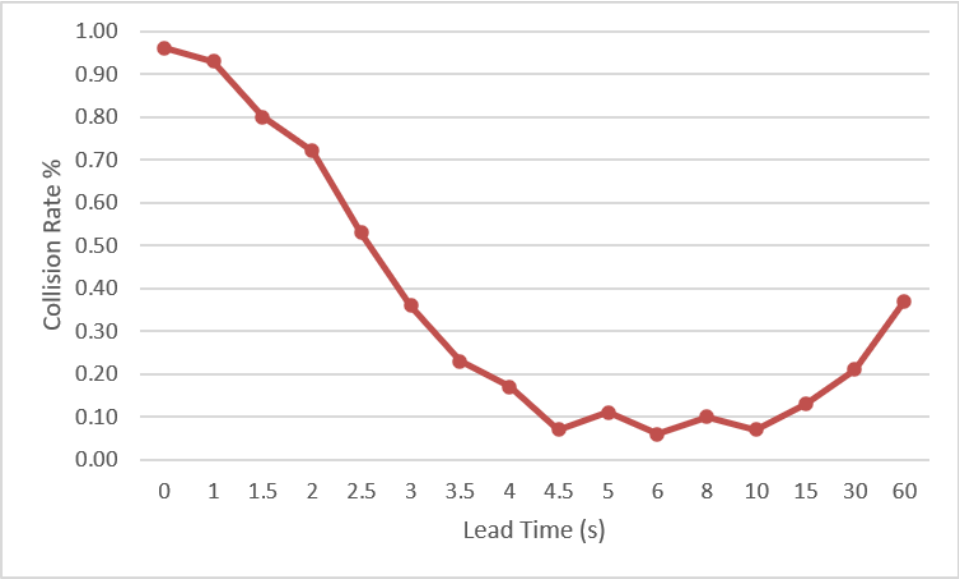

Figure 7.18: Collision rates as function of lead time, reported by Wan, Wu, & Zhang (2016).

C.2.2. Level 4 ADS Pedestrian Detection Basis

This section documents the basis for the ADS (L4) camera and LiDAR pedestrian-detection probabilities referenced in **Section 3.2.2.3** and detailed in **Section C.2.6.1 (Sensor-System Failures**).

Unlike the RLVW scenario, where ADS perception performance is anchored to third-party traffic-signal-detection benchmarks, vehicle-mounted pedestrian detection in Scenario B is parameterized from a separate literature base, reflecting differences in sensor mounting height, viewing geometry, and detection range relative to infrastructure-mounted systems. The weather-conditioned degradation applied to the vehicle-mounted camera and LiDAR nodes draws on Mirza et al. (2021)[147], who benchmarked single- and dual-modality object detectors under real degraded-weather conditions (rain, fog, snow) rather than the clear-weather-only baseline and found that detectors performing well in clear weather do not

[147] M. J. Mirza et al., "Robustness of Object Detectors in Degrading Weather Conditions," IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC, vol. 2021-September, pp. 2719–2724, Jun. 2021, doi: 10.1109/ITSC48978.2021.9564505.

necessarily generalize to degraded conditions. Camera-side occlusion penalties are anchored to Gilroy et al. (2023)[148], who benchmarked seven pedestrian-detection models across a continuous 0–99% occlusion range and found that missed-detection and false-negative rates rise monotonically with occlusion severity.

LiDAR-side detection performance, including the treatment of pedestrians as a comparatively rare/small class relative to vehicles, draws on Ma et al. (2023)[149], who showed that multi-modal late fusion of independently trained LiDAR and camera detectors improves rare-class (including VRU) detection accuracy relative to either single-modality detector alone. As with the infrastructure sensor nodes, occlusion (NLOS) is the dominant degradation mechanism for both modalities; unlike the infrastructure nodes, vehicle-mounted detection values are treated as identical between intersection and midblock crossings, since the vehicle's sensing geometry relative to the pedestrian does not change systematically with road type.

C.2.3. Level 2 Response and PAEB Basis

The L2 sub-scenario (Section 3.2.2.4) reuses the L0 and L4 models as follows and adds a pedestrian automatic emergency braking (PAEB) recovery path:

- **Reused from L0:** the driver detection failure under unwarned conditions (Table 7.28), the driver response to SDSM-derived warnings under high/low time availability (Table 7.22), and the driver perception-reaction time and deceleration parameters (Table 7.11, Table 7.26). Only the driver can ignore a warning.
- **Reused from L4:** the vehicle-mounted camera detection probabilities (Table 7.33; camera only), and the ADS braking model (reaction time and deceleration profiles, Table 7.13, Table 7.27), applied to the L2 detection and response path.

[148] S. Gilroy, D. Mullins, A. Parsi, E. Jones, and M. Glavin, “Replacing the human driver: An objective benchmark for occluded pedestrian detection,” Biomim. Intell. Robot., vol. 3, no. 3, Sep. 2023, doi: 10.1016/j.birob.2023.100115.

[149] Y. Ma et al., “Long-Tailed 3D Detection via Multi-Modal Fusion,” arXiv, Dec. 2023, Accessed: Aug. 06, 2026. [Online]. Available: https://arxiv.org/pdf/2312.10986

- **Combination:** a pedestrian is detected if either the driver or the L2 system registers it, and once a warning has been received either path can initiate braking. A conflict occurs only if both paths fail, after which PAEB acts as the final, message-independent barrier.

PAEB basis: Rear-end collision-avoidance systems bound the plausible benefit of well-timed warnings: forward collision warning alone, low-speed automatic emergency braking, and the combination have been found to reduce rear-end striking crash rates by 27%, 43%, and 50% respectively[150]. Multiple elements can affect the efficiency of these crash avoidance technologies, in addition to driver attentiveness, including weather conditions affecting object detection functionalities, as well as road geometry and surface conditions affecting the automated braking response[151,152]. Several academic and industry-led studies have shown that AEB could reduce rear-end crashes by 25% to 50% [153,154,155,156,157]. In this case, the PAEB functionality acts as a safety barrier against driver's late or lack of reactions to warnings, instead of the SDSM message being incorporated into the vehicle's automated brake response.

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[150] J. B. Cicchino, "Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates," Accid. Anal. Prev., vol. 99, pp. 142–152, Feb. 2017, doi: 10.1016/J.AAP.2016.11.009.

[151] A. Aukema, et al., "Real-world effectiveness of model year 2015–2020 advanced driver assistance systems," in *Proc. 27th Int. Tech. Conf. Enhanced Safety of Vehicles (ESV)*, Paper 23-0170, 2023. [Online]. Available: https://swov.nl/sites/default/files/bestanden/downloads/Aukema%20et%20al.%202023%20Real%20world%20effectiveness_0.pdf

[152] L. Yang et al., "A Systematic Review of Autonomous Emergency Braking System: Impact Factor, Technology, and Performance Evaluation," Journal of Advanced Transportation, vol. 2022, p. e1188089, Apr. 2022, doi: 10.1155/2022/1188089.

[153] National Highway Traffic Safety Administration, "PARTS | Partnership for Analytics Research in Traffic Safety," U.S. Department of Transportation. [Online]. Available: https://www.nhtsa.gov/parts-partnership-for-analytics-research-in-traffic-safety

[154] J. B. Cicchino, "Convenience or safety system? Crash rates of vehicles equipped with partial driving automation," Traffic Injury Prevention, vol. 26, no. 6, pp. 631–641, 2025, doi: 10.1080/15389588.2024.2448511. [Online]. Available: https://www.iihs.org/topics/bibliography/ref/2309

[155] A. J. Leslie, R. J. Kiefer, M. R. Meitzner, and C. A. Flannagan, "Field effectiveness of general motors advanced driver assistance and headlighting systems," Accident Analysis & Prevention, vol. 159, p. 106275, July 2021, doi: 10.1016/j.aap.2021.106275.

[156] J. B. Cicchino, "Effectiveness of forward collision warning and autonomous emergency braking systems in reducing front-to-rear crash rates," Accident Analysis & Prevention, vol. 99, pp. 142–152, Feb. 2017, doi: 10.1016/j.aap.2016.11.009.

[157] L. Yang et al., "A Systematic Review of Autonomous Emergency Braking System: Impact Factor, Technology, and Performance Evaluation," Journal of Advanced Transportation, vol. 2022, pp. 1–13, Apr. 2022, doi: 10.1155/2022/1188089.

The PAEB effectiveness estimates (Cicchino, 2022; PARTS, 2025) and the implemented CPT are presented in Section C.2.6.1 (B.4.2.3, Table 7.30).

C.2.4. Event Sequence Diagram

There are two models, one for intersection conflicts and the other for midblock crossing conflicts. The intersection scenario is modeled as a four-leg signalized intersection in which a host vehicle approaches. No assumption is made on the traffic signal of the vehicle nor the pedestrians, as this scenario targets distracted drivers or occluded pedestrians incoming to the vehicle path. The initiating event is the vehicle entering the intersection influence zone, and the vehicle's approach speed will therefore determine the available time for potential pedestrian-related conflict warnings. The midblock scenario replicates the same structure, however, different penalizations to driver, vehicle-mounted, and infrastructure-mounted perception systems are applied. **Figure 7.19** presents the full ESD structure. The scenario unfolds through three key events:

- First, the RSU must successfully generate and transmit the SDSM to the approaching HV. This depends on the quality of the infrastructure sensor system input data (assuming independent camera and LiDAR detection streams) as well as RSU hardware reliability and message transmission success.
- Second, upon receiving SDSM, the HV must stop before entering the intersection. The failure model at this node differs depending on whether the vehicle is human-driven (Level 0), assisted by lower-level automation features (Level 2), or ADS-equipped (Level 4), with distinct performance shaping factors and system reliability considerations respectively. In the case of human-driven vehicles (L0, L2) it is assumed that the host vehicle has the capacity to generate onboard driver warnings, consistent with existing features such as FCW. While independent sensor systems may verify pedestrian detections prior to triggering control actions (such as in the L4 case), it is assumed that neither L0/L2 vehicles have the capacity to do so. Therefore, as long as latency and security credentials (the latter not modeled) criteria are cleared, the SDSMs will trigger onboard driver warnings.
- If the host vehicle fails to avoid the conflict, the scenario enters the crash exposure branch, where outcomes are conditioned on severity (property damage only (PDO), injury, or fatality) calibrated to local crash data. Secondary crash risk derived from HV braking is not considered in this model.

As in scenario A, even though SDSM are continuously broadcast by the infrastructure-RSU, warning availability for L0/L2 are modeled under two conditions: high time availability (approximately 5s to conflict) and low time availability (approximately 3s to conflict), consistent with crash warning literature (refer to **Section C.2.1**). The same structure is maintained for L2 and L4 for replicability purposes.

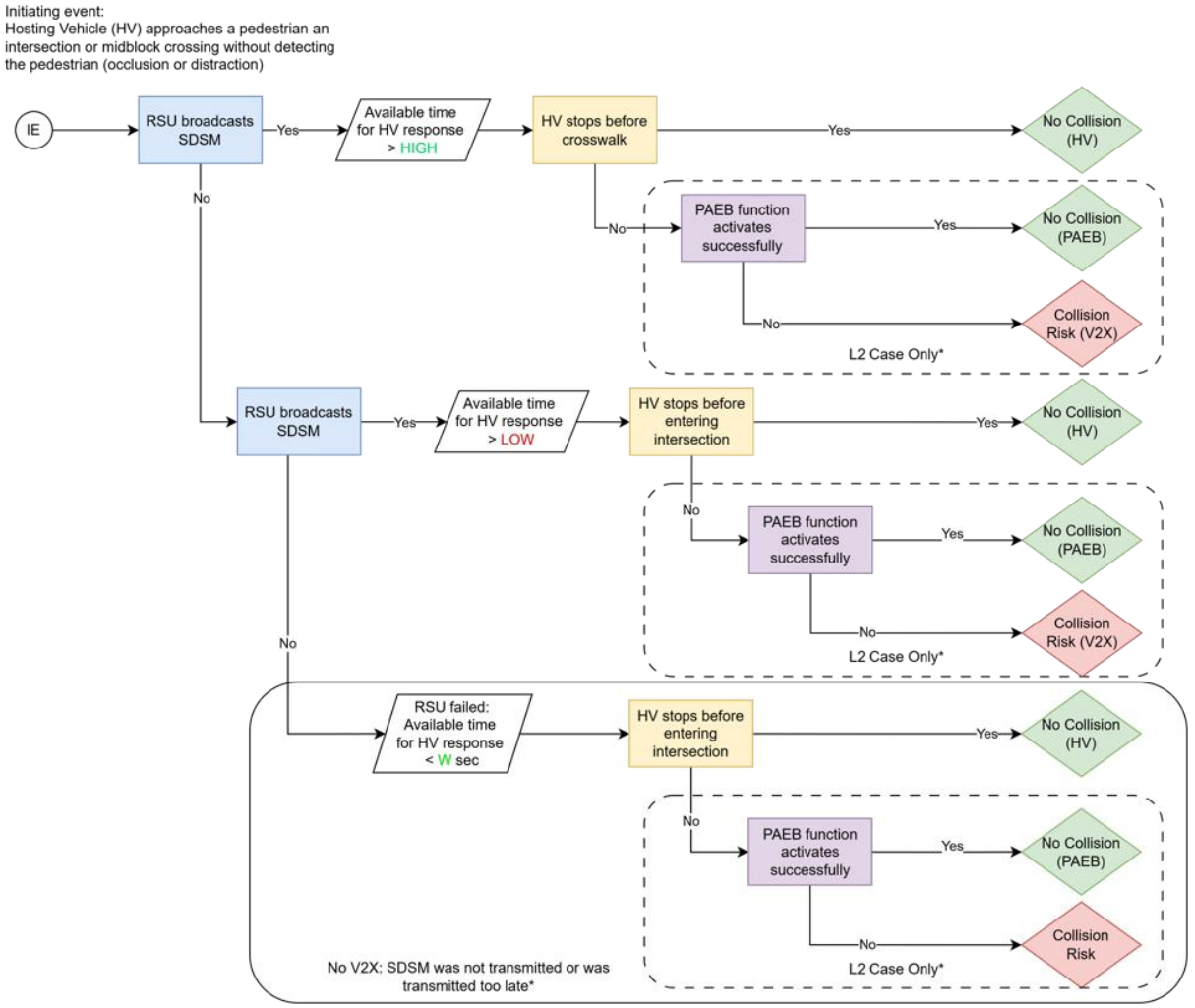

Figure 7.19: Pedestrian Collision Warning Scenario (ESD Model).

C.2.5. Fault Tree Models

C.2.5.1. B.1. Infrastructure-sensing and communication-related failure modes

This model has two branches reflecting the quality and correctness of the (i) input and (ii) output data, and applies to all scenarios (L0, L2, L4). **Figure 7.20** depicts the RSU-related fault tree, with the top event occurring when the roadside unit fails to generate a sensor-data-sharing message (SDSM) populated with correct pedestrian information or fails to transmit that message to the host vehicle.

B.1.1 RSU Input Data Quality (Incorrect or Incomplete)

This branch captures the probability that the SDSM is populated by incorrect or missing input data. Two events contribute to this branch, corresponding to (i) the roadside unit's sensor system performance degradation, and (ii) SDSM processing errors.

B.1.1.1 Detection Errors (LiDAR, Camera): This event refers to the probability of the infrastructure sensor system not detecting a pedestrian. Independent detection across modalities is assumed, such that successful detection by either the camera or the LiDAR is sufficient for SDSM construction, i.e., fusion-specific architectures are not modeled in detail.

The *Detection Errors* event is represented by a BBN model detailed in **Section C.2.6.1 (Sensor-System Failures)**, consisting of (i) camera missed-detection probability as a function of weather, light condition, and line of sight, and (ii) LiDAR missed-detection probability as a function of weather and line of sight[158]. The two nodes share common weather and line-of-sight parent nodes, so that occlusion-driven correlation between the modalities is represented structurally within the model. Occlusion is the dominant degradation mode across modalities reported in literature: pedestrian missed-detection rates increase substantially as occlusion level rises, with the magnitude of degradation varying across detection

[158] T. Zhang *et al*., "Roadside Sensor Systems for Vulnerable Road User Protection: A Review of Methods and Applications," in *IEEE Access*, vol. 13, pp. 62717-62738, 2025, doi: 10.1109/ACCESS.2025.3558174

architectures[159]. Partial occlusion by queued vehicles, buses, or infrastructure elements is the principal scenario-specific risk at urban intersections[160].

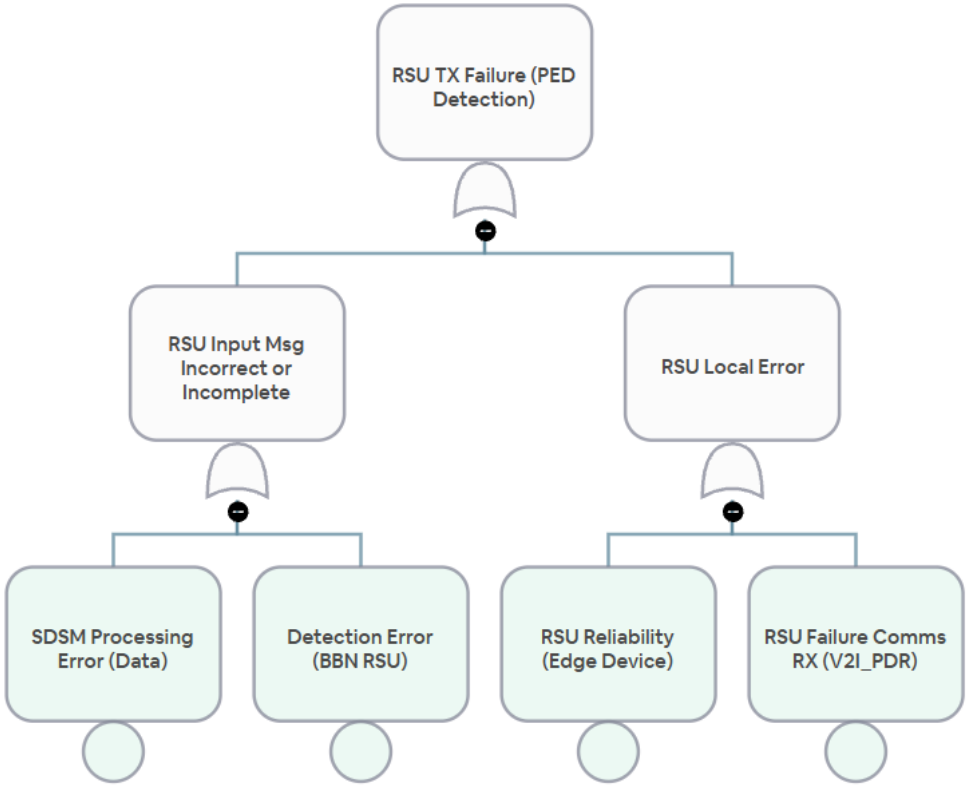

Figure 7.20: PED-CP Scenario, RSU Transmission Failure.

Two failure modes were considered for each modality: detection failure (the sensor does not register a present pedestrian) and localization or tracking failure (the sensor detects the pedestrian but reports a position error large enough to misplace

[159] P. Dollar, C. Wojek, B. Schiele and P. Perona, "Pedestrian Detection: An Evaluation of the State of the Art," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 4, pp. 743-761, April 2012, doi: 10.1109/TPAMI.2011.155.

[160] T. T. Zhang, Y. Ge, A. Chen, M. Sartipi, and P. J. Jin, “Hash-Based Gaussian Mixture Model (HGMM) for Roadside LiDAR Smart Infrastructure Applications,” IEEE Transactions on Intelligent Transportation Systems, vol. 25, no. 10, pp. 12968–12979, Oct. 2024, doi: 10.1109/tits.2024.3434749.

the pedestrian relative to the conflict zone). The localization and tracking sub-branches were excluded from the final model for three reasons. First, pedestrian crossing speeds are low, limiting the safety relevance of frame-to-frame tracking errors. Second, because the analysis simulates discrete per-encounter events rather than continuous broadcast behavior, object-association and track-continuity consistency are secondary to detection results. Third, documented infrastructure-camera localization errors are below the lane-half-width threshold (1.8-2.0m, refer to Scenario A) for both camera (0.62 m)[161][162] and roadside-LiDAR position accuracy (0.1-0.3m)[163,164]. Under the fitted single-roadside-unit position-error distributions, the probability that position error exceeds the lane-half-width threshold is on the order of 10^{-3} for the camera (*lognormal, p50=0.33 m, EF=2.82*) and 10^{-13} for the LiDAR (*Gamma, shape 3.65, scale 0.0485m*).

The LiDAR detection error estimations are based on roadside-LiDAR field deployments at signalized intersections. Object-level pedestrian recall above 90% is reported under nominal conditions[165,166], while a two-site signalized-intersection deployment reports recall falling to approximately 78% under occlusion produced by queued vehicles during the red-light phase, in which vehicles in farther lanes are blocked by vehicles in nearer lanes[167]. This provides a measured occluded-condition missed-detection rate of approximately 22% percent at a real intersection under nominal traffic conditions. Occlusion and outlier effects are likewise identified as the primary roadside-LiDAR error sources[168].

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[161] D. Vignarca, M. Vignati, S. Arrigoni, and E. Sabbioni, "Infrastructure-Based Vehicle Localization through Camera Calibration for I2V Communication Warning," *Sensors*, vol. 23, no. 16, p. 7136, 2023, doi: 10.3390/s23167136. [Online]. Available: https://www.mdpi.com/1424-8220/23/16/7136

[162] T. Wang *et al*., "Exploring Communication and Roadside Perception Requirements for Cooperative Warning Systems at Intersections," *2025 IEEE Intelligent Vehicles Symposium (IV)*, Cluj-Napoca, Romania, 2025, pp. 773-780, doi: 10.1109/IV64158.2025.11097734.

[163] J. Zhao, H. Xu, H. Liu, J. Wu, Y. Zheng, and D. Wu, “Detection and tracking of pedestrians and vehicles using roadside LiDAR sensors,” Transportation Research Part C: Emerging Technologies, vol. 100, pp. 68–87, Mar. 2019, doi: 10.1016/j.trc.2019.01.007.

[164] E. D. Saldivar-Carranza, J. Desai, A. Thompson, M. Taylor, J. Sturdevant, and D. M. Bullock, "Vehicle and pedestrian traffic signal performance measures using LiDAR-derived trajectory data," *Sensors*, vol. 24, no. 19, p. 6410, 2024, doi: 10.3390/s24196410. [Online]. Available: https://www.mdpi.com/1424-8220/24/19/6410

[165] E. D. Saldivar-Carranza, J. Desai, A. Thompson, M. Taylor, J. Sturdevant, and D. M. Bullock, "Vehicle and pedestrian traffic signal performance measures using LiDAR-derived trajectory data," *Sensors*, vol. 24, no. 19, p. 6410, 2024, doi: 10.3390/s24196410. [Online]. Available: https://www.mdpi.com/1424-8220/24/19/6410

[166] J. Castrillo, M. Soilán, N. Caparrini, and J. Balado, "A scoping review of LiDAR solutions for urban safety of vulnerable road users," *Geomatics*, vol. 6, no. 3, p. 59, 2026, doi: 10.3390/geomatics6030059. [Online]. Available: https://www.mdpi.com/2673-7418/6/3/59

[167] T. T. Zhang, Y. Ge, A. Chen, M. Sartipi, and P. J. Jin, “Hash-Based Gaussian Mixture Model (HGMM) for Roadside LiDAR Smart Infrastructure Applications,” IEEE Transactions on Intelligent Transportation Systems, vol. 25, no. 10, pp. 12968–12979, Oct. 2024, doi: 10.1109/tits.2024.3434749.

[168] J. Zhao, H. Xu, H. Liu, J. Wu, Y. Zheng, and D. Wu, “Detection and tracking of pedestrians and vehicles using roadside LiDAR sensors,” Transportation Research Part C: Emerging Technologies, vol. 100, pp. 68–87, Mar. 2019, doi: 10.1016/j.trc.2019.01.007.

The camera detection error estimations assume a standard visible-spectrum, infrastructure-mounted camera, and are based on two standard roadside (infrastructure-mounted) detection benchmarks[169,170], which span day, night, and dusk lighting; rain, clear, and cloudy weather; and graded occlusion. Additional considerations for distance and sensor range are applied in the case of the midblock crossings (assuming intersection infrastructure-sensor systems). Thermal cameras have improved performance under low-light conditions but are excluded in this model. The conditional probabilities adopted for the independent sensor streams are presented in **Table 7.21**. Detailed parametrization of both infrastructure-mounted camera and LiDAR sensor systems as function of weather, light, and infrastructure LOS/NLOS conditions are presented in **Section C.2.6.1 (Crash Exposure Model)**.

B.1.1.2 SDSM Processing Error: This node captures residual processing failures between local pedestrian detection and a valid SDSM. Processing latency is not treated as a binding constraint for this application[171]. At a 10 Hz broadcast rate, received pedestrian position can be up to 100ms stale, corresponding to approximately 0.14m of position error at a walking speed of 1.4 m/s. As a simplification, the latency impact is not considered in this model, as latency-induced position error is negligible relative to both the localization threshold and the detection-failure rate (as explained in the previous section).

Table 7.21: Resulting infrastructure-mounted detection probability assuming independent sources.

Camera-based Detection	LiDAR-based Detection	P(detection)
Detected	Detected	1
	Missed detection	1
Missed detection	Detected	1

[169] X. Ye et al., “Rope3D: The Roadside Perception Dataset for Autonomous Driving and Monocular 3D Object Detection Task,” Thecvf.com, pp. 21341–21350, 2022, Accessed: Aug. 05, 2026. [Online]. Available: https://openaccess.thecvf.com/content/CVPR2022/html/Ye_Rope3D_The_Roadside_Perception_Dataset_for_Autonomous_Driving_and_Monocular_CVPR_2022_paper.html

[170] H. Yu et al., “DAIR-V2X: A Large-Scale Dataset for Vehicle-Infrastructure Cooperative 3D Object Detection,” arXiv (Cornell University), Apr. 2022, doi: 10.48550/arxiv.2204.05575.

[171] T. Wang *et al*., "Exploring Communication and Roadside Perception Requirements for Cooperative Warning Systems at Intersections," *2025 IEEE Intelligent Vehicles Symposium (IV)*, Cluj-Napoca, Romania, 2025, pp. 773-780, doi: 10.1109/IV64158.2025.11097734.

Camera-based Detection	LiDAR-based Detection	P(detection)
	Missed detection	0

While software-related errors are usually treated as systematic (per ISO 26262-5; IEC 61508-3), for modeling purposes, the software contribution is represented by a random-failure proxy in which the application is assumed to meet its allocated ASIL B/C[172]. Adopting the per-demand convention used for the hardware device class (**Section C.1.5.1**), the equivalent lognormal ($M_{50} = 1 \times 10^{-6}$ and Error Factor $EF = 10$) is implemented to represent this failure mode.

B.1.2 RSU Output Failures

This branch captures the probability that the SDSM is not transmitted correctly. Two independent sub-branches contribute to this top event, corresponding to the V2I RSU-to-HV path and the RSU device reliability.

B.1.2.1 Device Failure (Failure Model): This is a generic failure model re-used in multiple instances of the model. Both roadside-unit and on-board-unit hardware failures are modeled as on-demand failure events, consistent with the discrete-demand nature of event-triggered applications at each intersection or midblock approach. See **Section C.1.5.1 (RSU-RLVW Generation and Transmission Failure)** for more information.

B.1.2.2 Connectivity (V2I RSU-to-HV path): This represents the failure of the SDSM transmission from the infrastructure-to-vehicle node as a factor contributing to the vehicle not (i) generating the on-board driver warnings (L0/L2) or (ii) detecting the pedestrians (L4). See **Section C.2.6.2 (V2X Communication Model)** for more information.

C.2.5.2. B.2. Host Vehicle Failure to Stop

This model represents the probability of a vehicle failing to stop before the pedestrian crossing (either at intersections or midblock crossings), with separate contributions from warned and non-warned actors (drivers or ADS) given available time and road conditions. Warned actors may fail to stop before the crossing if (i) they do not comply with the SDSM-derived

[172] T. G. R. Reid, A. Neish, and B. Manning, "Localization & mapping requirements for level 2+ autonomous vehicles," arXiv preprint arXiv:2212.08231, Dec. 2022. [Online]. Available: https://arxiv.org/abs/2212.08231

warnings (L0/L2), (ii) the information shared through SDSM cannot be validated by the system (L4), or (iii) the resulting braking time after SDSM is received is unfeasible (all levels). Non-warned actors may fail to stop at the crossing if (i) they continue towards the crosswalk without detecting the potential pedestrian conflict or (ii) they independently determine to stop, but the resulting braking time is unfeasible. The fault trees for L0 and L4 are presented in **Figure 7.21** and **Figure 7.22**, respectively. Crash calibration values are used to ensure base case (no V2X) replicate existing crash statistics (refer to **Appendix C.3**).

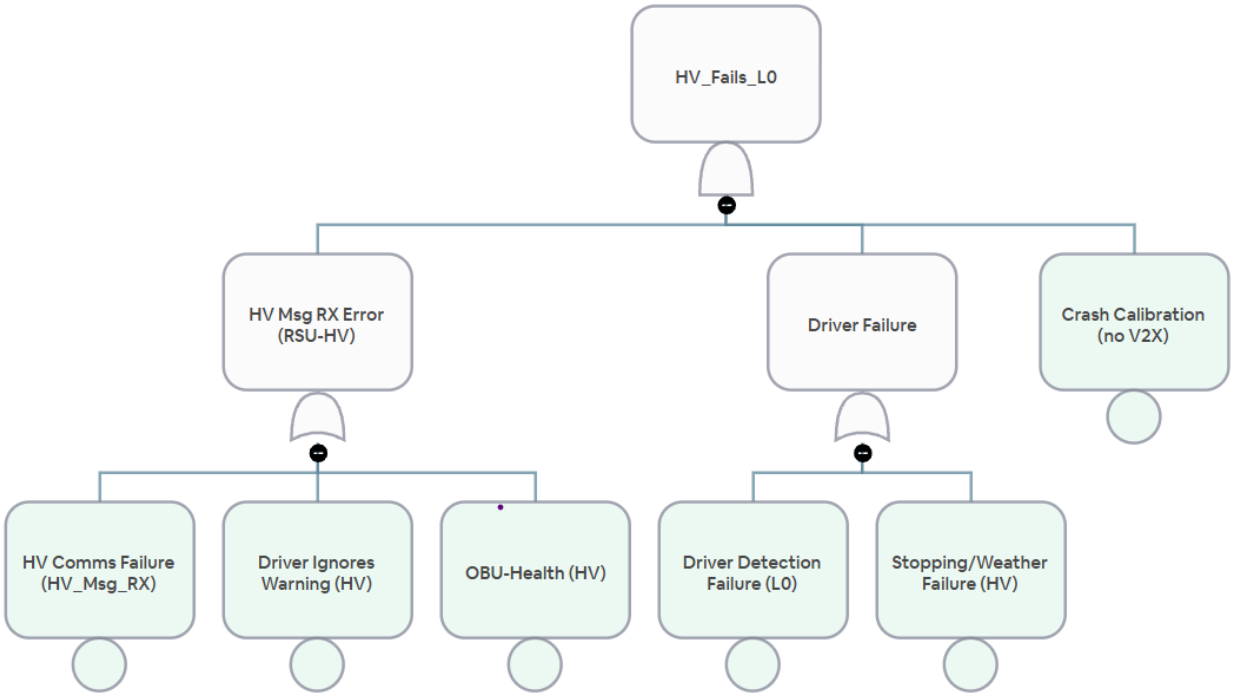

Figure 7.21: CP-PED Scenario, Host Vehicle L0 Failure (V2X Enabled).

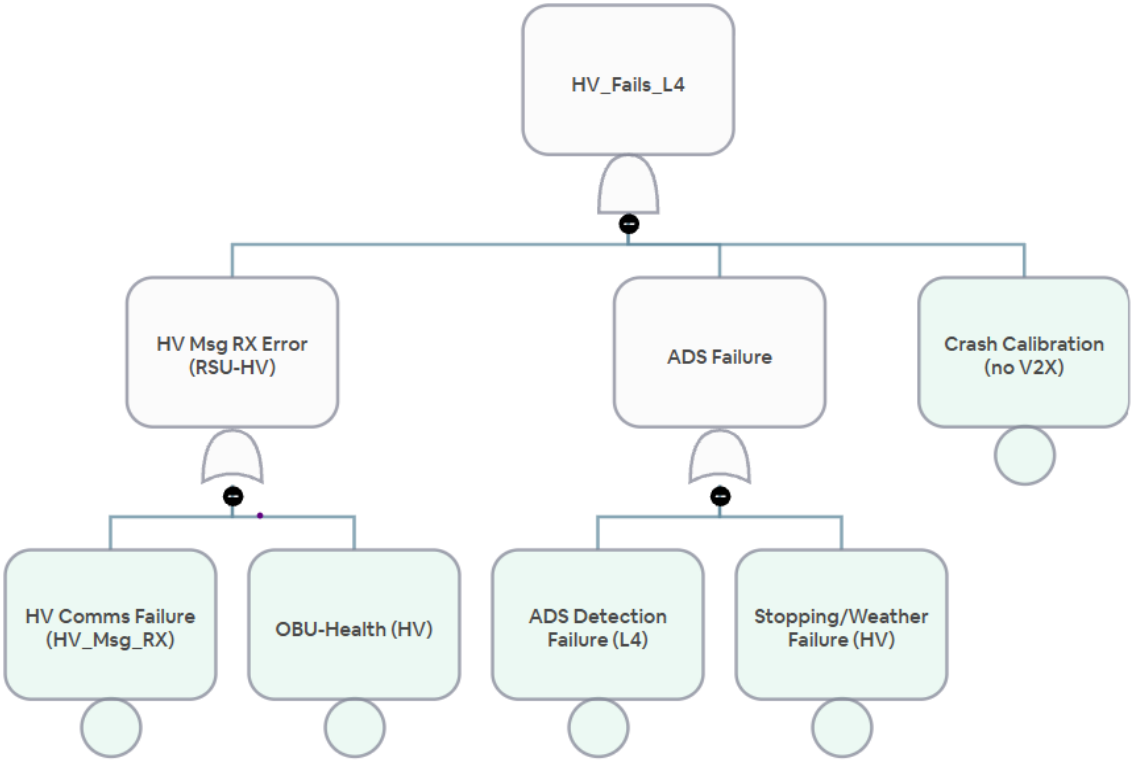

Figure 7.22: CP-PED Scenario, Host Vehicle L4 Failure (V2X Enabled).

B.2.1 Message-related failures (HV Msg RX Error)

This branch captures failure modes through which the (i) SDSM-derived warning fails to produce a stop response in the driver (L0/L2) or the (ii) SDSM does not impact the downstream vehicle actions (L4), including not receiving or not responding to it. It is structured as an OR gate over three contributing events:

B.2.1.1 V2I communication failure (V2I HV-to-RSU path). The V2I link from RSU to HV may fail to deliver the SDSM message. This node is fed by the BBN, which conditions packet delivery probability on LOS, SDSM transmission success,

and CV market penetration (see **Section C.2.6.2, V2X Communication Model**). Nominal baseline $PDR \approx 0.97 - 0.99$; degraded under congestion or NLOS conditions. This model applies to all levels of driving automation.

B.2.1.2 HV ignores warning:

- **L0 Scenario:** This probability is conditioned on the available stopping time relative to CST (as derived **in Section C.1.1**) and is the dominant failure mode in the message branch at nominal communication reliability. Two parameter values are used, corresponding to the high- and low-availability branches of the ESD in **Table 7.22** below.

Table 7.22: Driver Ignores Warning (HV) values.

Parameter	P(driver fails | warned) ~ Uniform	Reference
P(failure to react to SDSM-derived warning | high time availability $t_w > 5s$)	0.06-0.10	Wan, Wu & Zhang (2016)[173]
P(failure to react to SDSM-derived warning | low time availability $3s < t_w < 5s$)	0.0625-0.17	Miao & Yan (2021)[174]

- **L2 Scenario:** Only the driver can ignore the SDSM-derived warning, and the L0 values in Table 7.22 are used. Once the warning is not ignored, either the driver or the L2 system can initiate braking (Section C.2.3).

- **L4 Scenario:** this is not considered in the model, as it is dependent on the rules implemented to message acceptance and use of the information by the downstream ADS applications, i.e., every message received may not be accepted,

[173] J. Wan, C. Wu, and Y. Zhang, "Effects of lead time of verbal collision warning messages on driving behavior in connected vehicle settings," Journal of Safety Research, vol. 58, pp. 89–98, Aug. 2016, doi: 10.1016/j.jsr.2016.07.003

[174] Y. Miao and X. Yan, "The Impacts of Warning Release Time and Speed Limit on Driving Behaviour and Pedestrian-Vehicle Collision Rate on Side-parking Road," IOP Conference Series: Earth and Environmental Science, vol. 638, no. 1, p. 012034, Feb. 2021, doi: 10.1088/1755-1315/638/1/012034.

partially or totally. However, errors in SDSM content that would lead to message rejection are incorporated into the input data related failures.

B.2.1.3 OBU device reliability (Failure Model): The onboard unit may fail to process or display the received message due to hardware or software faults. This failure mode is the same as implemented in Scenario A and applies to all levels of driving automation (refer to **Section C.1.5.1, A.1.2.2 Device Failure**).

B.2.2 Stopping-related failures

This represents failures of the vehicle not stopping before entering the intersection or midblock crossing, depending on whether (i) the message was received, but there is not enough time to stop based on the driving conditions or (ii) the message was not received (i.e., base probability of not detecting the pedestrian conflict). Different fault tree structures are considered for L0/L2/L4 scenarios.

B.2.2.1 Base conflict condition: HV detection failure (non-V2X):

- **L0 Scenario:** This node represents the unconditional probability that an unwarned driver fails to detect and react to a pedestrian conflict, encompassing driver inattention, misjudged actions, and insufficient reaction time from a late pedestrian dart-out. This probability is parameterized as a function of weather, light condition, and vehicle-side LOS/NLOS conditions, as detailed in **Table 7.28**.
- **L2 Scenario:** A pedestrian conflict is detected if either the driver (L0 model, Table 7.28) or the L2 system's onboard camera (L4 camera detection probabilities, Table 7.33) registers it. PAEB acts as a final recovery path when both the driver and the L2 system fail to detect or react in time. PAEB actuation probabilities, conditioned on light and vehicle-side LOS/NLOS conditions, are given in **Table 7.30**.
- **L4 scenario:** This node represents independent per-modality detection failure between the vehicle-mounted camera and LiDAR systems, each parameterized as a function of weather, light condition, and vehicle-side LOS/NLOS conditions (**Table 7.33-Table 7.34**), following the same independent-sensor OR-gate fusion logic described in **Table 7.29**.

Detailed parameterization is given in **Section C.2.6.1 (Crash Exposure Model**).

B.2.2.2 Insufficient stopping time given road conditions (Stopping/Weather):

- **L0 Scenario:** A similar approach is taken as described for Scenario A. Even a driver intending to stop may be physically unable to do so if the available deceleration is insufficient given approach speed and road surface conditions. This node is derived from the stopping feasibility (**Section 3.1.2.2**) conditioned on weather-dependent deceleration and is propagated through the BBN as a function of weather state (clear, cloudy, rain), vehicle approach speed, and warning timing (high/low time availability). Different reaction time and deceleration profiles are considered to represent Scenario B for high/low time available warning scenarios.
- **L2 Scenario:** The driver path uses the L0 structure and the L2 path reuses the L4 braking model. Insufficient stopping time results in a failure only if both paths fail, after which PAEB acts as the final barrier.
- **L4 Scenario:** This node replicates the same structure as for the L0 Scenario, with updated assumptions regarding reaction and braking times.

When there is no V2X available ($t_w < 3s$), it is assumed that the only failure modes applicable are B.2.2.1-B.2.2.2. Further, the HV's stopping probability is governed by the low-time availability values. Detailed parameterization is given in **Section C.2.6.1 (Crash Exposure Model).**

C.2.6. Bayesian Network Model

For scenario B, two models, one for intersection crashes and the other for midblock crossings. The communication nodes are the same, but the crash exposure models represent different conditions. A simplified graph is presented in **Figure 7.23**.

C.2.6.1. B.4. Crash Exposure Model

The nodes in this section characterize the conditional probability of a vehicle-pedestrian crash exposure at intersections and midblock crossings as a function of environmental and roadway conditions. Parameters are derived from FARS/CRSS crash records and are intended to represent contributing factor distributions in police-reported crashes; values are therefore area-dependent and are presented here for the Downtown Los Angeles (DTLA) reference area. As in Scenario A (RLVW),

these parameters affect the magnitude of modeled crash exposure but do not impact structural modeling choices in the BBN. Further details on data extraction and area-specific calibration are provided in Appendix C.3.

B.4.1. Base Crash Exposure

Priors to the base crash exposure for scenario B have parent nodes for weather, light conditions, speeding, and either (i) intersection type, or (ii) road type. These priors are presented in Table 7.23.

B.4.1.1 Weather: This is a shared parent node serving three downstream components: (i) the base crash probability at the intersection/midblock crossing, the conditional stopping probabilities when warned under (ii) high/low warning time availability for L0/L2/L4 scenarios, and (iii) the conditional stopping probabilities in non-warning conditions for L0/L2/L4 scenarios. In addition, it is also a parent node to the vehicle- and infrastructure-mounted sensor systems (camera, LiDAR). Prior probabilities are derived from OpenWeatherMap historical data for the DTLA area (**Appendix C.3**) on an average annual basis.

B.4.1.2 Light conditions: This is a fixed node at 50%-50% chance of day-night conditions. It is a parent node to the conditional stopping probabilities in non-warning conditions for L4 Scenarios (B.4.2.2), to the vehicle- and infrastructure-mounted sensor systems (camera, LiDAR), and the PAEB (L2) node.

B.4.1.3 Speeding: The speeding indicator is a fixed binary node with priors derived from FARS crash records for the modeled area, with different values for intersection and for midblock crossings (See **Appendix C.3**).

B.4.1.4a Intersection Type (Intersection Crossings): Intersection type is simplified to 4-way versus 3-way, with the latter category encompassing T- and Y-intersections. Priors are derived from GIS data for the DTLA area (See **Appendix C.3**).

B.4.1.4b Roadway Type (Midblock Crossings): Road type is simplified to primary, secondary, tertiary, and residential. Priors are derived from GIS data for the DTLA area (See **Appendix C.3**).

B.4.1.5 Base Crash Probability: This node represents the conditional probability of a crash given a vehicle encounter under the specified conditions, i.e., P(crash exposure | conditions). Values presented in **Table 7.24-Table 7.25** are derived from five years of FARS data (2019–2023) filtered under two conditions:

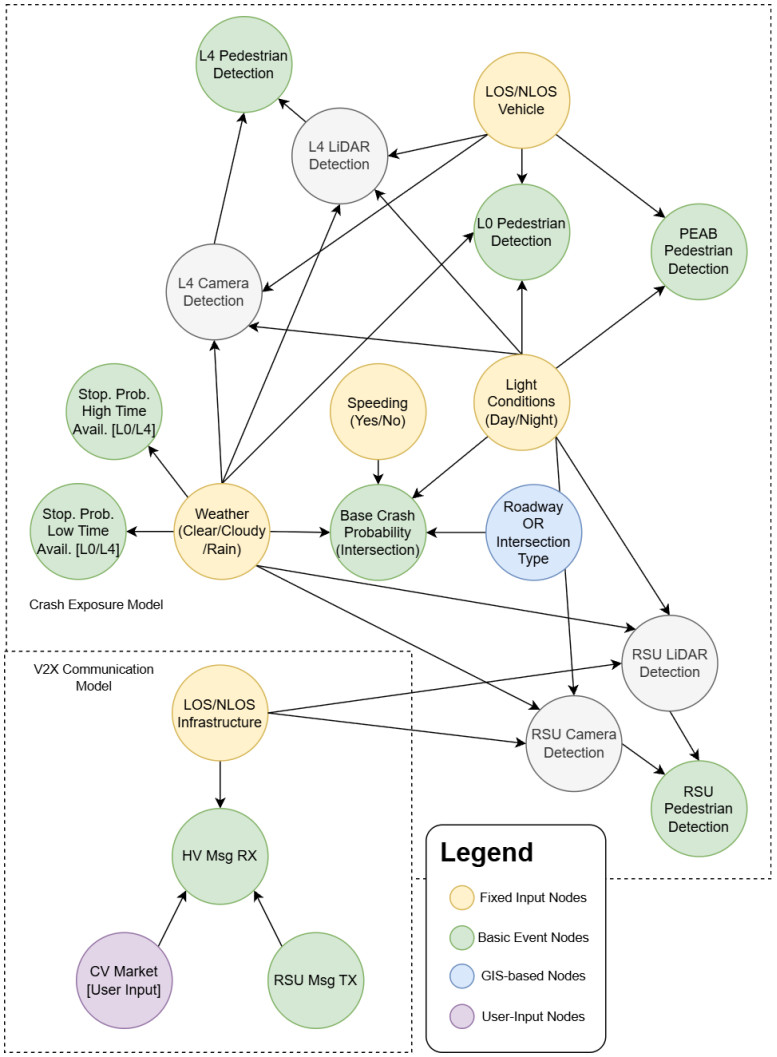

Figure 7.23: BBN Structure for Scenario B - CP-PED.

Table 7.23: Parent nodes to Base Crash Probability for Scenario B.

Node	States	Prior Values P(State)
Weather	Clear	0.5842
	Cloudy	0.3698
	Rain	0.0460
Light Condition	Daytime	0.5000
	Nighttime	0.5000
Speeding (Intersection Crossing)	Speeding	0.16
	Not Speeding	0.84
Speeding (Midblock Crossing)	Speeding	0.20
	Not Speeding	0.80
Intersection Type (Intersection Crossing)	4-Way	0.8241
	3-Way	0.1758
Roadway Type (Midblock Crossing)	Primary	0.453
	Secondary	0.408
	Tertiary	0.036
	Residential	0.102

- Intersection crossings: single-vehicle non-interstate, urban arterial intersection crashes where the first harmful event is related to pedestrians in Los Angeles City, excluding work zone and special jurisdiction records.

- Midblock crossings: single-vehicle non-interstate, urban arterial crashes where the first harmful event is related to pedestrians in Los Angeles City, excluding junctions/intersections, work zones and special jurisdiction records. As granular details specifically related to pedestrian midblock crossings are not available, the crash numbers are overestimated here.

Note that the selected sample is sparse for several weather conditions, which reflects the composition of the underlying crash record for this specific filtered scenario population. Full filter specifications and crash model calibrations for L0-L2-L4 Scenarios are provided in **Appendix C.3**.

Table 7.24: Base Crash Probability for Scenario B (Intersections).

Weather	Speeding	Intersection Type	Light Condition	P(No Crash Exposure)	P(Crash Exposure)
clear	speeding	4 way	daylight	9.84E-01	1.58E-02
clear	speeding	4 way	nighttime	9.95E-01	5.26E-03
clear	speeding	3 way	daylight	8.95E-01	1.05E-01
clear	speeding	3 way	nighttime	9.84E-01	1.58E-02
rain	speeding	3 way	daylight	9.89E-01	1.05E-02
rain	no speeding	4 way	daylight	8.53E-01	1.47E-01
rain	no speeding	4 way	nighttime	9.68E-01	3.16E-02
rain	no speeding	3 way	daylight	6.74E-01	3.26E-01
rain	no speeding	3 way	nighttime	7.63E-01	2.37E-01
cloudy	no speeding	4 way	daylight	9.95E-01	5.26E-03
cloudy	no speeding	3 way	daylight	9.53E-01	4.74E-02

Weather	Speeding	Intersection Type	Light Condition	P(No Crash Exposure)	P(Crash Exposure)
cloudy	no speeding	3 way	nighttime	9.89E-01	1.05E-02

* Combinations not represented reflect insufficient cell counts in the filtered FARS sample. Not interpreted as a zero-risk condition. See Appendix C.3.

Table 7.25: Base Crash Probability for Scenario B (Midblock).

Weather	Speeding	Roadway Type	Light Condition	P(No Crash Exposure)	P(Crash Exposure)
clear	speeding	primary	daylight	9.88E-01	1.19E-02
clear	speeding	primary	nighttime	9.29E-01	7.14E-02
clear	speeding	secondary	daylight	9.96E-01	3.97E-03
clear	speeding	secondary	nighttime	9.64E-01	3.57E-02
clear	speeding	residential	daylight	9.92E-01	7.94E-03
clear	speeding	residential	nighttime	9.96E-01	3.97E-03
clear	no speeding	primary	daylight	8.89E-01	1.11E-01
clear	no speeding	primary	nighttime	5.91E-01	4.09E-01
clear	no speeding	secondary	daylight	9.76E-01	2.38E-02
clear	no speeding	secondary	nighttime	8.57E-01	1.43E-01
clear	no speeding	tertiary	daylight	9.84E-01	1.59E-02
clear	no speeding	tertiary	nighttime	9.68E-01	3.17E-02
clear	no speeding	residential	daylight	9.80E-01	1.98E-02

Weather	Speeding	Roadway Type	Light Condition	P(No Crash Exposure)	P(Crash Exposure)
clear	no speeding	residential	nighttime	9.88E-01	1.19E-02
cloudy	speeding	primary	nighttime	9.92E-01	7.94E-03
cloudy	speeding	secondary	nighttime	9.96E-01	3.97E-03
cloudy	speeding	residential	nighttime	9.92E-01	7.94E-03
cloudy	no speeding	primary	daylight	9.96E-01	3.97E-03
cloudy	no speeding	primary	nighttime	9.80E-01	1.98E-02
cloudy	no speeding	secondary	nighttime	9.92E-01	7.94E-03

* Combinations not represented reflect insufficient cell counts in the filtered FARS sample. Not interpreted as a zero-risk condition. See Appendix C.3.

B.4.2 Vehicle Failure Nodes

These nodes alter base events probabilities discussed in **Section C.2.5** regarding driver and ADS-related failure events. The trigger for both the warning generation and/or the independent's vehicle reaction (driver or ADS) is the detection of the pedestrian conflict in the vehicle's path. For the three cases L0/L2/L4, the stopping failure probabilities cover cases when vehicle fails to stop when the pedestrian has been detected and when it fails to stop after the SDSM has triggered the onboard warning (L0/L2) or the downstream vehicle behavior (L4).

B.4.2.1 Stopping under warned conditions

L0/L2 Scenarios:

A simple model was developed to derive the stopping probability of a warned driver under various warning and weather conditions, with adjusted approach speeds and driver reaction times to reflect Scenario B, representing distracted drivers

or pedestrian conflicts stemming from partial to total occlusion reacting to warnings >4s prior to conflict[175]. This model quantifies the conditional probability that a warned driver can physically complete a full stop before entering the intersection or approaching the midblock crossing, represented as P(vehicle stops in time | weather condition, initial speed, available time window). Note that the probability of success of the braking action is prior to the L2 PAEB functionality. Refer to **B.4.2.2-B.4.2.3** for more details on the implementation.

Values for reaction times and vehicle deceleration were considered under clear, cloudy and rainy conditions. In this scenario, an extended driver PRT was considered, representing reaction to unexpected driving conditions (as described in **Section 3.2.2.2**), with values 1.25s ± 0.39s is considered across all weather conditions[176]. As in Scenario A, three vehicle deceleration values were considered to represent plausible braking behavior for a warned driver intending to stop under clear and mild rain weather conditions (**Table 7.11**). Representative conditions for each ESD time-availability branch were selected for the BBN node states, as shown in **Table 7.26**. Note that these represent only the warned, stopping probabilities based on assumed physical bounds. Real-world compliance rates for FCW are lower, 16-21 % crash reduction, with PAEB increasing towards 42%-53%[177], but those include the warning response and have been factored in the overall calibration of the L2 model.

Figure 7.24 presents a summary of the obtained stopping probabilities for $T_{avail} = 6.5s$ for the high time availability scenario and $T_{avail} = 4.0s$ for the low time availability scenario, respectively. **Figure 7.25** presents the cumulative probability distribution curve at different approach speeds as a function of T_{avail}, highlighting the anchors selected for the BBN nodes

[175] L. Yue, M. Abdel-Aty, Y. Wu, J. Yuan, and M. Morris, “Influence of pedestrian-to-vehicle technology on drivers’ response and safety benefits considering pre-crash conditions,” Transportation Research Part F: Traffic Psychology and Behaviour, vol. 73, pp. 50–65, July 2020, doi: 10.1016/j.trf.2020.06.012.

[176] N. Lubbe, “Brake reactions of distracted drivers to pedestrian Forward Collision Warning systems,” Journal of Safety Research, vol. 61, pp. 23–32, Mar. 2017, doi: 10.1016/j.jsr.2017.02.002.

[177] Partnership for Analytics Research in Traffic Safety (PARTS), "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

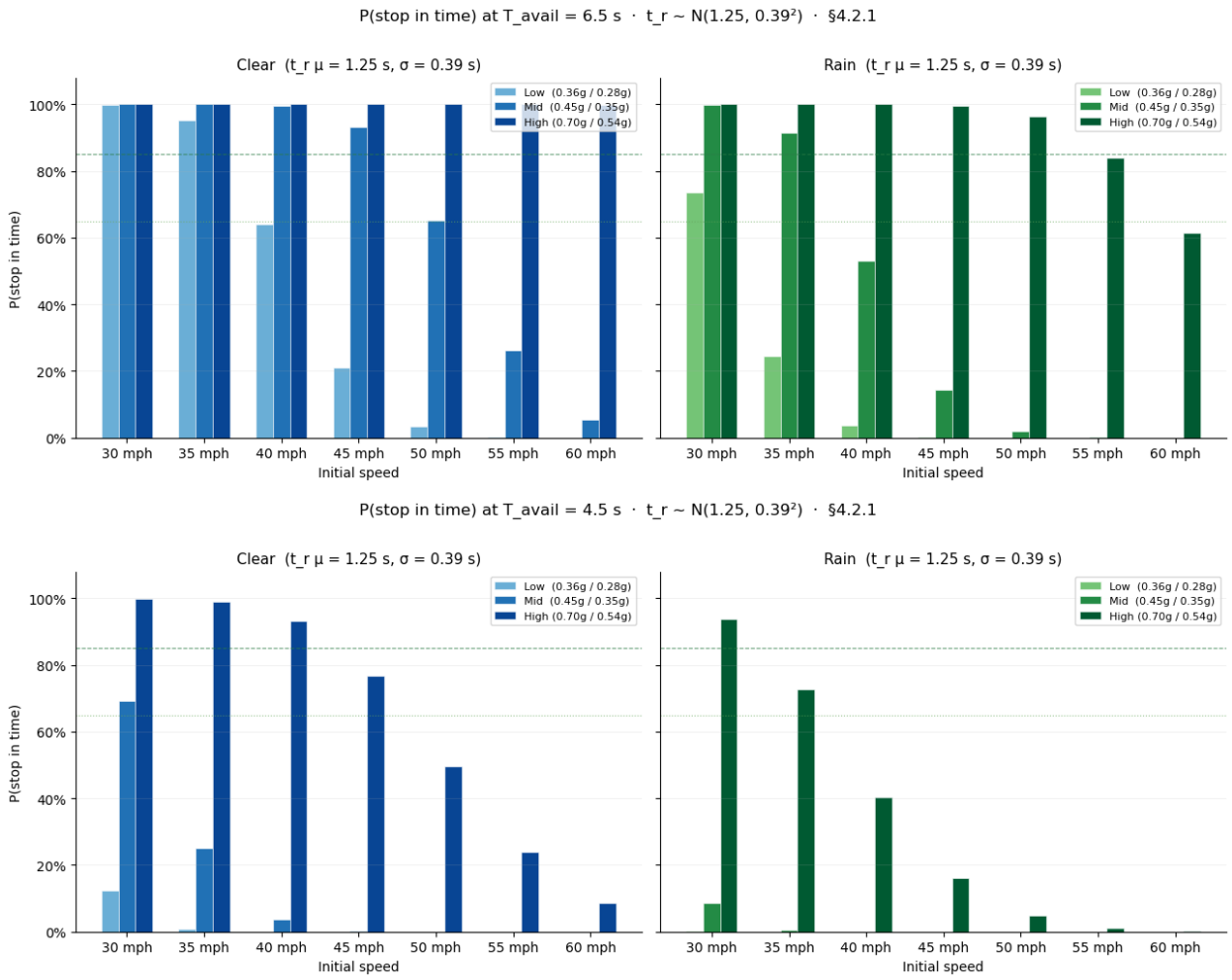

Figure 7.24: Stopping probability at 4-6.5 second warnings (SDSM, L0).

Table 7.26: Representative stopping probability values for BBN nodes (SDSM, L0).

Node	Vehicle Approach Speed	Deceleration Scenario	Representative Time Available	Clear / Cloudy	Rain
Stop. Prob. (High Time)	40mph	Mid	6.5s	0.99	0.53
Stop. Prob. (Low Time)	30mph	High	4s	0.97	0.68

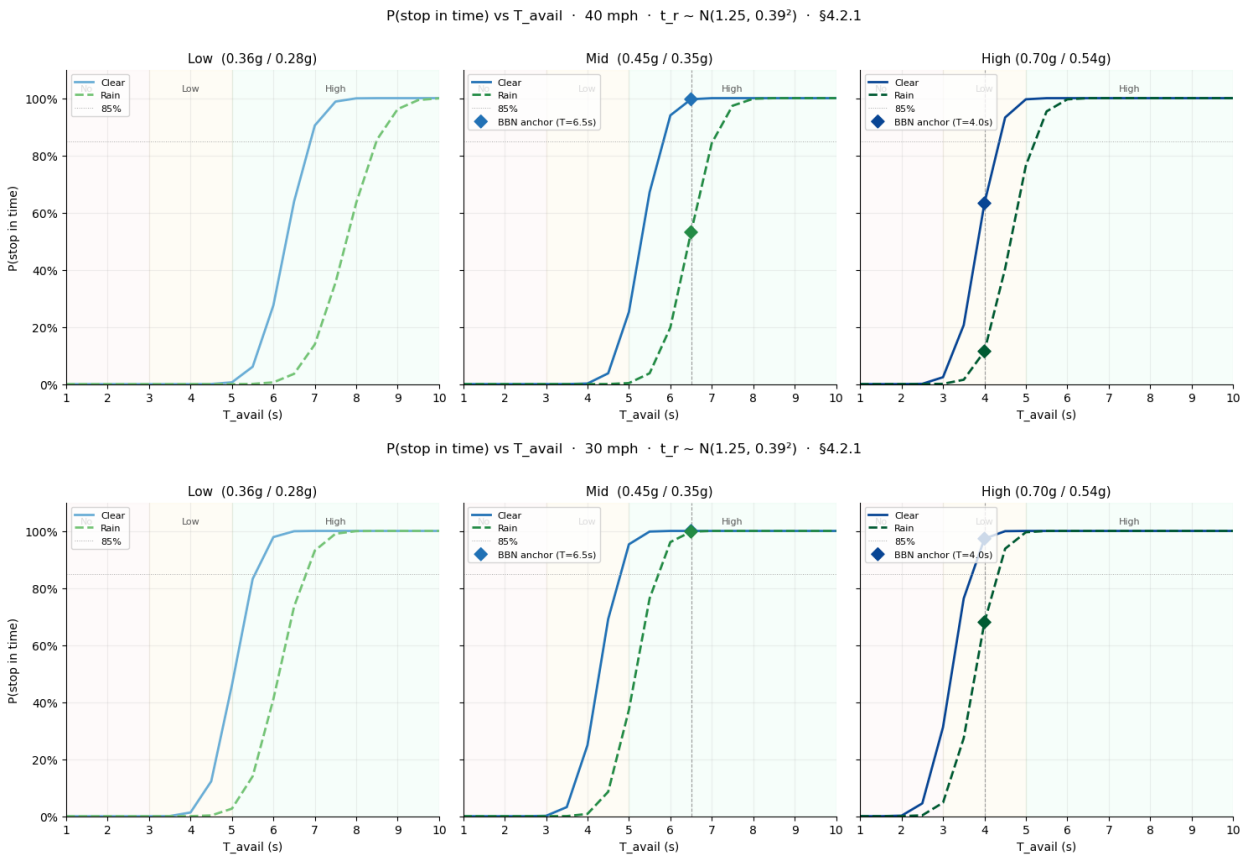

Figure 7.25: Cumulative probability functions at 35-40mph (SDSM, L0).

L4 Scenarios:

The described physics-based stopping model is retained for the L4 ADS, with one modification compared to Scenario A (RLVW). The reaction time is conserved, $t_r \sim N(0.10, 0.02^2)\ s$, reflecting end-to-end ADS latency from V2X message receipt through brake actuation. Similarly, the deceleration profiles are conserved (refer to **Table 7.13**), however, different approach speeds are considered. The same L4 parameters are used for the L2 braking response path (Section C.2.3).

Representative conditions for each ESD time-availability branch were selected for the BBN node states, as shown in **Table 7.27**. **Figure 7.26** presents a summary of the obtained stopping probabilities for $T_{avail} = 6.5s$ for the high time availability scenario and $T_{avail} = 4.0s$ for the low time availability scenario, respectively. **Figure 7.27** presents the cumulative probability distribution curve at different approach speeds as a function of T_{avail}, highlighting the anchors selected for the BBN nodes.

Table 7.27: Representative stopping probability values for BBN nodes (SDSM, L4).

Node	Vehicle Approach Speed	Deceleration Scenario	Representative Time Available	Clear / Cloudy	Rain
Stop. Prob. (High Time)	40mph	Mid	6.5s	0.99	0.78
Stop. Prob. (Low Time)	30mph	High	4s	0.99	0.96

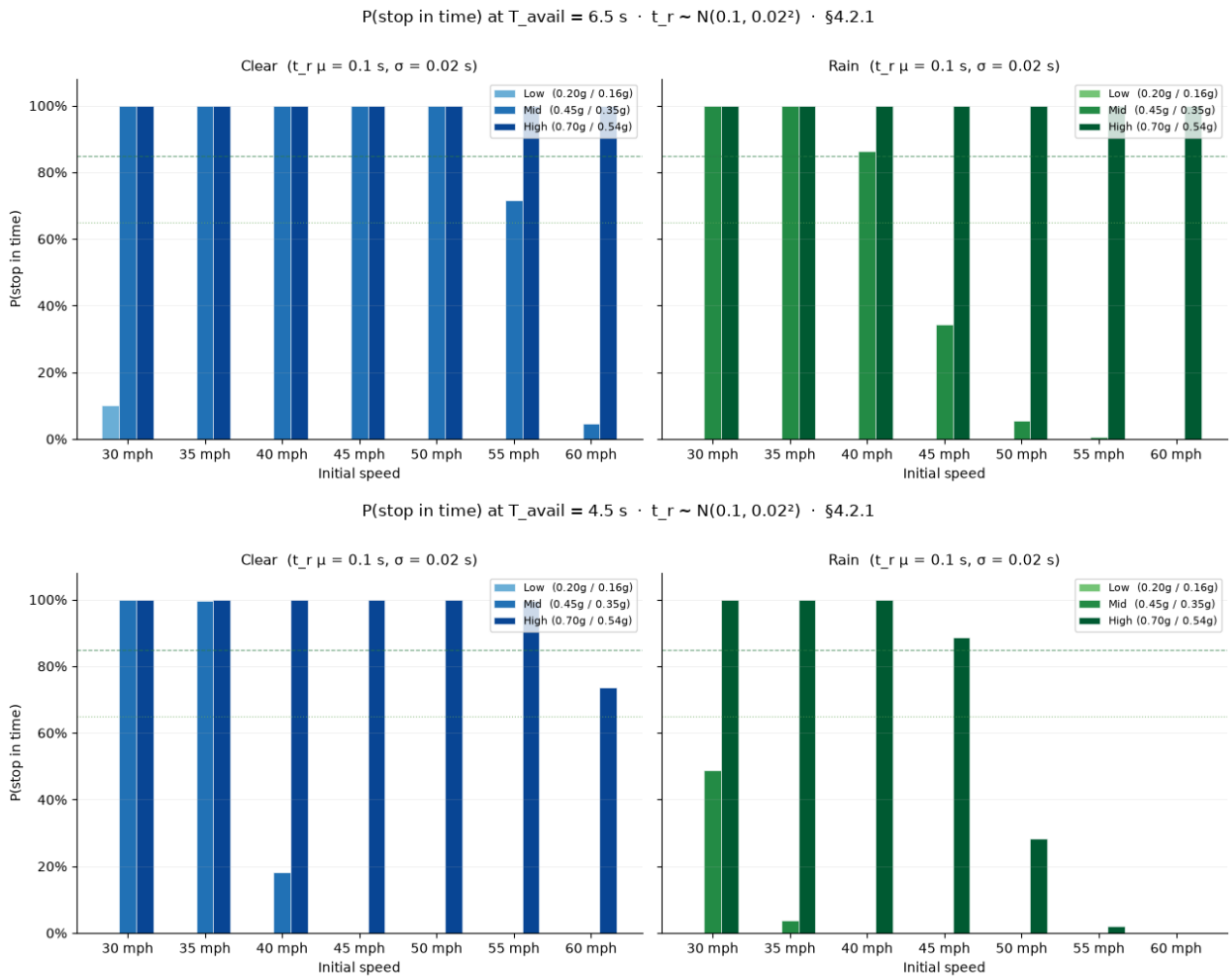

Figure 7.26: Stopping probability at 4-6.5 second warnings (SDSM, L4).

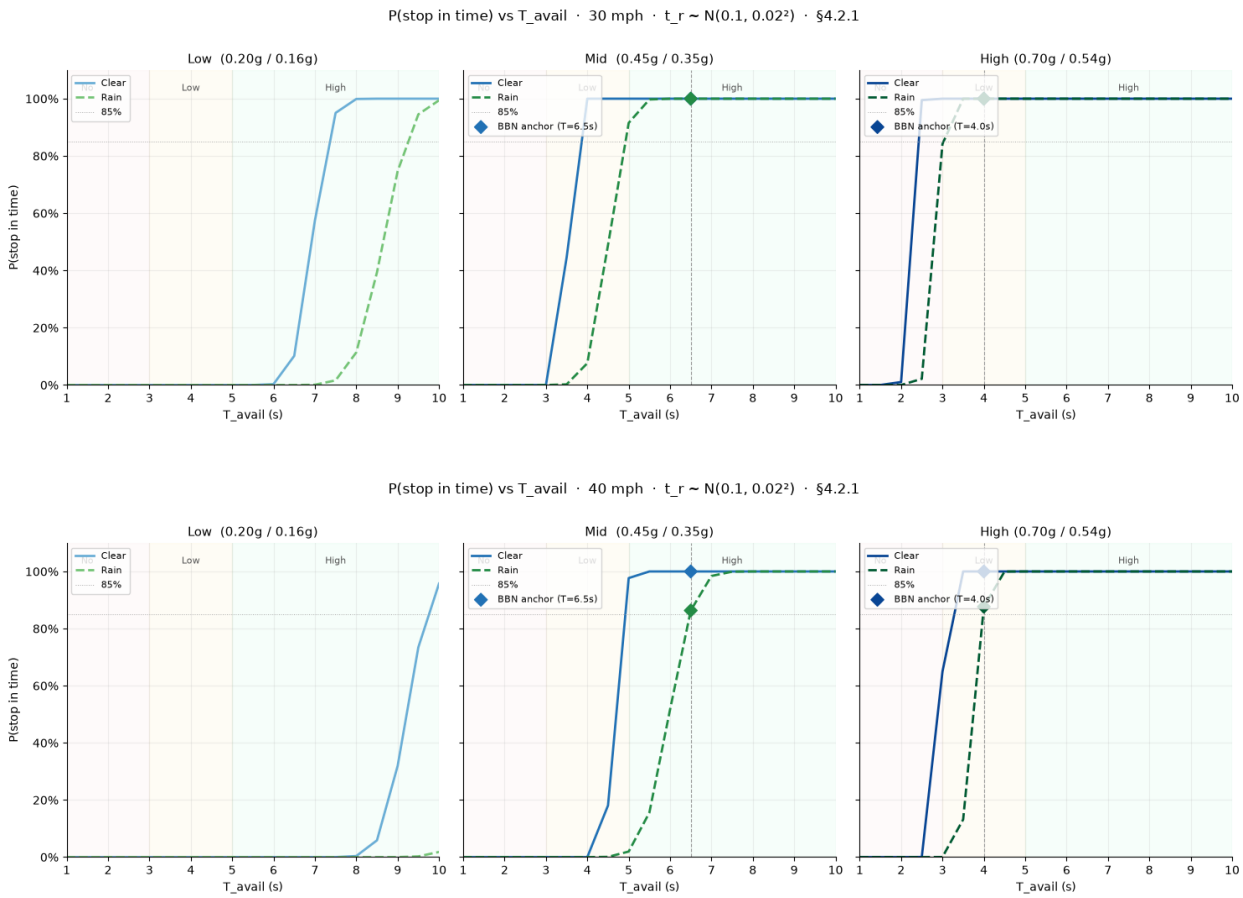

Figure 7.27: Cumulative probability functions at 35-40mph (SDSM, L4).

B.4.2.2 Stopping under unwarned conditions

L0/L2 Scenarios:

This node represents the probability that an unwarned driver avoids a potential pedestrian conflict as a function of weather, light, and LOS conditions. This includes conflicts stemming from perception issues – driver inattention (no evasive actions), misjudged actions, insufficient times stemming from dart outs, other (including speeding, impairment). The Day/Clear anchor (0.45) is consistent with the NHTSA typology placing ~55–70% of crashes at non-detection, treating Day/Clear as the lowest-risk cell. The Night/Rain anchor (0.85) reflects the IIHS finding that PAEB provides no benefit in dark unlit conditions[178]. The intermediate cells are interpolated from the two-factor structure: lighting contributes roughly a 0.25 multiplicative increase in non-detection probability; weather contributes roughly 0.05–0.15 additional depending on severity. The final values implemented are presented in **Table 7.28** below.

Table 7.28: Derived Pedestrian Conflict Probability (L0 Scenarios).

Weather	Light Condition	LOS Condition	P(conflict)*
Clear	Daytime	LOS	8.00E-02
	Nighttime	NLOS	9.00E-01
	Daytime	LOS	2.40E-01
	Nighttime	NLOS	9.50E-01
Cloudy	Daytime	LOS	1.80E-01
	Nighttime	NLOS	9.20E-01
	Daytime	LOS	3.40E-01

[178] J. B. Cicchino, "Convenience or safety system? Crash rates of vehicles equipped with partial driving automation," Traffic Injury Prevention, vol. 26, no. 6, pp. 631–641, 2025, doi: 10.1080/15389588.2024.2448511. [Online]. Available: https://www.iihs.org/topics/bibliography/ref/2309

Weather	Light Condition	LOS Condition	P(conflict)*
	Nighttime	NLOS	9.60E-01
Rain	Daytime	LOS	8.00E-02
	Nighttime	NLOS	9.00E-01
	Daytime	LOS	2.40E-01
	Nighttime	NLOS	9.50E-01

For L2 Scenarios, the driver detection probabilities in Table 7.28 are combined with the L2 onboard camera detection probabilities (Table 7.33): a pedestrian conflict is missed only if both the driver and the L2 camera fail to detect it.

L4 Scenarios:

This node represents the probability that an unwarned ADS-equipped vehicle avoids a potential pedestrian conflict as a function of weather, light, and LOS conditions. This failure mode is dominated by camera and LiDAR-based detection systems, following the same independent-sensor-stream simplification used elsewhere in this model, without losing generality regarding specific sensor fusion, detection, or tracking algorithms. The implemented CPT is presented in **Table 7.29**. Sensor-specific detection probabilities are presented in **Section C.2.6.1 (Vehicle-Mounted Sensor Systems)**.

Table 7.29: Resulting vehicle-mounted detection probability assuming independent sources.

Camera-based Detection	LiDAR-based Detection	P(detection)
Detected	Detected	1
	Missed detection	1
Missed detection	Detected	1

Camera-based Detection	LiDAR-based Detection	P(detection)
	Missed detection	0

B.4.2.3 Stopping failure recovery path (L2)

L2 Scenario (PAEB):

This node represents the L2 PAEB values, after the driver has failed to intervene correctly (either under warned or unwarned conditions). PAEB actuation introduces a new recovery path, here considered independent to the driver's braking failure probability. Pedestrian AEB was associated with reductions of 25–27% in pedestrian crash risk overall and reductions in pedestrian injury crash risk were 29–30%. However, in this initial study, crash reductions did not occur in the dark, at speed limits 50+ mph, or while turning[179]. A larger PARTS (2025) study showed a 9% reduction in single-vehicle frontal crashes with non-motorists, including pedestrians, cyclists, scooters, and wheelchairs. AEB overall improved from 46% effectiveness across MY2015–2017 to 52% across MY2021–2023[180]. Given that, the implemented CPT is shown below (**Table 7.30**) given light and LOS conditions. Given reduced control/actuation equivalent PRT for L2, this model only looks at function-level outcomes (rather than dividing PRT and braking times accordingly). Night performance, especially under partially occluded conditions, is minimal.

Table 7.30: PAEB Conflict Probability (L2 Scenarios).

Light Condition	LOS Condition	P(conflict)*
Daytime	LOS	6.20E-01

[179] J. B. Cicchino, "Effects of automatic emergency braking systems on pedestrian crash risk," Accident Analysis & Prevention, vol. 172, p. 106686, July 2022, doi: 10.1016/j.aap.2022.106686.

[180] Partnership for Analytics Research in Traffic Safety (PARTS), "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

Light Condition	LOS Condition	P(conflict)*
	NLOS	9.70E-01
Nighttime	LOS	7.20E-01
	NLOS	9.80E-01

*Derived from Cicchino (2022)[181]; PARTS (2025)[182].

B.4.3 Sensor-System Failures

B.4.3.1 Infrastructure-mounted sensor systems (L0, L2, L4)

The conditional probability tables for the roadside-unit camera and LiDAR pedestrian-detection nodes are drawn from infrastructure-mounted sensing studies reporting recall, miss rate, or equivalent false-negative measures. This approach is taken as commonly reported average-precision (AP) benchmarks integrate the precision-recall tradeoff across all confidence thresholds at a fixed overlap criterion and cannot be interpreted directly as a per-encounter missed-detection probability. The modeling assumption is that a valid SDSM requires only one modality to detect the pedestrian, which is represented by the structure discussed in **Section C.2.5**.

Both nodes are conditioned on the same parent structure, with the camera node conditioned on light condition, weather, roadside-unit line of sight, and the LiDAR node conditioned on weather and line of sight. Cloudy conditions are collapsed to clear for both sensors as a documented modeling simplification, reflecting the absence of evidence that diffuse-overcast illumination materially degrades either modality relative to clear conditions. As both nodes have common roadside-unit LOS parent, the correlation between camera and LiDAR failures under occlusion is represented structurally within the model.

[181] J. B. Cicchino, “Effects of automatic emergency braking systems on pedestrian crash risk,” Accident Analysis & Prevention, vol. 172, p. 106686, July 2022, doi: 10.1016/j.aap.2022.106686.
[182] Partnership for Analytics Research in Traffic Safety (PARTS), "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

Camera-based detections: The clear-daylight unobstructed baseline (Day/Clear/LOS miss rate of approximately 0.04) is anchored to infrastructure-to-vehicle camera deployment data reporting a missed-detection rate of approximately 4% under nominal condition[183]. The nighttime degradation (to a miss rate of approximately 0.42) is derived as a ratio transfer rather than a direct measurement: a day/night recall ratio of approximately 0.65 from a multispectral (RGB-only) benchmark[184] is cross-checked against a signalized-intersection field study reporting 26% visible-camera accuracy versus 89% thermal-camera accuracy[185]. The occlusion (NLOS) penalty is anchored to Caltech Pedestrian Benchmark and Rope3D-Hard occlusion evidence, under which missed-detection rates rise by a multiple growing with occlusion fraction[186,187].; this value is set higher than the corresponding LiDAR NLOS penalty as a structural assumption — infrastructure cameras, unlike LiDAR, have no overhead point-return advantage under occlusion — rather than reflecting an independently measured joint camera-NLOS figure. The rain modifier reflects general contrast- and spray-related degradation; a dedicated per-modality rain benchmark for infrastructure cameras was not identified in the literature reviewed, so this value should be treated as a qualitative assumption rather than an empirically anchored one. The resulting derived values are shown in **Table 7.31**.

Table 7.31: Infrastructure-mounted camera-based pedestrian detection per-encounter performance.

Scenario	Light	Weather	LOS (RSU)	P(Detect)
Intersection	Day	Clear	LOS	0.96
	Day	Clear	NLOS	0.55

[183] D. Vignarca, M. Vignati, S. Arrigoni, and E. Sabbioni, "Infrastructure-Based Vehicle Localization through Camera Calibration for I2V Communication Warning," *Sensors*, vol. 23, no. 16, p. 7136, 2023, doi: 10.3390/s23167136. [Online]. Available: https://www.mdpi.com/1424-8220/23/16/7136

[184] P.-S. Lin, A. Kourtellis, M. Momenitabar, and C. Cui, “Evaluation of Innovative Pedestrian Detection Systems to Increase Safety Final Report,” 2025. Accessed: Aug. 05, 2026. [Online]. Available: https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/research/reports/fdot-bed25-977-14-rpt.pdf?sfvrsn=ccc8707f_3

[185] S. Hwang, J. Park, N. Kim, Y. Choi, and I. S. Kweon, "Multispectral pedestrian detection: Benchmark dataset and baseline," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015, pp. 1037–1045, doi: 10.1109/CVPR.2015.7298706. [Online]. Available: https://openaccess.thecvf.com/content_cvpr_2015/papers/Hwang_Multispectral_Pedestrian_Detection_2015_CVPR_paper.pdf

[186] P. Dollar, C. Wojek, B. Schiele and P. Perona, "Pedestrian Detection: An Evaluation of the State of the Art," in *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 34, no. 4, pp. 743-761, April 2012, doi: 10.1109/TPAMI.2011.155.

[187] X. Ye, M. Shu, H. Li, Y. Shi, Y. Li, G. Wang, X. Tan, and E. Ding, "Rope3D: The roadside perception dataset for autonomous driving and monocular 3D object detection task," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2022, pp. 21341–21350. [Online]. Available: https://openaccess.thecvf.com/content/CVPR2022/html/Ye_Rope3D_The_Roadside_Perception_Dataset_for_Autonomous_Driving_and_Monocular_CVPR_2022_paper.html

Scenario	Light	Weather	LOS (RSU)	P(Detect)
	Day	Rain	LOS	0.85
	Day	Rain	NLOS	0.45
	Day	Cloudy	LOS	0.96
	Day	Cloudy	NLOS	0.55
	Night	Clear	LOS	0.58
	Night	Clear	NLOS	0.22
	Night	Rain	LOS	0.51
	Night	Rain	NLOS	0.18
	Night	Cloudy	LOS	0.58
	Night	Cloudy	NLOS	0.22
Midblock	Day	Clear	LOS	0.60
	Day	Clear	NLOS	0.35
	Day	Rain	LOS	0.60
	Day	Rain	NLOS	0.35
	Day	Cloudy	LOS	0.32
	Day	Cloudy	NLOS	0.11
	Night	Clear	LOS	0.54
	Night	Clear	NLOS	0.28
	Night	Rain	LOS	0.37

Scenario	Light	Weather	LOS (RSU)	P(Detect)
	Night	Rain	NLOS	0.14
	Night	Cloudy	LOS	0.37
	Night	Cloudy	NLOS	0.14

LiDAR-based detections: The clear-daylight unobstructed baseline is anchored to roadside-LiDAR pedestrian-detection field studies reporting a miss rate of approximately 6%[188,189]. The weather effect is calibrated to empirical rain-attenuation testing indicating that detection performance begins to decline only above precipitation rates substantially higher than those typical of the study area, so that the modeled rain penalty is modest[190]. The LOS effect is the principal degradation mechanism for LiDAR and is drawn from a signalized-intersection field deployment in which pedestrian recall fell to approximately 78% under occlusion produced by queuing vehicles during the red-light phase[191]. The additional rain (+0.03 percentage points) and night (+0.01 percentage points) adjustments applied to the NLOS state are additive estimates rather than values separately measured in the source study and should be treated as derived rather than directly sourced. More severe occlusion configurations, such as a single large vehicle fully blocking a crosswalk, may produce higher per-encounter miss rates not fully captured by this aggregate figure. The resulting derived values are shown in **Table 7.32**.

Table 7.32: Infrastructure-mounted LiDAR-based pedestrian detection per-encounter performance.

Scenario	Light	Weather	LOS (RSU)	P(Detect)
Intersection	Day	Clear	LOS	0.94
	Day	Clear	NLOS	0.78

[188] E. D. Saldivar-Carranza, J. Desai, A. Thompson, M. Taylor, J. Sturdevant, and D. M. Bullock, "Vehicle and pedestrian traffic signal performance measures using LiDAR-derived trajectory data," *Sensors*, vol. 24, no. 19, p. 6410, 2024, doi: 10.3390/s24196410. [Online]. Available: https://www.mdpi.com/1424-8220/24/19/6410

[189] J. Castrillo, M. Soilán, N. Caparrini, and J. Balado, "A scoping review of LiDAR solutions for urban safety of vulnerable road users," *Geomatics*, vol. 6, no. 3, p. 59, 2026, doi: 10.3390/geomatics6030059. [Online]. Available: https://www.mdpi.com/2673-7418/6/3/59

[190] J. Kim, B.-j. Park, and J. Kim, "Empirical analysis of autonomous vehicle's LiDAR detection performance degradation for actual road driving in rain and fog," *Sensors*, vol. 23, no. 6, p. 2972, 2023, doi: 10.3390/s23062972. [Online]. Available: https://www.mdpi.com/1424-8220/23/6/2972

[191] T. T. Zhang, Y. Ge, A. Chen, M. Sartipi, and P. J. Jin, "Hash-Based Gaussian Mixture Model (HGMM) for Roadside LiDAR Smart Infrastructure Applications," IEEE Transactions on Intelligent Transportation Systems, vol. 25, no. 10, pp. 12968–12979, Oct. 2024, doi: 10.1109/tits.2024.3434749.

Scenario	Light	Weather	LOS (RSU)	P(Detect)
	Day	Rain	LOS	0.91
	Day	Rain	NLOS	0.75
	Day	Cloudy	LOS	0.94
	Day	Cloudy	NLOS	0.78
	Night	Clear	LOS	0.93
	Night	Clear	NLOS	0.77
	Night	Rain	LOS	0.90
	Night	Rain	NLOS	0.74
	Night	Cloudy	LOS	0.93
	Night	Cloudy	NLOS	0.77
Midblock	Day	Clear	LOS	0.86
	Day	Clear	NLOS	0.71
	Day	Rain	LOS	0.86
	Day	Rain	NLOS	0.71
	Day	Cloudy	LOS	0.82
	Day	Cloudy	NLOS	0.68
	Night	Clear	LOS	0.83
	Night	Clear	NLOS	0.69
	Night	Rain	LOS	0.85

Scenario	Light	Weather	LOS (RSU)	P(Detect)
	Night	Rain	NLOS	0.70
	Night	Cloudy	LOS	0.85
	Night	Cloudy	NLOS	0.70

Midblock crossings differ from intersection crossings primarily in RSU-to-pedestrian range and camera/LiDAR viewing geometry, since infrastructure sensors are mounted at the intersection and must cover adjacent midblock segments at greater distance. Intersection-level detection values are treated as the upper bound for both modalities.

For LiDAR, midblock detection probabilities are derived by applying a multiplicative range penalty of $0.91\times$ the corresponding intersection value, reflecting the comparatively graceful degradation of modern LiDAR systems with range and beam count. This is consistent with Cui et al. (2026)[192], whose multi-resolution roadside LiDAR benchmark (16-, 32-, 80-, and 128-beam configurations) found that detection performance depends jointly on beam count, beam distribution, target distance, and occlusion, and that beam distribution can matter as much as raw beam count. It is further consistent with Xu et al. (2026)[193], who demonstrated in a CARLA-based simulation that infrastructure-mounted LiDAR can supply usable 3D-detection supervision to vehicles at range, supporting the assumption that roadside LiDAR retains meaningful pedestrian-detection capability at midblock distances.

For camera-based detection, a larger multiplicative penalty of $0.63\times$ is applied at midblock, reflecting both the greater range and the smaller apparent (pixel) size of a pedestrian target at typical midblock distances relative to intersection-level

[192] S. Cui et al., “MR-LiDAR: A Multi-Resolution Roadside LiDAR Benchmark for Perception Diagnostics and Deployment Guidance,” May 2026, Accessed: Aug. 06, 2026. [Online]. Available: https://arxiv.org/pdf/2605.24777

[193] Z. Xu et al., “When the City Teaches the Car: Label-Free 3D Perception from Infrastructure,” Mar. 2026, Accessed: Aug. 06, 2026. [Online]. Available: https://arxiv.org/pdf/2603.16742

detection[194]. This is consistent with Fürst et al. (2020)[195], who found that camera/LiDAR fusion approaches underperform specifically at long range for pedestrian-scale (small) objects, and with Abbasi et al. (2023)[196], who reported that vision-only pedestrian-intention prediction accuracy degrades substantially at distances beyond approximately 70 meters and under low-light conditions — motivating the roughly 60% degradation used as an approximate upper-bound penalty for the far-range band in this model. Camera-based midblock detection is treated as a lower-confidence simplification relative to the LiDAR-based estimate: infrastructure camera performance at pedestrian scale over these ranges is not well characterized in the literature, so the resulting midblock camera values should be interpreted with additional caution (see **Section 4.3.2)**.

B.4.3.2 Vehicle-mounted sensor systems (L2, L4)

A similar modeling approach is taken for vehicle-mounted camera and LiDAR sensors, following the same independent-detection, OR-gate fusion logic described for the infrastructure RSU node (**Table 7.29**). As with the infrastructure sensors, NLOS (occlusion) is the dominant degradation mechanism for both modalities; however, vehicle-mounted sensors are parameterized from a separate literature base rather than sharing anchors with the infrastructure RSU nodes, reflecting differences in mounting height, viewing geometry, and typical detection range between roadside and vehicle-mounted platforms. The literature basis for the parameterization presented in **Table 7.33** and **Table 7.34** is discussed in **Section C.2.2 (ADS Pedestrian-Detection Basis). For L2, only the camera-based detection probabilities (Table 7.33) are used.**

Unlike the infrastructure sensor nodes, vehicle-mounted detection values are treated as identical between intersection and midblock crossings, since the vehicle's sensing geometry relative to the pedestrian does not change systematically with road type.

Table 7.33: Camera-based Detection (L2/L4 Scenarios).

[194] X. Zhang, L. Cheng, B. Li, and H. M. Hu, “Too Far to See? Not Really:- Pedestrian Detection with Scale-Aware Localization Policy,” IEEE Trans. Image Process., vol. 27, no. 8, pp. 3703–3715, Aug. 2018, doi: 10.1109/TIP.2018.2818018.

[195] M. Fürst, O. Wasenmüller, and D. Stricker, “LRPD: Long Range 3D Pedestrian Detection Leveraging Specific Strengths of LiDAR and RGB,” 2020 IEEE 23rd Int. Conf. Intell. Transp. Syst. ITSC 2020, Jun. 2020, doi: 10.1109/ITSC45102.2020.9294537.

[196] J. A. Abbasi, N. M. Imran, L. C. Das, and M. Won, “WatchPed: Pedestrian Crossing Intention Prediction Using Embedded Sensors of Smartwatch,” IEEE Int. Conf. Intell. Robot. Syst., pp. 9574–9581, 2023, doi: 10.1109/IROS55552.2023.10341607.

Weather	Light Condition	LOS Condition	P(Detect)
Clear	Daytime	LOS	0.96
	Daytime	NLOS	0.32
	Nighttime	LOS	0.85
	Nighttime	NLOS	0.28
Cloudy	Daytime	LOS	0.51
	Daytime	NLOS	0.18
	Nighttime	LOS	0.58
	Nighttime	NLOS	0.22
Rain	Daytime	LOS	0.96
	Daytime	NLOS	0.32
	Nighttime	LOS	0.58
	Nighttime	NLOS	0.22

Table 7.34: LiDAR-based Detection (L4 Scenarios).

Weather	Light Condition	LOS Condition	P(Detect)
Clear	Daytime	LOS	0.94
	Daytime	NLOS	0.74
	Nighttime	LOS	0.91

Weather	Light Condition	LOS Condition	P(Detect)
	Nighttime	NLOS	0.72
Cloudy	Daytime	LOS	0.90
	Daytime	NLOS	0.71
	Nighttime	LOS	0.93
	Nighttime	NLOS	0.73
Rain	Daytime	LOS	0.94
	Daytime	NLOS	0.74
	Nighttime	LOS	0.93
	Nighttime	NLOS	0.73

An important, shared prior across both the detection and communication nodes is the probability of effective line-of-sight (LOS). Two distinct LOS relationships are modeled: (i) vehicle-pedestrian LOS, representing the probability that an onboard driver or ADS sensor has an unobstructed view of the pedestrian, which conditions the vehicle-mounted detection nodes (**Table 7.33-Table 7.34**) and the L0/L2 unwarned-detection node (**Table 7.28**); and (ii) infrastructure-vehicle/pedestrian LOS, representing the probability of unobstructed geometry between the RSU and the vehicle or pedestrian, which conditions both the infrastructure sensor-detection nodes (**Table 7.31-Table 7.32**) and the V2X communication model. **Table 7.35** presents the implemented values for both relationships.

Table 7.35: LOS/NLOS priors for infrastructure and vehicle (Scenario B).

Use Case	P(effective LOS)	P(effective NLOS)
Vehicle-Pedestrian	0.70	0.30

Use Case	P(effective LOS)	P(effective NLOS)
Infrastructure-Vehicle/Pedestrian	0.85	0.15

C.2.6.2. B.5. V2X Communication Model

A similar approach is taken as in Scenario A. In this case, only RSU TX and HV RX are important, based on the prior and then the reception probability based on weather/NLOS effects. The impact of CV% is dominant. The model is structured in two components: a link quality node that represents the probability of effective LOS between the RSU and vehicle as a function of weather, and a conditional message transmission/reception model that assigns delivery probabilities given the effective link state. This portion of the model is applied to all L0/L2/L4 Scenarios.

B.5.1 Line of Sight Conditions

The LOS/NLOS is a simplified binary node that represents the effective link quality sufficient for message delivery between the RSU and the host vehicle, as influenced by intersection geometry. The impact of weather is dropped in this case, as this plays a more significant role in the infrastructure-mounted sensor performance nodes rather than the communication nodes. The values are the ones shown in **Table 7.35**.

B.5.2 V2X Communication Models

Message delivery reliability for RSU-to-OBU transmissions is modeled using a simplified binary success/failure structure conditioned on effective link quality (LOS or NLOS) and the CV market penetration (0%-100%). As explained in section A.5.2, a nominal transmission success probability of $P(MsgTX \mid LOS) = 0.97$ is assumed for LOS conditions, representing a conservative floor relative to available field evidence.

The following conditional probability tables are implemented to characterize the modeled SDSM-PED scenario. Transmission-related event probabilities are provided in **Table 7.36**, while reception-related event probabilities are provided in **Table 7.37**, as a function of the CV market penetration.

Table 7.36: Communication Failure Probabilities (No TX) for RSU.

Event	Node	TX	No TX
RSU Message Transmission*	RSU_Msg_TX	0.97	0.03

* Note that RSU Message Transmission is treated as unconditional while LOS/NLOS and weather effects are collected in the LOS/NLOS node.

Table 7.37: Communication Failure Probabilities (No RX) for host vehicles as a function of CV market penetration rate.

Host & Encountering Vehicles Reception	LOS/NLOS State	RSU Message Transmission	RX	No RX
P0	LOS	TX	0.00	1.00
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.00	1.00
	NLOS	No_TX	0.00	1.00
P25	LOS	TX	0.24	0.76
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.23	0.78
	NLOS	No_TX	0.00	1.00
P50	LOS	TX	0.49	0.52
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.45	0.55
	NLOS	No_TX	0.00	1.00

Host & Encountering Vehicles Reception	LOS/NLOS State	RSU Message Transmission	RX	No RX
P75	LOS	TX	0.73	0.27
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.68	0.33
	NLOS	No_TX	0.00	1.00
P100	LOS	TX	0.97	0.03
	LOS	No_TX	0.00	1.00
	NLOS	TX	0.90	0.10
	NLOS	No_TX	0.00	1.00

C.3. Crash Data for Calibration

C.3.1. Level 0 Models

This calibration process draws on both CRSS and FARS crash records: FARS provides the fatality-level detail needed to distinguish among the scenario-relevant crash populations at the local (Los Angeles) level, while CRSS provides the national severity distribution used to scale fatality counts into injury and property-damage-only (PDO) estimates. Crashes from both sources are filtered by scenario-relevant conditions and by the weather categories collected for the DTLA study area (clear, cloudy, rain), with national statistics retained for comparison. The filters applied to the available crash data are:

1. Vehicle Crashes at Intersections [
2. **Table** 7.38]:
    a. FARS (Los Angeles City): Crash Type: Two-Vehicle Crash; First Harmful Event: Motor Vehicle In-Transport; Interstate: Non-Interstate; Intersection: At Intersection; Involving A Pedestrian: No; Involving A Pedalcyclist:

No; Relationship To The Trafficway: On Roadway; Roadway Function Class: Principal arterial, other ; or Minor arterial ; or Collector; Land Use (Rural/Urban): Urban; Native American Reservations: No; Special Jurisdiction: No Special Jurisdiction; Type of Intersection (since 2010): Four-Way Intersection ; or T-Intersection ; or Y-Intersection; Work Zone: None.

b. CRSS (National): Crash Type: Two-Vehicle Crash; or More Than Two-Vehicle Crash; First Harmful Event: Motor Vehicle In-Transport; Involving A Pedestrian: No; Involving A Pedalcyclist: No; Relationship To The Trafficway: On Roadway; Work Zone: None.

3. Pedestrian Crashes at Intersections [

4. **Table** 7.39]:

a. FARS (Los Angeles City): Single-Vehicle Crash; First Harmful Event: Pedestrian; Interstate: Non-Interstate; Intersection: At Intersection; Involving A Pedestrian: Yes; Relationship To The Trafficway: On Roadway; Roadway Function Class: Principal arterial, other ; or Minor arterial ; or Collector; Land Use (Rural/Urban): Urban; Native American Reservations (see Research Note)4: No; Special Jurisdiction: No Special Jurisdiction; Type of Intersection (since 2010): Four-Way Intersection ; or T-Intersection ; or Y-Intersection; Work Zone: None.

b. CRSS (National): Crash Type: Single-Vehicle Crash; First Harmful Event: Pedestrian; Interstate: Non-Interstate; Intersection: At Intersection; Relationship To The Trafficway: On Roadway; Work Zone: None.

5. Pedestrian Crashes not at Intersections [

6. **Table** 7.40]:

a. FARS (Los Angeles City): Single-Vehicle Crash; First Harmful Event: Pedestrian; Interstate: Non-Interstate; Intersection: Not At Intersection; Involving A Pedestrian: Yes; Roadway Function Class: Principal arterial, other ; or Minor arterial ; or Collector ; or Local ; or Unknown; Land Use (Rural/Urban): Urban; Native American Reservations4: No; Relation to Junction-Specific Location(since 2010): Non-Junction; Special Jurisdiction: No Special Jurisdiction; Work Zone: None.

b. CRSS (National): Crash Type: Single-Vehicle Crash; First Harmful Event: Pedestrian; Interstate: Non-Interstate; Intersection: Not At Intersection; Relationship To The Trafficway: On Roadway; Work Zone: None.

Table 7.38: Fatality Crash Exposure Scenario A (City: Los Angeles), FARS 2019-2023.

Intersection Type	**4-Way**											
Speeding	Yes						No					
Weather	Clear		Rain		Cloudy		Clear		Rain		Cloudy	
Light Condition	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Crash Counts	22	37	0	0	1	2	27	34	0	0	1	3
Crash Proportion (%)	13.50%	22.70%	0.00%	0.00%	0.61%	1.23%	16.56%	20.86%	0.00%	0.00%	0.61%	1.84%
Difference with National (%)	7.69%	16.89%	-5.81%	-5.81%	-5.19%	-4.58%	10.76%	15.05%	-5.81%	-5.81%	-5.19%	-3.97%
Intersection Type	3-Way											
Speeding	Yes						No					
Weather	Clear		Rain		Cloudy		Clear		Rain		Cloudy	
Light Condition	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Crash Count	7	9	0	0	1	0	8	6	0	0	1	1
Crash Proportion (%)	4.29%	5.52%	0.00%	0.00%	0.61%	0.00%	4.91%	3.68%	0.00%	0.00%	0.61%	0.61%

Difference with National (%)	-1.51%	-0.29%	-5.81%	-5.81%	-5.19%	-5.81%	-0.90%	-2.13%	-5.81%	-5.81%	-5.19%	-5.19%

Table 7.39: Fatality Crash Exposure Scenario B - Intersection (City: Los Angeles), FARS 2019-2023.

Intersection Type	**4-Way**											
Speeding	Yes						No					
Weather	Clear		Rain		Cloudy		Clear		Rain		Cloudy	
Light Condition	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Crash Counts	3	20	0	0	0	2	28	62	0	0	1	9
Crash Proportion (%)	1.58%	10.53%	0.00%	0.00%	0.00%	1.05%	14.74%	32.63%	0.00%	0.00%	0.53%	4.74%
Difference with National (%)	0.84%	9.78%	-0.74%	-0.74%	-0.74%	0.31%	14.00%	31.89%	-0.74%	-0.74%	-0.22%	4.00%
Intersection Type	3-Way											
Speeding	Yes						No					
Weather	Clear		Rain		Cloudy		Clear		Rain		Cloudy	
Light Condition	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Crash Count	1	3	0	0	0	0	6	45	0	0	0	2

Crash Proportion (%)	0.53%	1.58%	0.00%	0.00%	0.00%	0.00%	3.16%	23.68%	0.00%	0.00%	0.00%	1.05%
Difference with National (%)	-0.22%	0.84%	-0.74%	-0.74%	-0.74%	-0.74%	2.42%	22.94%	-0.74%	-0.74%	-0.74%	0.31%

Table 7.40: Fatality Crash Exposure Scenario B - Midblock (City: Los Angeles), FARS 2019-2023.

Roadway Function	**Principle Arterial**											
Speeding	Yes						No					
Weather	Clear		Rain		Cloudy		Clear		Rain		Cloudy	
Light Condition	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Crash Counts	3	18	0	0	0	2	28	103	0	0	1	5
Crash Proportion (%)	1.19%	7.14%	0.00%	0.00%	0.00%	0.79%	11.11%	40.87%	0.00%	0.00%	0.40%	1.98%
Difference with National (%)	0.71%	6.66%	-0.48%	-0.48%	-0.48%	0.32%	10.63%	40.39%	-0.48%	-0.48%	-0.08%	1.51%
Roadway Function	Minor Arterial											
Speeding	Yes						No					
Weather	Clear		Rain		Cloudy		Clear		Rain		Cloudy	
Light Condition	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night

Crash Count	1	9	0	0	0	1	6	36	0	0	0	2
Crash Proportion (%)	0.40%	3.57%	0.00%	0.00%	0.00%	0.40%	2.38%	14.29%	0.00%	0.00%	0.00%	0.79%
Difference with National (%)	-0.08%	3.09%	-0.48%	-0.48%	-0.48%	-0.08%	1.90%	13.81%	-0.48%	-0.48%	-0.48%	0.32%
Roadway Function	Collector											
Speeding	Yes						No					
Weather	Clear		Rain		Cloudy		Clear		Rain		Cloudy	
Light Condition	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Crash Count	0	0	0	0	0	0	4	8	0	0	0	0
Crash Proportion (%)	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	1.59%	3.17%	0.00%	0.00%	0.00%	0.00%
Difference with National (%)	-0.48%	-0.48%	-0.48%	-0.48%	-0.48%	-0.48%	1.11%	2.70%	-0.48%	-0.48%	-0.48%	-0.48%
Roadway Function	Local											
Speeding	Yes						No					
Weather	Clear		Rain		Cloudy		Clear		Rain		Cloudy	
Light Condition	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
Crash Count	2	1	0	0	0	2	5	3	0	0	0	0
Crash Proportion (%)	0.79%	0.40%	0.00%	0.00%	0.00%	0.79%	1.98%	1.19%	0.00%	0.00%	0.00%	0.00%

Difference with National (%)	0.32%	-0.08%	-0.48%	-0.48%	-0.48%	0.32%	1.51%	0.71%	-0.48%	-0.48%	-0.48%	-0.48%

Crash probability per-encounter is derived from national statistics. As detailed in **Table 7.41**, on average $d = 2.32 \times 10^8$ licensed drivers accumulated $D = 3.15 \times 10^{12}$ VMT per year between 2019-2023, resulting in approximately $m = 13{,}539$ VMT per driver. Equation (5) depicts the probability of at least one crash occurring per driver a year, by crash severity, for the three crash populations are estimated based on the crash rate per VMT r as follows:

$$P(C|m,r) = 1 - \exp^{-m \times r} \quad \textbf{(5)}$$

Table 7.41: Licensed Drivers and Total VMT, 2019-2023.

Year	Licensed Drivers	Vehicle Miles Traveled (Millions)
2019	228,915,520	3,261,772
2020	228,195,802	2,903,622
2021	232,781,797	3,132,411
2022	235,086,153	3,196,191
2023	237,655,885	3,246,817
Average	232,527,031	3,148,163

Based on the statistics collected for Scenario A (Table 7.42) and B (Table 7.43), Table 7.44 presents the estimated annual crash probabilities per driver and the total estimated crashes for each population by crash severity.

Table 7.42: Scenario A National Crash Counts, 2019-2023.

Total Crashes				Intersection-related crashes		
Year	Fatality	Injury	PDO	Fatality	Injury	PDO
2019	33,487	1,916,344	4,806,253	4,473	721,488	1,726,487
2020	35,935	1,593,390	3,621,681	4,850	563,105	1,219,516
2021	39,785	1,727,608	4,335,820	5,326	615,330	1,469,108
2022	39,422	1,664,598	4,226,677	5,443	628,969	1,523,277
2023	37,654	1,697,252	4,403,453	5,311	652,552	1,626,226
Average	37,257	1,719,838	4,278,777	5,081	636,289	1,512,923
SD	2,607	120,650	427,644	408	57,819	191,417
Total	186,283	8,599,192	21,393,884	25,403	3,181,444	7,564,614
Crash Rate	1.18	54.63	135.91	0.16	20.21	48.06

Table 7.43: Scenario B National Crash Counts, 2019-2023.

Total Crashes				Intersection-related crashes			Non-intersection-related crashes		
Year	Fatality	Injury	PDO	Fatality	Injury	PDO	Fatality	Injury	PDO
2019	33,487	1,916,344	4,806,253	1,466	38,829	241	3,119	24,266	159
2020	35,935	1,593,390	3,621,681	1,326	25,062	382	3,261	20,554	759
2021	39,785	1,727,608	4,335,820	1,501	25,902	194	3,820	23,361	549
2022	39,422	1,664,598	4,226,677	1,532	31,313	875	3,848	25,112	388
2023	37,654	1,697,252	4,403,453	1,516	32,170	445	3,727	23,987	532
Average	37,257	1,719,838	4,278,777	1,468	30,655	427	3,555	23,456	477
SD	2,607	120,650	427,644	83	5,555	270	340	1,740	222
Total	186,283	8,599,192	21,393,884	7,341	153,276	2,137	17,775	117,280	2,387
Crash Rate	0.02	0.73	1.82	0.05	0.97	0.01	0.11	0.75	0.02

Fatality crashes serve as the scaling point, using the local (FARS, Los Angeles) fatality counts in combination with the national fatality/injury/PDO crash-severity proportions from CRSS. For Scenario A, the annual average of 32.6 fatality crashes at intersections (

Table 7.38) is scaled by the 27% share of red-light-running conflicts established in Section 3.1.1. For Scenario B, the annual averages are 38 fatality crashes at intersections (

Table 7.39) and and 50.4 fatality crashes at non-intersection locations (

Table 7.40). These city-wide totals are then scaled to the 92-intersection, 1-square-mile reference deployment area, which represents approximately 4.5% of Los Angeles's total traffic volume, producing the crash-count equivalents in Table 7.44. Replicating these crash counts on the V2XPRA interface leads to the crash-calibration nodes in the corresponding Fault Tree models depicted in Figure 7.8 and Figure 7.11 for Scenario A, and Figure 7.21 for Scenario B.

Table 7.44: Estimated crash probability per crash severity (L0).

Scenario	Crash Values	Fatality	Injury	PDO	Total	No Collision
A – Intersections, Vehicle Crashes; 27% Red-light running conflicts.	Crash Probability (CRSS)	6.118E-06	7.651E-04	1.816E-03	2.587E-03	9.908E-01
	Crash Count Equivalent (1sq mile)	0.41	51.49	122.21	174.11	66,676
B – Intersection, Vehicle-Pedestrian Crashes	Crash Probability (CRSS)	6.314E-06	1.318E-04	1.838E-06	1.400E-04	9.999E-01
	Crash Count Equivalent (1sq mile)	1.71	35.78	0.50	38	271,415
B – Non-Intersection, Vehicle-Pedestrian Crashes	Crash Probability (CRSS)	1.529E-05	1.009E-04	2.053E-06	1.182E-04	9.999E-01
	Crash Count Equivalent (1sq mile)	2.27	15.00	0.31	17.58	148,675

C.3.2. Level 2-4 Models

Level 2 and Level 4 crash probabilities are approximated by applying reported industry crash-reduction statistics directly to the Level 0 estimates above. No secondary reductions in crash severity are modeled; the available evidence supports only a direct scaling of crash probability, not a shift in the severity distribution conditional on a crash occurring. The most relevant real-world data points are:

AEB and PAEB (Level 2): As a conservative baseline, AEB and PAEB actuation introduce a new recovery path, here considered independent to the driver's braking failure probability. For Scenario A, AEB effectiveness is anchored to the PARTS (2025) estimate for crashes at intersections (44.4%), adopted as a ceiling for angle crashes (Section C.1.3). Pedestrian AEB was associated with reductions of 25–27% in pedestrian crash risk overall and reductions in pedestrian injury crash risk were 29–30%. However, in this initial study, crash reductions did not occur in the dark, at speed limits 50+ mph, or while turning[197]. A larger PARTS (2025) study showed a 9% reduction in single-vehicle frontal crashes with non-motorists, including pedestrians, cyclists, scooters, and wheelchairs. AEB overall improved from 46% effectiveness across MY2015–2017 to 52% across MY2021–2023[198]. Based on this evidence, a flat 26% crash-rate reduction is applied to both midblock and intersection crossings in Scenario B, resulting in Table 7.45. For Scenario A, the L2 crash probabilities follow from the AEB node (A.4.2.3) combined with the L0 driver model, resulting in an L2 no-V2X baseline approximately 44% below L0. These values feed the PAEB efficiency modifier in the Scenario B Bayesian network (Table 7.30).

ADS (Level 4): At 56.7 million miles through January 2025, Waymo's driverless fleet showed a 96% reduction in any-injury-reported vehicle-to-vehicle intersection crashes relative to a human-driver benchmark (87–99% confidence interval), the largest reduction observed across crash types[199]. Comparing Waymo's reported crash rates against this project's own Level 0 baseline crash probabilities yields scenario-specific reduction factors of 85% for intersection vehicle conflicts (Scenario A, Los Angeles-level) and 92% for pedestrian conflicts (Scenario B, national-level); these factors are applied directly to the

[197] J. B. Cicchino, "Effects of automatic emergency braking systems on pedestrian crash risk," Accident Analysis & Prevention, vol. 172, p. 106686, July 2022, doi: 10.1016/j.aap.2022.106686.

[198] Partnership for Analytics Research in Traffic Safety (PARTS), "A study on real-world effectiveness of model year 2015–2023 advanced driver assistance systems," The MITRE Corp., McLean, VA, USA, Rep. PR 25-0114, Jan. 2025. [Online]. Available: https://www.mitre.org/sites/default/files/2025-01/PR-25-0114-Study-Real-world-Effectiveness-Model-year-2015%E2%80%932023-ADAS.pdf

[199] K. D. Kusano, J. M. Scanlon, Y. H. Chen, T. L. McMurry, T. Gode, and T. Victor, "Comparison of Waymo Rider-Only crash rates by crash type to human benchmarks at 56.7 million miles," Traffic Injury Prevention, vol. 26, no. sup1, May 2025, doi: 10.1080/15389588.2025.2499887.

Level 0 probabilities to produce Table 7.46. Replicating the estimated crash counts on the V2XPRA interface produces the crash-calibration nodes depicted in Figure 7.9 and Figure 7.12 (Scenario A), and Figure 7.22 (Scenario B).

Table 7.45: Estimated crash probability per crash severity (L2).

Scenario	Crash Values	Fatality	Injury	PDO	Total	No Collision
A – Intersections, Vehicle Crashes; 27% Red-light running conflicts.	Crash Probability (CRSS)	3.401E-06	4.254E-04	1.010E-03	1.438E-03	9.986E-01
	Crash Count Equivalent (1sq mile)	0.23	28.63	67.95	96.81	67,201
B – Intersection, Vehicle-Pedestrian Crashes	Crash Probability (CRSS)	4.672E-06	9.755E-05	1.360E-06	1.036E-04	9.998E-01
	Crash Count Equivalent (1sq mile)	1.27	26.48	0.37	28.12	271,425
B – Non-Intersection, Vehicle-Pedestrian Crashes	Crash Probability (CRSS)	1.131E-05	7.464E-05	1.519E-06	8.748E-05	9.999E-01
	Crash Count Equivalent (1sq mile)	1.68	11.10	0.23	13.01	148,680

Table 7.46: Estimated crash probability per crash severity (L4).

Scenario	Crash Values	Fatality	Injury	PDO	Total	No Collision
A – Intersections, Vehicle Crashes; 27% Red-light running conflicts.	Crash Probability (CRSS)	9.177E-07	1.148E-04	2.724E-04	3.881E-04	9.996E-01
	Crash Count Equivalent (1sq mile)	0.06	7.72	18.33	26.12	67,272
B – Intersection,	Crash Probability (CRSS)	5.051E-07	1.055E-05	1.470E-07	1.120E-05	~1.000E+00

Scenario	Crash Values	Fatality	Injury	PDO	Total	No Collision
Vehicle-Pedestrian Crashes	Crash Count Equivalent (1sq mile)	0.14	2.86	0.04	3.04	271,451
B – Non-Intersection, Vehicle-Pedestrian Crashes	Crash Probability (CRSS)	1.2231E-06	8.0695E-06	1.6425E-07	9.457E-06	~1.000E+00
	Crash Count Equivalent (1sq mile)	0.18	1.20	0.02	1.41	148,691

Appendix D. Results – Supporting Material

D.1. Scenario A: RLVW

D.1.1. Crash and associated costs

Table 7.47: Point estimates for crashes and costs, avoided and total (at equipped locations only and total study area) per V2I and CV deployment rates for no automation case (L0), enhanced RLVW.

V2I Deployment %	CV Deployment %	Avoided		Equipped Locations Only		Total Study Area	
		Crashes	Cost (million USD)	Crashes	Cost (million USD)	Crashes	Cost (million USD)
V2I: 25%	CV:0%	n/a	n/a	28.25	$4.08	116.57	$16.84
	CV:25%	8.13	$1.17	20.13	$2.91	108.44	$15.67
	CV:50%	14.99	$2.17	13.27	$1.92	101.58	$14.68
	CV:75%	20.32	$2.94	7.93	$1.15	96.25	$13.91
	CV:100%	23.95	$3.46	4.31	$0.62	92.62	$13.38
V2I: 50%	CV:0%	n/a	n/a	61.64	$8.91	116.57	$16.84
	CV:25%	17.77	$2.57	43.87	$6.34	98.80	$14.27
	CV:50%	32.74	$4.73	28.90	$4.18	83.83	$12.11
	CV:75%	44.37	$6.41	17.27	$2.50	72.20	$10.43
	CV:100%	52.27	$7.55	9.37	$1.35	64.30	$9.29
V2I: 75%	CV:0%	n/a	n/a	92.42	$13.35	116.57	$16.84
	CV:25%	26.60	$3.84	65.82	$9.51	89.97	$13.00
	CV:50%	49.04	$7.09	43.38	$6.27	67.53	$9.76
	CV:75%	66.48	$9.60	25.94	$3.75	50.09	$7.24
	CV:100%	78.34	$11.32	14.08	$2.03	38.23	$5.52
V2I: 100%	CV:0%	n/a	n/a	116.57	$16.84	116.57	$16.84
	CV:25%	33.56	$4.85	83.01	$11.99	83.01	$11.99

V2I Deployment %	CV Deployment %	Avoided		Equipped Locations Only		Total Study Area	
		Crashes	Cost (million USD)	Crashes	Cost (million USD)	Crashes	Cost (million USD)
	CV:50%	61.86	$8.94	54.70	$7.90	54.70	$7.90
	CV:75%	83.86	$12.12	32.71	$4.73	32.71	$4.73
	CV:100%	98.81	$14.28	17.76	$2.57	17.76	$2.57

Table 7.48: Point estimates for crashes and costs, avoided and total (equipped locations and study area) per V2I and CV deployment rates for Level 2 automation case (L2), enhanced RLVW.

V2I Deployment %	CV Deployment %	Avoided		Equipped Location		Study Area	
		Crashes	Cost (million USD)	Crashes	Cost (million USD)	Crashes	Cost (million USD)
V2I: 25%	CV:0%	n/a	n/a	15.71	$2.27	64.81	$9.36
	CV:25%	5.43	$0.79	10.27	$1.48	59.38	$8.58
	CV:50%	9.78	$1.41	5.93	$0.86	55.03	$7.95
	CV:75%	12.88	$1.86	2.83	$0.41	51.94	$7.50
	CV:100%	14.67	$2.12	1.04	$0.15	50.14	$7.24
V2I: 50%	CV:0%	n/a	n/a	34.27	$4.95	64.81	$9.36
	CV:25%	11.84	$1.71	22.43	$3.24	52.97	$7.65
	CV:50%	21.32	$3.08	12.95	$1.87	43.49	$6.28
	CV:75%	28.09	$4.06	6.19	$0.89	36.73	$5.31
	CV:100%	32.01	$4.62	2.27	$0.33	32.81	$4.74
V2I: 75%	CV:0%	n/a	n/a	51.39	$7.42	64.81	$9.36
	CV:25%	17.77	$2.57	33.62	$4.86	47.04	$6.80
	CV:50%	31.98	$4.62	19.41	$2.80	32.84	$4.74
	CV:75%	42.12	$6.08	9.27	$1.34	22.70	$3.28
	CV:100%	47.99	$6.93	3.39	$0.49	16.82	$2.43
V2I: 100%	CV:0%	n/a	n/a	64.81	$9.36	64.81	$9.36
	CV:25%	22.41	$3.24	42.41	$6.13	42.41	$6.13
	CV:50%	40.33	$5.83	24.48	$3.54	24.48	$3.54
	CV:75%	53.12	$7.67	11.69	$1.69	11.69	$1.69
	CV:100%	60.53	$8.75	4.28	$0.62	4.28	$0.62

Table 7.49: Point estimates for crashes and costs, avoided and total (equipped locations and study area) per V2I and CV deployment rates for Level 4 automation case (L4), enhanced RLVW.

V2I Deployment %	CV Deployment %	Avoided		Equipped Location		Study Area	
		Crashes	Cost (million USD)	Crashes	Cost (million USD)	Crashes	Cost (million USD)
V2I: 25%	CV:0%	n/a	n/a	4.24	$0.61	17.49	$2.53
	CV:25%	1.13	$0.16	3.11	$0.45	16.36	$2.36
	CV:50%	2.15	$0.31	2.09	$0.30	15.33	$2.22
	CV:75%	3.03	$0.44	1.21	$0.17	14.46	$2.09
	CV:100%	3.74	$0.54	0.50	$0.07	13.74	$1.99
V2I: 50%	CV:0%	n/a	n/a	9.25	$1.34	17.49	$2.53
	CV:25%	2.50	$0.36	6.74	$0.97	14.98	$2.16
	CV:50%	4.72	$0.68	4.52	$0.65	12.76	$1.84
	CV:75%	6.62	$0.96	2.62	$0.38	10.86	$1.57
	CV:100%	8.17	$1.18	1.08	$0.16	9.32	$1.35
V2I: 75%	CV:0%	n/a	n/a	13.86	$2.00	17.49	$2.53
	CV:25%	3.71	$0.54	10.16	$1.47	13.78	$1.99
	CV:50%	7.05	$1.02	6.81	$0.98	10.43	$1.51
	CV:75%	9.91	$1.43	3.95	$0.57	7.57	$1.09
	CV:100%	12.24	$1.77	1.62	$0.23	5.24	$0.76
V2I: 100%	CV:0%	n/a	n/a	17.49	$2.53	17.49	$2.53
	CV:25%	4.68	$0.68	12.80	$1.85	12.80	$1.85
	CV:50%	8.90	$1.29	8.58	$1.24	8.58	$1.24
	CV:75%	12.51	$1.81	4.98	$0.72	4.98	$0.72
	CV:100%	15.44	$2.23	2.05	$0.30	2.05	$0.30

D.1.2. Importance measures

Table 7.50: Importance Measures for Scenario A, L0.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
HV Comms Failure (RX)	2.800	1.860		1.540	1.390	
Red Light Running (HV)	2.320	1.040	1.180	2.530	1.110	1.400
EV_Msg_RX (BN)	2.150	2.150		1.450	1.450	
HV Failure Comms (TX)	1.770	1.770		1.390	1.390	
Driver Fails to Stop (EV)	1.323	1.323	1.073	4.100	4.104	1.860
Stopping Failure (HV)	1.110	1.050	1.070	5.160	1.760	2.040
SPaT/MAP Data Error (DATA)	1.040	1.040		2.080	2.080	
RSU Failure Comms (TX)	1.034	1.034		2.076	2.076	
HV Ignores Warning (HV)	1.030	1.010		1.220	1.010	
BSM Incorrect (DATA)	1.030	1.030		1.360	1.360	
Driver Ignores Warning (EV)	1.014	1.014		1.110	1.110	
RSU Reliability (Edge Device)	1.000	1.000		2.076	2.076	
OBU-Health (HV/EV)	1.000	1.000		1.110	1.110	

Table 7.51: Importance Measures for Scenario A, L2.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
AEB	372.000	372.000	1.340	1.730	1.730	1.180
Red Light Running (HV)	10.800	1.120	1.030	3.420	1.280	1.050
HV Comms Failure (RX)	7.110	2.410		1.720	1.490	
EV_Msg_RX (BN)	3.010	3.010		1.560	1.560	
HV Failure Comms (TX)	1.960	1.960		1.430	1.430	
OBU-Health (HV/EV)	1.320	1.320		1.000	1.000	
ADS Fails to Stop (EV)	1.050	1.050	1.010	4.370	4.370	1.100
RSU Reliability (Edge Device)	1.000	1.000		0.034	0.034	
L2 Stop (Warned)	1.000	1.000		1.400	1.030	
Stopping Failure (HV)	0.996	0.992	0.992	0.669	0.811	0.816
RSU Failure Comms (TX)	0.975	0.975		0.034	0.034	
SPaT/MAP Data Error (DATA)	0.973	0.973		0.034	0.034	
BSM Incorrect (DATA)	0.947	0.947		0.259	0.259	

Table 7.52: Importance Measures for Scenario A, L4.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
HV Comms Failure (RX)	5.380	3.620		0.796	0.715	
EV_Msg_RX (BN)	4.190	4.190		0.735	0.735	
Red Light Running (HV)	4.080	2.070	2.380	21.300	2.400	7.400
HV Failure Comms (TX)	3.910	3.910		0.734	0.734	
ADS Fails to Stop (EV)	2.490	2.490	2.240	9.700	9.700	5.720
BSM Incorrect (DATA)	2.150	2.150		1.040	1.040	
SPaT/MAP Data Error (DATA)	2.140	2.140		1.740	1.740	
RSU Failure Comms (TX)	2.130	2.130		1.740	1.740	
Stopping Failure (HV)	1.970	2.120	2.430	44.500	4.120	10.000
RSU Reliability (Edge Device)	1.970	1.970		1.740	1.740	
OBU-Health (HV/EV)	1.970	1.970		0.552	0.552	

D.2. Scenario B: PED-CP

D.2.1. Crash and associated costs

Table 7.53: Point estimates for crashes and costs, avoided and total (equipped locations and study area) per V2I and CV deployment rates for no automation case (L0).

V2I Deployment %	CV Deployment %	Avoided		Equipped Location		Study Area	
		Crashes	Cost (million USD)	Crashes	Cost (million USD)	Crashes	Cost (million USD)
V2I: 25%	CV:0%	n/a	n/a	13.69	$20.14	55.77	$79.09
	CV:25%	4.61	$6.76	9.08	$13.38	51.16	$72.33
	CV:50%	7.60	$11.35	6.09	$8.79	48.17	$67.74
	CV:75%	9.16	$13.95	4.52	$6.19	46.60	$65.14
	CV:100%	9.78	$15.08	3.91	$5.06	45.99	$64.01
V2I: 50%	CV:0%	n/a	n/a	32.07	$45.59	55.77	$79.09
	CV:25%	11.01	$15.44	21.06	$30.15	44.75	$63.65
	CV:50%	18.00	$25.82	14.07	$19.77	37.76	$53.27
	CV:75%	21.60	$31.60	10.47	$14.00	34.16	$47.49
	CV:100%	22.98	$34.07	9.09	$11.52	32.79	$45.02
V2I: 75%	CV:0%	n/a	n/a	44.29	$63.37	55.77	$79.09
	CV:25%	14.93	$21.15	29.37	$42.22	40.84	$57.94
	CV:50%	24.58	$35.59	19.71	$27.77	31.18	$43.50
	CV:75%	29.57	$43.66	14.72	$19.71	26.20	$35.43
	CV:100%	31.49	$47.13	12.80	$16.24	24.28	$31.96
V2I: 100%	CV:0%	n/a	n/a	55.77	$79.09	55.77	$79.09
	CV:25%	18.85	$26.47	36.91	$52.62	36.91	$52.62
	CV:50%	30.98	$44.45	24.78	$34.64	24.78	$34.64
	CV:75%	37.22	$54.45	18.54	$24.64	18.54	$24.64
	CV:100%	39.61	$58.73	16.16	$20.36	16.16	$20.36

Table 7.54: Point estimates for crashes and costs, avoided and total (equipped locations and study area) per V2I and CV deployment rates for Level 2 automation case (L2).

V2I Deployment %	CV Deployment %	Avoided		Equipped Location		Study Area	
		Crashes	Cost (million USD)	Crashes	Cost (million USD)	Crashes	Cost (million USD)
V2I: 25%	CV:0%	n/a	n/a	10.13	$14.90	41.27	$58.53
	CV:25%	4.17	$5.78	5.96	$9.12	37.10	$52.74
	CV:50%	6.78	$9.61	3.34	$5.29	34.48	$48.92
	CV:75%	8.12	$11.72	2.01	$3.18	33.15	$46.80
	CV:100%	8.63	$12.62	1.50	$2.28	32.64	$45.90
V2I: 50%	CV:0%	n/a	n/a	23.73	$33.74	41.27	$58.53
	CV:25%	9.87	$13.21	13.87	$20.53	31.40	$45.31
	CV:50%	16.02	$21.92	7.71	$11.82	25.25	$36.61
	CV:75%	19.12	$26.65	4.62	$7.08	22.15	$31.87
	CV:100%	20.26	$28.62	3.48	$5.12	21.01	$29.91
V2I: 75%	CV:0%	n/a	n/a	32.78	$46.89	41.27	$58.53
	CV:25%	13.57	$18.28	19.20	$28.61	27.69	$40.25
	CV:50%	22.06	$30.38	10.71	$16.52	19.21	$28.15
	CV:75%	26.35	$36.98	6.43	$9.91	14.92	$21.55
	CV:100%	27.94	$39.73	4.84	$7.16	13.33	$18.80
V2I: 100%	CV:0%	n/a	n/a	41.27	$58.53	41.27	$58.53
	CV:25%	17.15	$22.90	24.12	$35.62	24.12	$35.62
	CV:50%	27.84	$38.01	13.43	$20.52	13.43	$20.52
	CV:75%	33.21	$46.21	8.05	$12.31	8.05	$12.31
	CV:100%	35.19	$49.61	6.08	$8.91	6.08	$8.91

Table 7.55: Point estimates for crashes and costs, avoided and total (equipped locations and study area) per V2I and CV deployment rates for Level 4 automation case (L4).

V2I Deployment %	CV Deployment %	Avoided		Equipped Location		Study Area	
		Crashes	Cost (million USD)	Crashes	Cost (million USD)	Crashes	Cost (million USD)
V2I: 25%	CV:0%	n/a	n/a	1.09	$1.61	4.46	$6.33
	CV:25%	0.30	$0.46	0.80	$1.15	4.16	$5.87
	CV:50%	0.49	$0.77	0.60	$0.84	3.97	$5.56
	CV:75%	0.59	$0.93	0.51	$0.68	3.87	$5.39
	CV:100%	0.62	$0.99	0.48	$0.62	3.85	$5.34
V2I: 50%	CV:0%	n/a	n/a	2.57	$3.65	4.46	$6.33
	CV:25%	0.73	$1.07	1.83	$2.58	3.73	$5.26
	CV:50%	1.18	$1.76	1.39	$1.89	3.28	$4.57
	CV:75%	1.39	$2.12	1.17	$1.53	3.07	$4.21
	CV:100%	1.46	$2.24	1.11	$1.41	3.01	$4.09
V2I: 75%	CV:0%	n/a	n/a	3.54	$5.07	4.46	$6.33
	CV:25%	0.98	$1.44	2.57	$3.62	3.48	$4.88
	CV:50%	1.60	$2.41	1.95	$2.66	2.87	$3.92
	CV:75%	1.89	$2.91	1.65	$2.15	2.57	$3.41
	CV:100%	1.98	$3.08	1.56	$1.99	2.48	$3.24
V2I: 100%	CV:0%	n/a	n/a	4.46	$6.33	4.46	$6.33
	CV:25%	1.23	$1.81	3.23	$4.52	3.23	$4.52
	CV:50%	2.01	$3.01	2.45	$3.32	2.45	$3.32
	CV:75%	2.38	$3.63	2.08	$2.70	2.08	$2.70
	CV:100%	2.49	$3.84	1.97	$2.49	1.97	$2.49

D.2.2. Importance measures

Table 7.56: Importance Measures for Scenario B, L0, Intersection.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
Stopping Failure (HV)	2.610	1.330	1.320	20.200	6.470	6.390
Driver Detection Failure (L0)	1.760	1.640	1.660	1.670	1.600	1.610
HV Comms Failure (RX)	1.460	1.340		1.270	1.220	
RSU Failure Comms (TX)	1.020	1.020		1.490	1.490	
Driver Ignores Warning (HV)	1.010	1.000		1.060	1.010	
Detection Error (RSU)	1.010	1.010		1.230	1.230	
RSU Reliability (Edge Device)	1.000	1.000		1.490	1.490	
SDSM Processing Error (Data)	1.000	1.000		1.490	1.490	
OBU-Health (HV)	1.000	1.000		1.010	1.010	

Table 7.57: Importance Measures for Scenario B, L0, Midblock.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
Driver Detection Failure (L0)	14.800	6.210	7.630	1.760	1.680	1.710

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
HV Comms Failure (RX)	2.820	1.850		1.570	1.400	
Detection Error (RSU)	1.110	1.110		1.870	1.870	
RSU Failure Comms (TX)	1.030	1.030		1.960	1.960	
Driver Ignores Warning (HV)	1.020	1.000		1.220	1.020	
RSU Reliability (Edge Device)	1.000	1.000		1.960	1.960	
SDSM Processing Error (Data)	1.000	1.000		1.960	1.960	
OBU-Health (HV)	1.000	1.000		1.020	1.020	
Stopping Failure (HV)	0.994	0.990	0.989	0.805	0.785	0.756

Table 7.58: Importance Measures for Scenario B, L2, Intersection.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
PAEB failure	22.900	1.860	1.760	1.340	1.160	1.150
HV Comms Failure (RX)	3.490	2.340		1.620	1.500	
L2 Detection Failure (Camera)	1.710	1.440	1.450	1.670	1.490	1.500
Stopping Failure (HV)	1.600	1.230	1.230	12.700	5.150	5.150
L2 Fails to Stop	1.340	1.020	1.020	13.600	2.770	2.790

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
Driver Ignores Warning (HV)	1.010	1.000		1.130	1.010	
RSU Reliability (Edge Device)	1.000	1.000		0.543	0.543	
SDSM Processing Error (Data)	1.000	1.000		0.543	0.543	
OBU-Health (HV)	1.000	1.000		1.130	1.010	
RSU Failure Comms (TX)	0.986	0.986		0.543	0.543	
Detection Error (RSU)	0.976	0.976		0.491	0.491	
Driver Detection Failure (L0)	0.768	1.910	1.870	1.610	1.730	1.720

Table 7.59: Importance Measures for Scenario B, L2, Midblock.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
Driver Detection Failure (L0)	5.250	4.130	1.630	1.660	1.610	4.430
PAEB failure	4.180	1.460	1.840	1.270	1.110	1.160
HV Comms Failure (RX)	2.740	1.820		1.560	1.400	
Detection Error (RSU)	1.110	1.110		1.830	1.830	
L2 Detection Failure (Camera)	1.040	1.010	1.020	1.050	1.020	1.030
RSU Failure Comms (TX)	1.030	1.030		1.940	1.940	

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
Driver Ignores Warning (HV)	1.020	1.000		1.220	1.020	
RSU Reliability (Edge Device)	1.000	1.000		1.940	1.940	
SDSM Processing Error (Data)	1.000	1.000		1.940	1.940	
OBU-Health (HV)	1.000	1.000		1.220	1.020	
L2 Fails to Stop	1.000	1.000	0.999	1.130	0.974	0.925
Stopping Failure (HV)	0.991	0.990	0.988	0.713	0.767	0.729

Table 7.60: Importance Measures for Scenario B, L4, Intersection.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
Stopping/Weather Failure (HV)	3.110	1.040	1.040	34.900	4.080	4.140
ADS Detection Failure (L4)	1.500	1.500	1.500	5.390	5.390	5.390
HV Comms Failure (RX)	1.340	1.260		1.220	1.180	
OBU-Health (HV)	1.000	1.000		1.040	1.040	
RSU Failure Comms (TX)	1.000	1.000		1.030	1.030	
SDSM Processing Error (Data)	1.000	1.000		1.030	1.030	

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
RSU Reliability (Edge Device)	1.000	1.000		1.030	1.030	
Detection Error (RSU)	0.995	0.995		0.893	0.893	

Table 7.61: Importance Measures for Scenario B, L4, Midblock.

Failure Mode / Node	RRW			RAW		
	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)	High Time Available (>5s)	Low Time Available (3s<t<5s)	Base (No V2X) (<3s)
ADS Detection Failure (L4)	4.190	4.190	4.190	10.400	10.400	10.400
HV Comms Failure (RX)	2.180	1.630		1.470	1.340	
Stopping/Weather Failure (HV)	1.210	1.020	1.030	9.760	2.340	3.390
Detection Error (RSU)	1.090	1.090		1.680	1.680	
RSU Failure Comms (TX)	1.030	1.030		1.820	1.820	
OBU-Health (HV)	1.000	1.000		1.160	1.160	
SDSM Processing Error (Data)	1.000	1.000		1.820	1.820	
RSU Reliability (Edge Device)	1.000	1.000		1.820	1.820	

Appendix E. Stakeholder Engagement

E.1. Questions for V2XPRA Agency Briefings

This section contains the questionnaire applied to the Accelerating V2X Cohort Meeting on June 1st, 2026 hosted by ITS Joint Program Office, U.S. Department of Transportation (U.S. DOT).

Q1. What type of organization do you represent?

Question type	Multiple choice
Answer options	State DOT Local/city transportation agency MPO/regional agency Transit agency Public safety / emergency response Private-sector technology provider Research/academic organization Other

Q2. What is your current level of involvement with V2X or connected infrastructure?

Question type	Multiple choice
Answer options	No current activity, but interested Early planning / feasibility study Pilot deployment underway Operational deployment at selected locations Broader corridor or regional deployment Not sure

Q3. Which decisions would a tool like V2XPRA help support in your agency?

Question type	Multiple select
Answer options	Prioritizing intersections or corridors for V2X deployment Estimating crashes avoided and safety benefits Supporting grant applications or benefit-cost analysis Comparing V2X use cases Communicating benefits to leadership or elected officials Planning phased deployment strategies Evaluating RSU / infrastructure investment levels Understanding uncertainty and risk Other

Q4. Which V2X safety applications would be most valuable for your agency to evaluate and would you like the V2XPRA to evaluate?

Question type	Ranking or multiple select
Answer options	Red-Light Violation Warning Pedestrian Collision Warning Curve Speed Warning Wrong-Way Driving Warning Emergency Vehicle Preemption / Warning Work Zone Warning Queue Warning / End-of-Queue Warning Signalized Intersection Movement Assist Transit Signal Priority safety impacts School zone warning Network V2X / cellular-based warning applications Freight or truck safety applications Railroad crossing warning Weather-related hazard warning Roadway obstruction / incident warning Other

Q5. What additional functions would make this tool more useful for your agency?

Question type	Multiple select with open-ended “Other”
Answer options	Upload our own crash data Upload our own traffic volume / AADT data Analyze user-selected corridors or intersections Compare multiple deployment scenarios side by side Estimate benefit-cost ratio for grant applications Include deployment cost assumptions Include operations and maintenance cost assumptions Include pedestrian and bicyclist exposure data Export a summary report for decision-makers Connect with agency GIS systems Support post-deployment evaluation Show uncertainty / sensitivity analysis for assumptions Other: _____

Q6. What are the biggest barriers to using V2X benefit analysis tools today?

Question type	Ranking
Answer options	Lack of local data Lack of staff time or technical capacity Uncertainty about V2X benefits Difficulty justifying investment Lack of standard methodology Lack of integration with existing GIS/planning tools Unclear deployment costs Unclear maintenance responsibilities Need for USDOT/state guidance Cybersecurity/privacy concerns

Q7. How valuable would a USDOT-supported V2X safety impact tool be for your agency?

Question type	Scale, 1-5
Answer options	1 = Not valuable 2 = Slightly valuable 3 = Moderately valuable 4 = Very valuable 5 = Extremely valuable

Q8. Would your agency be interested in participating in a future pilot, case study, or requirements workshop for this tool?

Question type	Multiple choice
Answer options	Yes, definitely Possibly, depending on scope Interested in learning more Not at this time Not sure

E.2. Questionnaire Answers

This section presents the answers from the Accelerating V2X Cohort Meeting of June 1st, 2026.

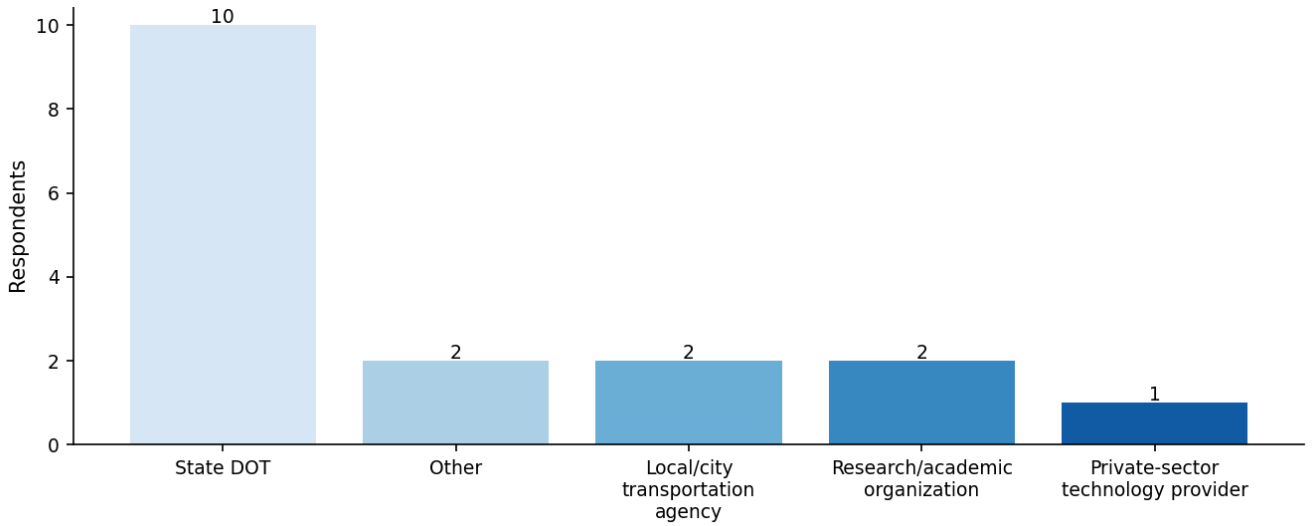

Figure 7.28: Q.1 - Organization Type (n=16 responders).

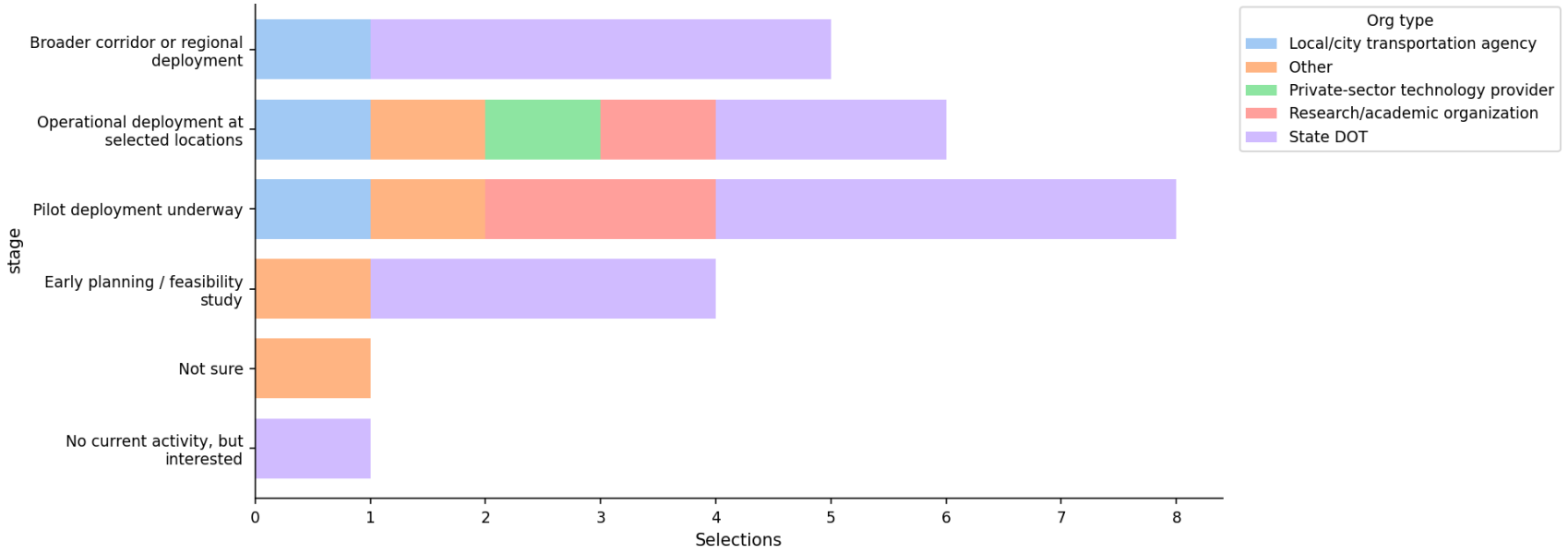

Figure 7.29: Q.2 - Current Level of V2X Involvement, by Organization Type.

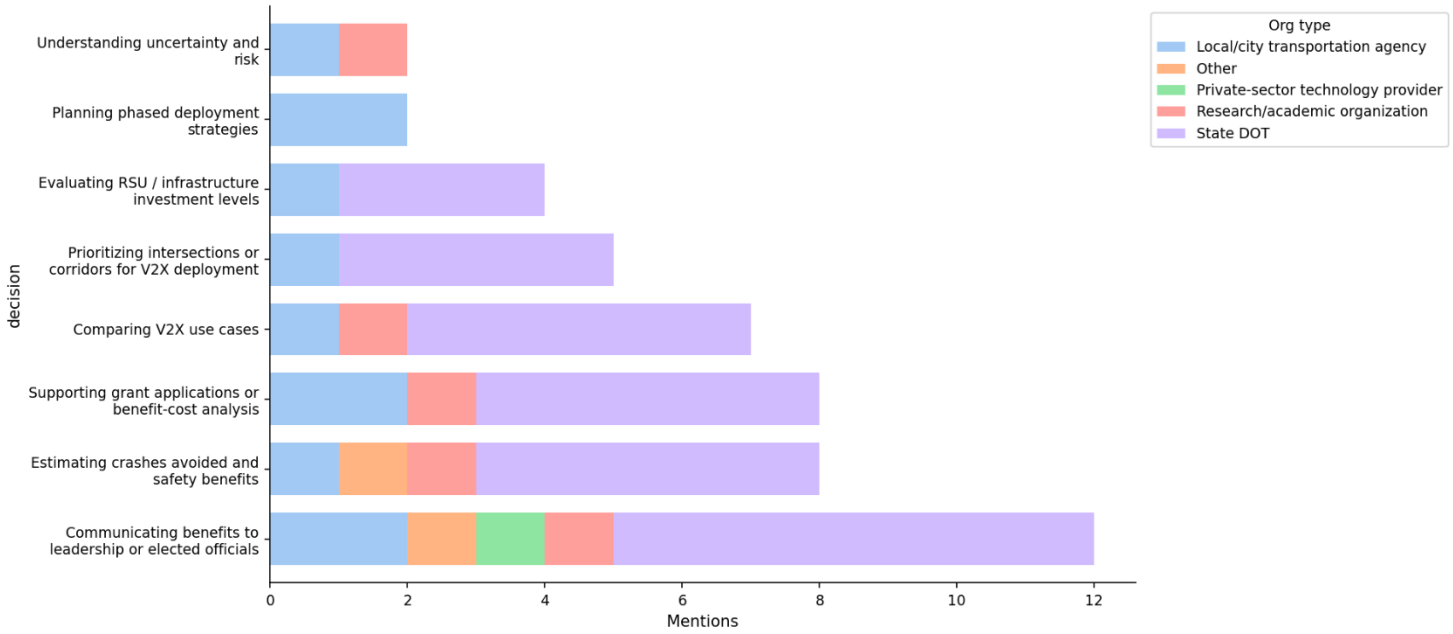

Figure 7.30: Q.3 – Decisions V2XPRA Would Support, by Organization Type.

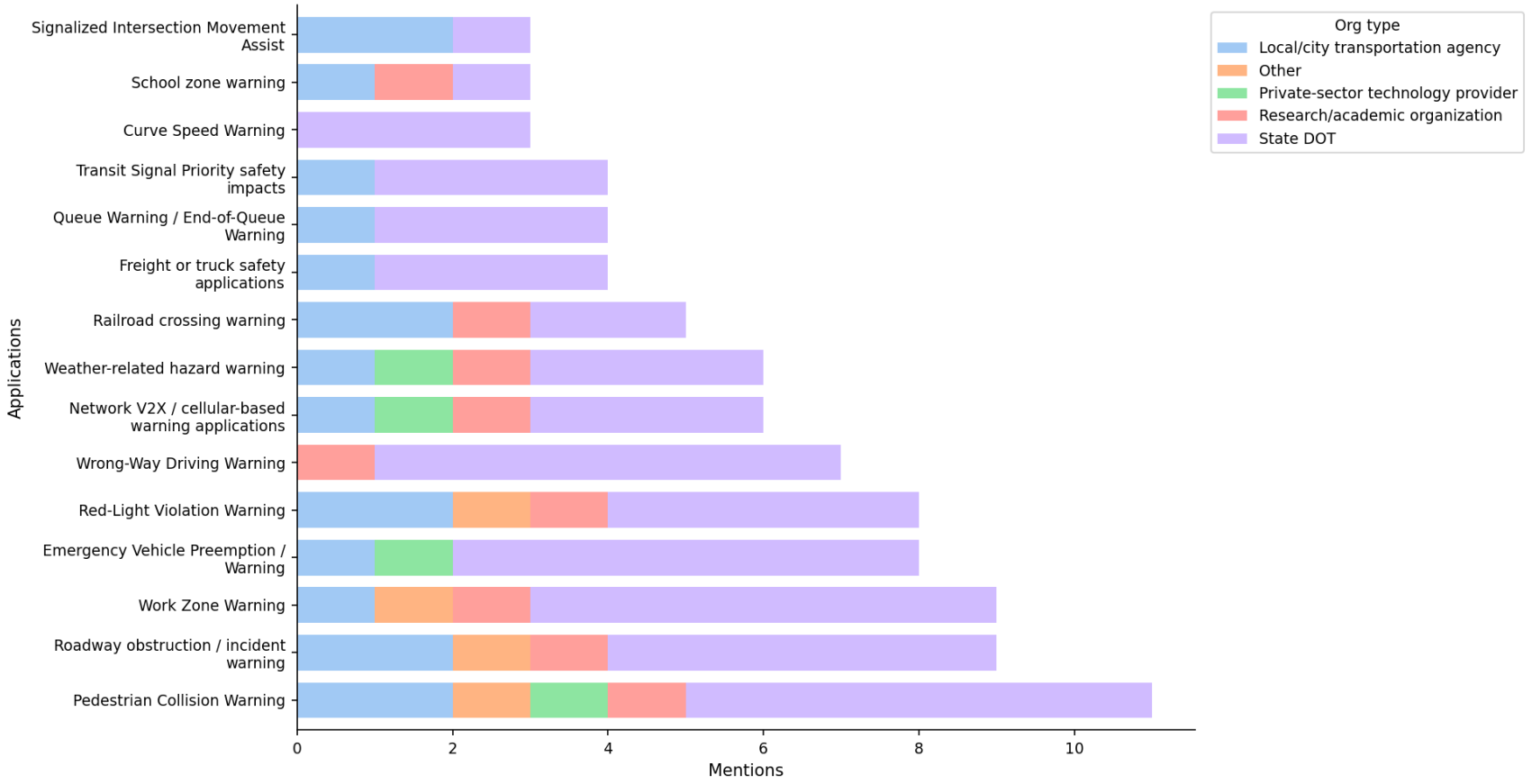

Figure 7.31: Q.4 – V2X Applications of Interest, by Organization Type.

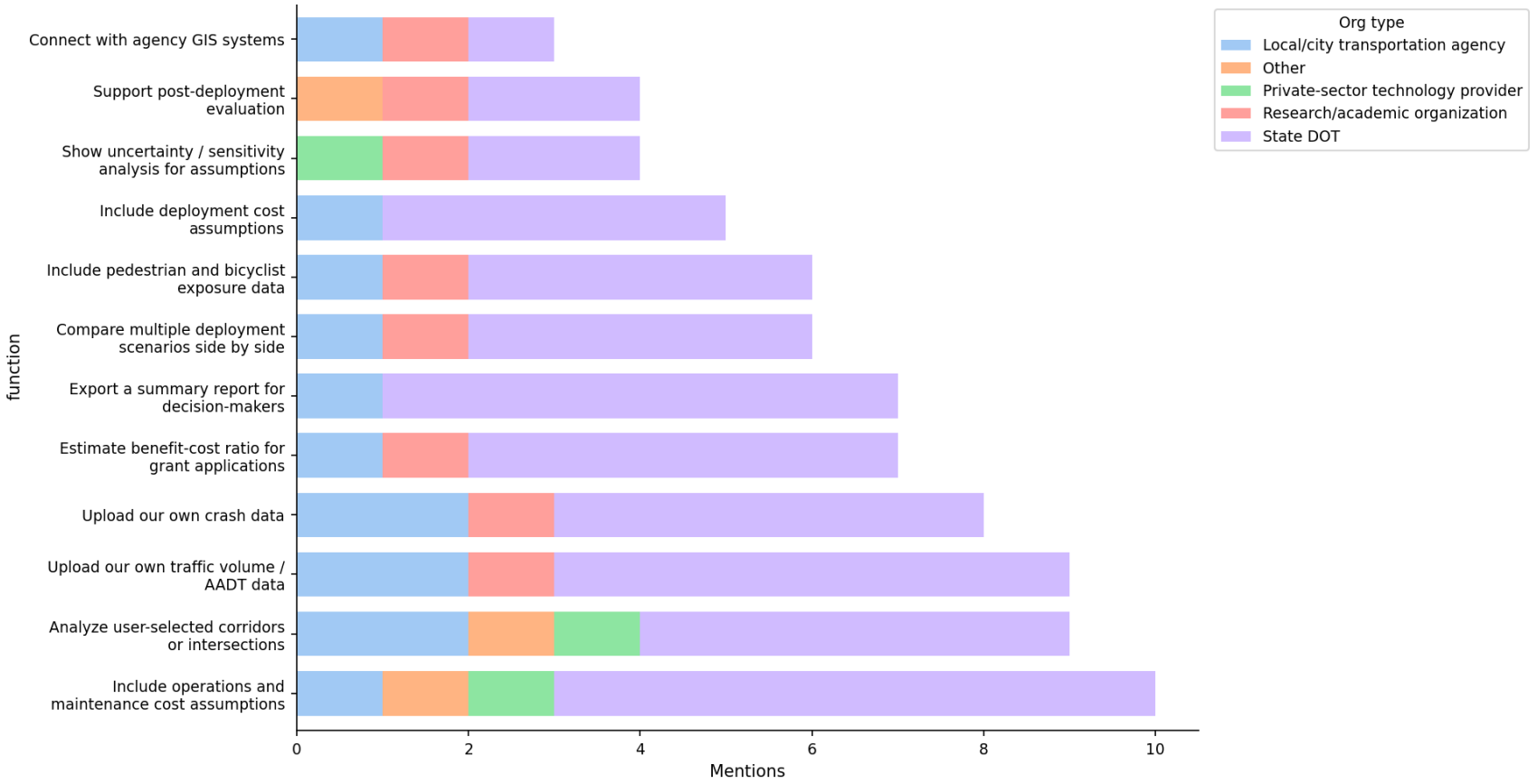

Figure 7.32: Q.5 – Additional Tool Functions Desired, by Organization Type.

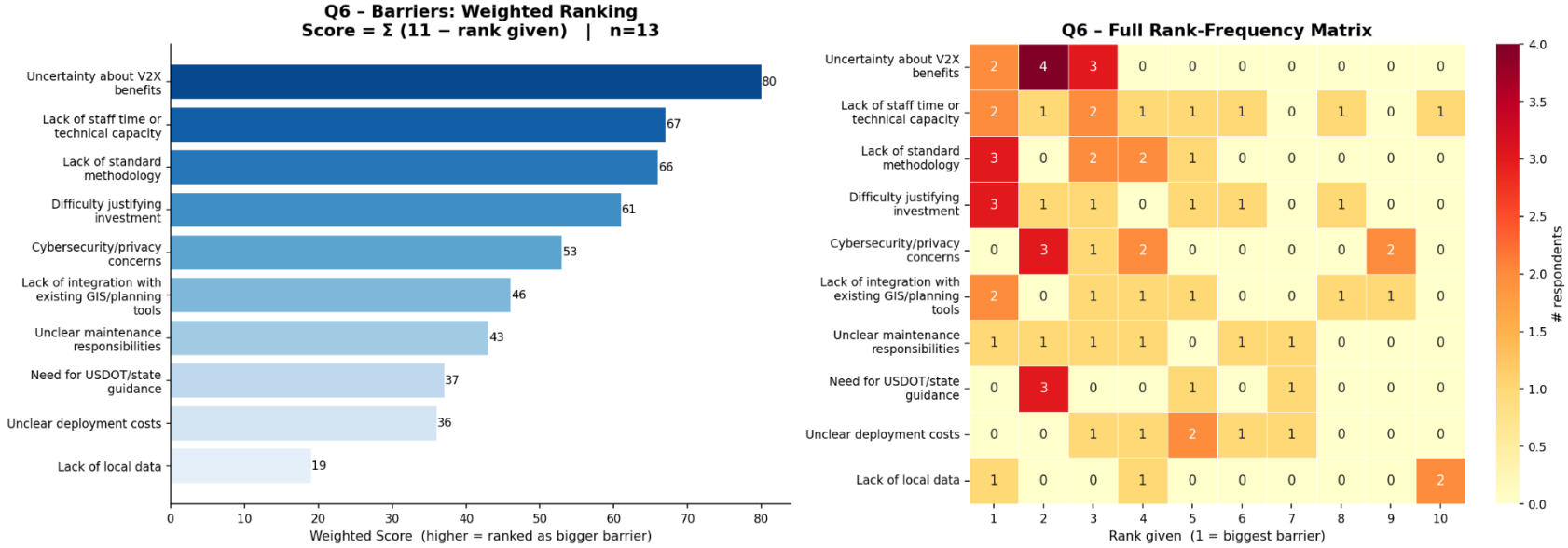

Figure 7.33: Q6 - Barriers for Deployment, Weighted Ranking (left) and Full Rank-Frequency Matrix (right).

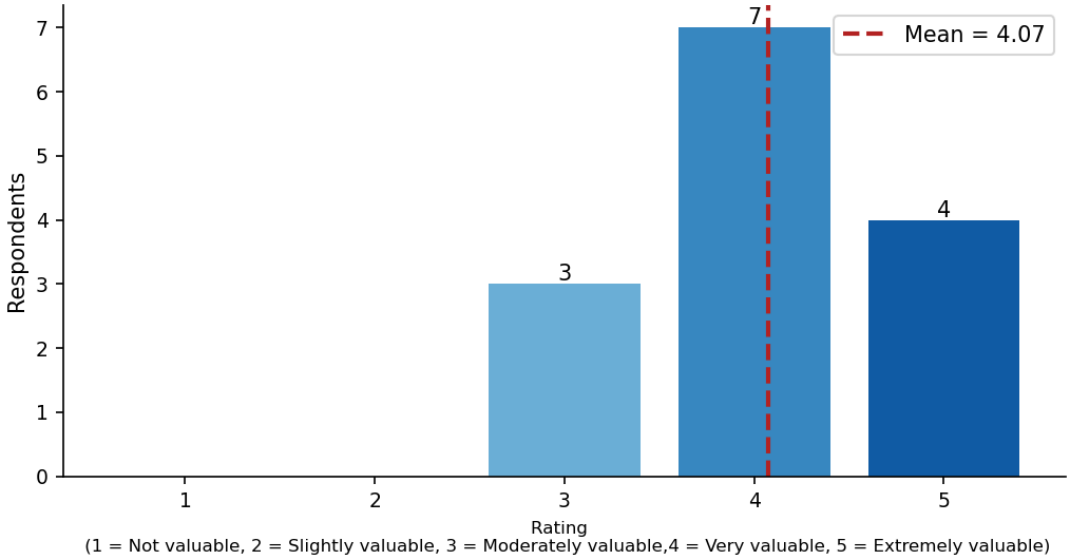

Figure 7.34: Q7 - Value Perceived of a V2X Safety Tool.

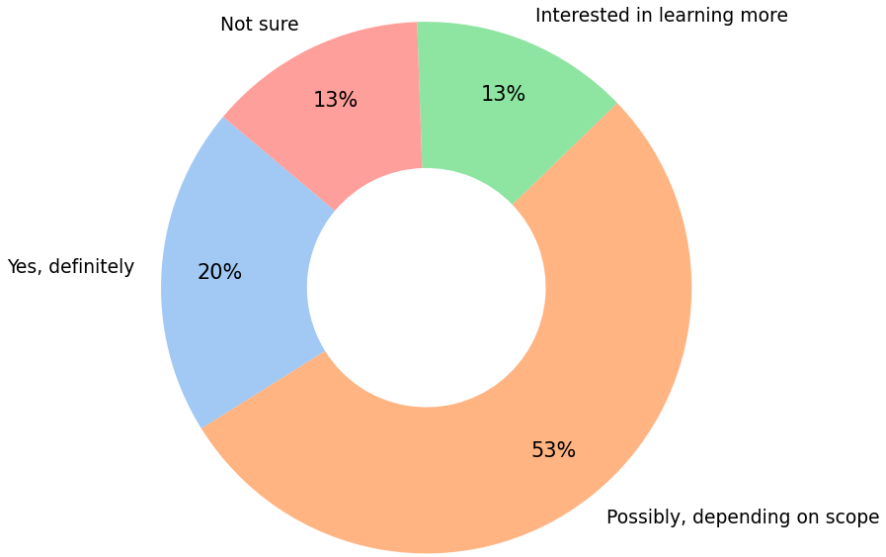

Figure 7.35: Q8 - Interest in Future Pilot/Workshop (n=14).

Appendix F. Tool Specifications and Market Analysis

TASK 3:
V2XPRA Prototype Tool Specification and technology transfer opportunities

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Part I. System Design Requirements

1. Introduction

1.1 Background

The V2XPRA platform is a geospatial, probabilistic risk assessment (PRA) tool designed to quantify and communicate the safety benefits of selected Vehicle-to-Everything (V2X) applications. Local and state agencies require explainable and clear decision-support tools to invest in infrastructure improvements to guide investment in connected infrastructure and to evaluate the potential safety impacts of adopting V2X technologies.

Building upon the work conducted in Phase I, V2XPRA dynamically calculates risk across geographic segments by instantiating Hybrid-Causal Logic (HCL) models using location-specific data and user-defined V2X interventions. This enables the quantification of crash likelihood reductions and secondary impacts such as congestion mitigation for targeted road segments.

1.2 Purpose

This System Design Requirements document provides a conceptual description of the V2XPRA tool, its intended functions, user interactions, and operational workflows. The specification outlines:

- User interface layout and interaction pathways
- Data inputs, transformations, and internal data flow
- Integration of HCL models and uncertainty quantification
- Use of GIS layers, traffic context, and incident history
- Methods for computing and visualizing safety benefit estimates

The document serves as the foundation for subsequent detailed functional requirements, design decisions, and implementation planning.

2. System Overview

2.1 System Description

The proposed system consists of a prototype tool (V2XPRA) that serves as a proof-of-concept for an web-based interactive dashboard showcasing risk-based safety impact estimations for selected V2X use cases. The dashboard allows users to select specific scenarios ("use cases") depicting Connected and Automated Vehicles (CAVs) and different levels of driving automation (L0, L2, L4) while focusing on Vehicle-to-Infrastructure (V2I) communication modality.

The V2XPRA tool will integrate probabilistic risk modeling, traffic-level contextualization using GIS data, and a user-centric interface. At its core, V2XPRA uses a probabilistic modeling engine based on HCL, which enables formal risk quantification, sensitivity analysis, and uncertainty propagation. The V2XPRA dashboard provides high-level safety benefit estimations based on avoided vehicle crashes and resulting congestion, depending on the user-selected scenarios.

2.2 System Objectives

The primary objectives of the V2XPRA system are to:

- Quantify the safety impacts of V2X and CAV interventions at road-link level.
- Provide an explainable and user-friendly interface that communicates expected safety benefits from avoided vehicle crashes and mitigated traffic congestion consequences.
- Incorporate traffic-level context such as roadway type, traffic volume and historical incident patterns to inform baseline risk conditions.
- Support scalable analysis through variable CAV market penetration levels and infrastructure deployment assumptions (i.e., deployed RSUs).
- Enable comparative evaluation of alternative strategies to support planning, policy development, and investment prioritization.

2.3 Constraints and Assumptions

The initial prototype is developed under the following constraints and assumptions:

2.3.1 User Access and Deployment

- Single-user operation for demonstration purposes to avoid concurrent model overwriting.
- Prototype deployment limited to predefined sample areas (approx. 1 sq. mile), constrained by the availability of GIS and infrastructure data.

Future expansions of the tool will incorporate additional user customization, such as importing agency-specific GIS data layers in formats specified by the developer and administrator team. This expanded functionality would enable agencies to tailor the road, weather, and traffic characteristics to other regions.

2.3.2 Modeling Assumptions

- Safety benefits are assumed to be localized to the selected road segment.

- Benefits across segments are assumed to aggregate independently (no propagation effects across adjacent links).
- Each use case is linked to a specific roadway context and associated automation level.
- Traffic and environmental data use annual averages, reflecting the tool's goal of estimating high-level effects rather than operational-hour variability.
- Consequences assessed include collisions and resulting traffic congestion.

2.3.3 V2X Message and System Behavior Assumptions

- Safety impact is tied to the purpose of the V2X message (e.g., pedestrian detection warning), regardless of specific message format (TIM, SDSM, etc.).
- Driver behavior is modeled through reaction-time related parameters; behavioral variability is not exposed as a user-selectable option.
- For this prototype, infrastructure availability and V2I communication are assumed to be the primary enablers for the modeled use cases.

3. System Requirements

The following requirements define the expected functionality, data handling, performance characteristics, and operational constraints of the V2XPRA prototype. These requirements ensure that the system fulfills the objectives described in Chapter 2 and provide a baseline for verification and validation activities.

3.1 Functional Requirements (FR)

The V2XPRA prototype shall:

3.1.1 Use Case Selection and Configuration

- FR-01 Provide intuitive access to predefined V2X and CAV use cases (e.g., RLVW, EVP) and their associated safety outputs.
- FR-02 Support selection of three to four predefined use cases for demonstration purposes.
- FR-03 Allow users to select levels of driving automation (L0, L2/ADAS, L4/ADS).
- FR-04 Allow configuration of intervention parameters including CAV market penetration, RSU deployment rate, and other environmental factors contributing to conflict exposure.

3.1.2 Scenario Comparison and Exploration

- FR-05 Enable side-by-side comparison of multiple intervention strategies.
- FR-06 Enable interactive “what-if” analyses based on user-configured parameters.

3.1.3 Geospatial Visualization

- FR-07 Provide heat-map-based geospatial visualization of road-link level safety impacts.
- FR-08 Display road-link characteristics including AADT, weather attributes, roadway type, and average operating speed.
- FR-09 Visualize estimated safety impacts (avoided crashes and reduced congestion) at both the link level and aggregate area level.
- FR-10 Present safety impacts as absolute and relative (delta) values and the economic equivalents (e.g., monetized crash reduction).

3.1.4 HCL Model Integration and Risk Computation

- FR-11 Instantiate predefined ("blueprint") HCL models corresponding to the selected use case and scenario parameters.
- FR-12 Use HCL models composed of Event Sequence Diagrams (ESDs), Fault Trees (FTs), and Bayesian Belief Networks (BBNs) to calculate end-state crash probabilities.
- FR-13 Distinguish between static inputs (historical data mapped to segments) and dynamic inputs (scenario toggles reflecting V2X interventions).
- FR-14 Dynamically updates local HCL model instances based on user inputs.
- FR-15 Compute end-state outcomes (severe crash, PDO crash, avoided crash) for each affected segment.

- FR-16 Convert scenario outcome (“end-state”) probabilities into estimated counts of avoided crashes, avoided congestion delays, and economic benefit values using a consequence-mapping matrix.
- FR-17 Aggregate safety benefits across road segments assuming statistical independence.
- FR-18 The system shall validate scenario inputs and notify the user when selections fall outside predefined valid ranges or incompatible combinations.

3.2 Performance Requirements (PR)

The V2XPRA prototype shall:

- PR-01 Be designed for horizontal scalability to support simultaneous evaluation of multiple segments or scenarios.
- PR-02 Be delivered as a modular, web-based system deployable on local or cloud infrastructure.
- PR-03 Allow flexible integration of updated datasets and models to support long-term adaptability.
- PR-04 Demonstrate functionality using a representative 1-square-mile urban area chosen based on infrastructure relevant to the selected use cases.
- PR-05 Use predefined RSU locations within the demonstration area.
- PR-06 Upon selection of use cases, the system shall initialize model parameters and perform baseline analysis for the specific segment, providing visual progress feedback to the user during this data-intensive operation (Baseline Initialization).
- PR-07 The system shall dynamically process intervention strategies, adapting the calculation duration based on the volume of data and number of road segments involved (Dynamic Interventions).
- PR-08: Scenario configuration changes and intervention updates shall occur asynchronously, updating the interface without requiring a manual page refresh (Asynchronous Updates).

3.3 External Interface Requirements (EIR)

The V2XPRA prototype shall:

- EIR-01 Operate as a self-contained system without real-time interaction with external data sources.
- EIR-02 Store all GIS-type inputs (traffic, weather, roadway attributes) in the backend database accessible to the HCL engine.

3.4 Data Requirements (DR)

The V2XPRA prototype shall incorporate the following categories of data:

- DR-01 Average annual traffic volumes (AADT) and roadway attributes.
- DR-02 Historical weather characteristics (annual or typical conditions).
- DR-03 Road-segment geometry and classification data.
- DR-04 Historical incident/crash data for baseline risk estimation per road segment.

- DR-05 Reliability data for hardware and software components used in HCL modeling encompassing V2X subsystems and ADS performance.
- DR-06 Human driver performance data (e.g., reaction times, warning response characteristics).
- DR-07 Behavioral and environmental contributors to crash likelihood (e.g., speeding, weather severity, road type).
- DR-08 Economic valuation parameters consistent with Benefit-Cost Analysis Guidance for Discretionary Grant Programs and the Updated Crash Costs for Highway Safety Analysis (USDOT).
- DR-09 All datasets shall include metadata indicating source, year, and preprocessing steps.
- DR-10 HCL model inputs shall be traceable to their corresponding data sources through a data dictionary.

3.5 Non-Functional Requirements (NFR)

The V2XPRA prototype shall:

- NFR-01 Provide full documentation, including system architecture, data dictionaries, HCL model descriptions, and user instructions.
- NFR-02 Include source code sufficient for transparency, reproducibility, and future operationalization.
- NFR-03 Maintain a clear traceability between user inputs, model computations, and displayed outputs.
- NFR-04 Support controlled stakeholder viewing following project completion, in coordination with FHWA and USDOT.
- NFR-05 Follow secure, maintainable software engineering practices appropriate for research prototypes.
- NFR-06 The system shall be implemented using industry-standard frameworks and widely adopted libraries to ensure long-term maintainability and ease of operational transfer.
- NFR-07 The prototype shall operate on current versions of major web browsers (e.g., Chrome, Edge, Firefox).

3.6 Security, Access Control, and Data Integrity Requirements (SEC)

The V2XPRA prototype shall:

3.6.1 Access Control Requirements

- SEC-01: Define "User" vs “Developer/Administrator” roles.
- SEC-02: Role permissions documented in the user guide.

3.6.2 Data Integrity and Protection Requirements

- SEC-03: The system shall implement basic access control mechanisms to preserve the integrity of datasets, HCL model structures, and risk computation logic.
- SEC-04: Restrict write access to underlying datasets and HCL model templates to developer-level users only.

- SEC-05: Maintain read-only access for end users interacting with the dashboard interface.

3.7 Verification Requirements (VR)

The following verification processes shall be implemented:

- VR-01 Each functional requirement shall be verified by inspection or demonstration during the prototype review meeting.
- VR-02 The correctness of HCL model instantiation shall be verified through analytical review of sample scenario configurations.
- VR-03 Geospatial visualizations shall be verified by inspection to confirm accurate mapping of road-link attributes.
- VR-04 Summary outputs (avoided crashes, avoided congestion, economic valuation) shall be verified by reproducing results from a known test case.
- VR-05 Performance requirements (PR-06 to PR-08) shall be verified through timed demonstrations using the designated test scenario.

3.8 Requirements Summary

The following table contains a summary of the requirements for the V2XPRA prototype.

Table 1: Requirements Summary Table.

Category	Requirement ID Prefix	Description
Functional Requirements	FR-01 to FR-18	Defines user interactions, scenario configuration, geospatial visualization, HCL-based risk computation, and input validation.
Performance Requirements	PR-01 to PR-08	Specifies scalability, modularity, update speed, map load time, and dynamic scenario responsiveness.
External Interface Requirements	EIR-01 to EIR-02	Describes external system dependencies and limits; ensures prototype operates as a self-contained system.
Data Requirements	DR-01 to DR-10	Defines traffic, weather, roadway, crash, reliability, and human-performance data inputs; includes metadata and traceability expectations.
Non-Functional Requirements	NFR-01 to NFR-07	Covers documentation, source code transparency, traceability, stakeholder access, maintainability, and use of widely supported libraries.
Security, Access Control, and Data Integrity Requirements	SEC-01 to SEC-05	Defines roles, permissions, access controls, data protection, and integrity safeguards.

Verification Requirements	VR-01 to VR-05	Defines verification by inspection, demonstration, analytical review, and replication using known test cases.

4. V2XPRA High-Level Design

This chapter describes the architectural structure, subsystem decomposition, key software components, data flow, and timing assumptions of the V2XPRA prototype. The design aligns with the system requirements in Chapter 3 and provides a conceptual basis for implementation and testing. Tables A1-A7 in the Appendix provide detailed requirements mapping to sections in this chapter.

4.1 Subsystem Decomposition

The V2XPRA prototype architecture consists of three interconnected layers, each fulfilling distinct roles in data processing, user interaction, and probabilistic risk modeling (Figure 1).

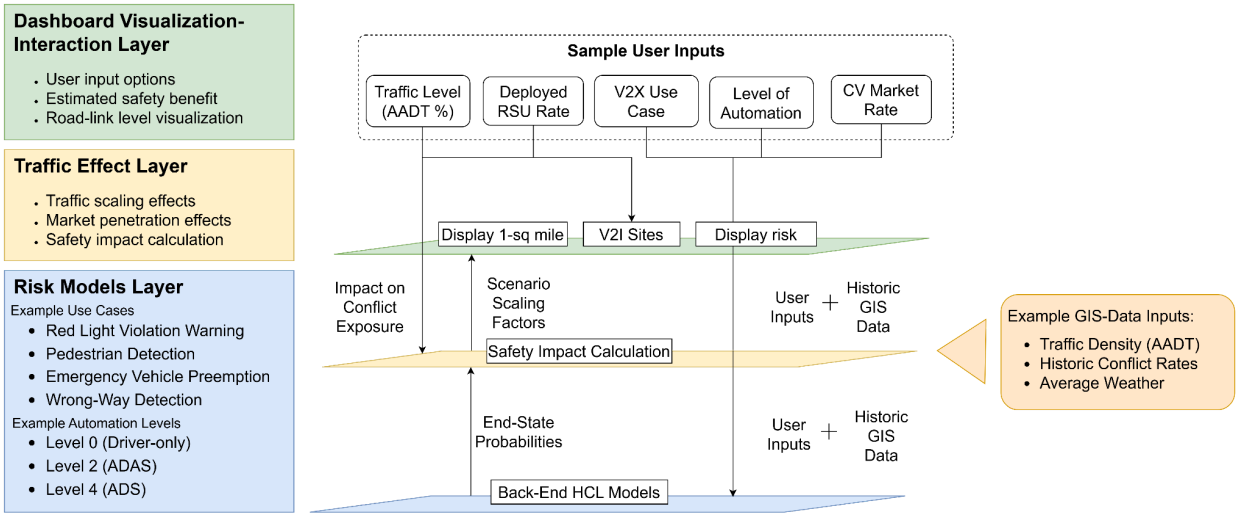

Figure 1: V2XPRA tool high-level architecture and data flow.

4.1.1 Subsystem 1: User-Facing Dashboard Layer (Upper Level)

Provides an interactive environment for configuring V2X intervention scenarios, selecting automation levels, adjusting environmental conditions, and visualizing resulting safety impacts at the road-link level.

Key Responsibilities:

- Implements FR-01 to FR-08 and FR-18, and presents outputs from FR-09 and FR-10. Supports PR-02, PR-08, NFR-07, SEC-01, and SEC-05.
- Presents geospatial visualizations (heatmaps, color scales, legends, tooltips) for a 1-sq mile sample area at road-link level.
- Displays estimated benefits from avoided crashes, avoided congestion, and equivalent economic benefits.
- Handles user toggles for V2X use case, automation level, traffic level (AADT%), RSU deployment rate, and CV market rate.
- Validates user scenario inputs and provides feedback when selections are incompatible (FR-18).

- Communicates user inputs to the intermediate layer (Subsystem 2) and core HCL layer (Subsystem 3) for model instantiation and recalculation.

4.1.2 Subsystem 2: Traffic and Contextual Layer (Intermediate Level).

Transforms user inputs and GIS contextual data into the scenario scaling factors and model-ready parameters that influence exposure likelihood and V2X effectiveness. This layer maps inputs from the dashboard layer (Subsystem 1) to the core HCL layer (Subsystem 3), and vice-versa, including (a) interacting with the V2XPRA backend database, (b) integrating imported GIS data as inputs to the instantiated HCL models, (c) retrieving segment-specific HCL results, and (d) converting the calculated end-state probabilities into expected crash counts and monetized consequences.

Key Responsibilities:

- Implements FR-13, FR-16, and FR-17; satisfies DR-01 to DR-04, DR-07, and DR-08; supports PR-01 and PR-03; and operationalizes EIR-02.
- Retrieves segment-specific GIS data (e.g., road geometry, traffic density, historic conflict rates, average weather) and maps it into model-ready parameters for Subsystem 3.
- Retrieves and stores HCL results per road segment to enable the delta risk calculation.
- Computes scenario scaling factors derived from user inputs, including traffic-level scaling (percentage of base AADT) and RSU deployment rate.

4.1.3 Subsystem 3: Core HCL Risk Modeling Layer (Lower Level)

Computes end-state crash probabilities and performs intervention-based recalculations based on the pre-defined HCL models (“blueprints”).

Core HCL Components:

- Event Sequence Diagrams (ESD), representing the dynamic evolution of crash scenarios corresponding to each use case (Figure 2).
- Fault Trees (FT), representing subsystem or component failure logic (Figure 3).
- Bayesian Belief Networks (BBN), represent causal-like relationships and dynamic updates (Figure 4).

Key Responsibilities:

- Satisfies FR-11 to FR-15, contributes to FR-17; supports PR-06 to PR-08, and VR-01 to VR-02 and VR-4 to VR-05. Model versioning supports NFR-02 and NFR-03.
- Instantiates HCL model blueprint for each segment during pre-computation using static inputs (historic GIS/contextual data) and use-case template structures (ESD/FT/BBN).
- Performs inference using historic and V2X-modified variables (e.g., CV market rate and deployed RSU rate from Subsystem 2) are used to modify model blueprints per segment.
- Compute baseline probabilities (no V2X intervention) and, upon user interaction, update dynamic V2X variables and compute modified probabilities.

- Computes end-state probabilities per end-state category (e.g., severe crash, PDO crash, avoided crash), where these categories are defined globally by the developer/ administrator.
- Aggregates safety benefits across road segments (after receiving results from Subsystem 3) into area-level summaries for dashboard display.

Core HCL Component Details

ESDs can be defined as generalized event trees (ETs), allowing them to represent better dynamic systems. ESDs depict a flowchart diagram which begins with an initiating event (IE) and follows the subsequent sequence of event successes or failures in safety systems up to a variety of potential resolutions of the situation (end states). Each success or failure is represented by a probability value and each end-state is associated with a severity.

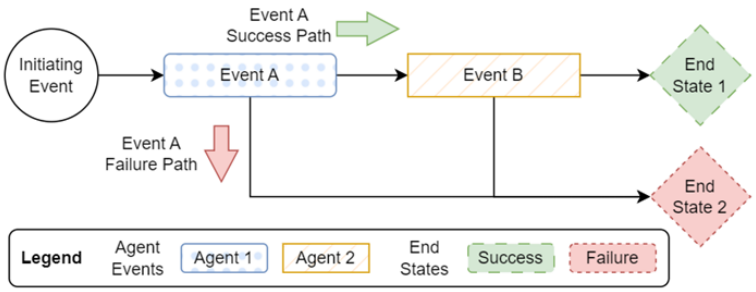

Figure 2: Sample Event Sequence Diagram.

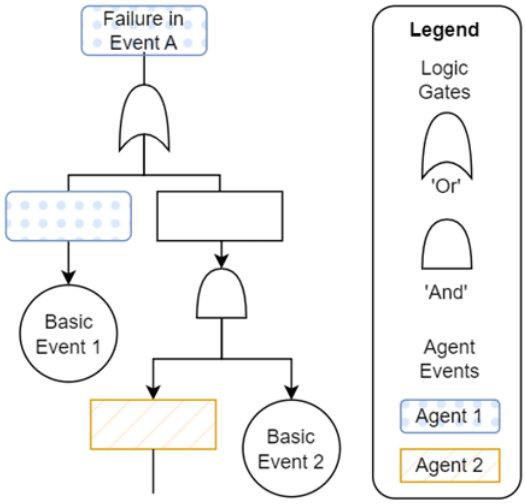

Figure 3: Sample Fault Tree Diagram.

FT models represent the possible lower-level failures that contribute to an undesirable event (the top event, commonly associated with an ESD event). FTs can be used to represent the behaviors of the physical system (hardware, software, and environmental factors) as possible causes, or contributing factors, to accidents and incidents. The structure of the FT is used to represent system failure through Boolean logic using *and/or* clauses.

Bayesian networks are models that integrate limited cause and effect knowledge with conditional probabilities. A BBN can be viewed as a probabilistic "expert system" in which the knowledge base is represented by the map of the network and the conditional probability tables of each node. By setting evidence (the state of a node is known), inferences can be made about the state of related nodes based on Bayesian updating methods.

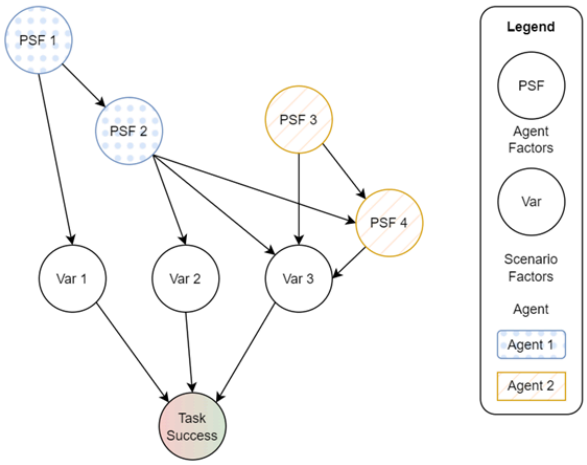

Figure 4: Sample Bayesian Belief Network Diagram.

HCL provides developers with the ability to construct system models and select methods to represent event probabilities.

- Each event in an ESD can be characterized by a failure probability, or it can be linked to other FT and ESD events, or directly to a BBN node. Likewise, each FT event may be represented by a failure probability or linked to other FTs or BBN nodes.
- Each ESD or FT event can be represented by a constant failure probability, a user-defined expression, and different probability distributions for failures occurring on-demand or during operation.

Probabilities may be represented by known constant values or different distributions. Failures on demand may be modeled through uniform, normal, or lognormal distributions, while Weibull and exponential distributions are available to represent failures during operation. In addition, non-parametric distributions are available given the user input data. HCL calculates probabilities of occurrence for each end-state.

More details can be found in the HCL User Guide.

4.2 Software Components

This section describes the principal software components and data structures that implement the subsystem functions. The structure is designed to maintain compatibility with requirement categories (functional, data, performance, and non-functional).

4.2.1 Core Data Structures & Definitions

Global Definitions

Prior to processing road-segments, the system establishes the "Language" of risk.

- **End State Categories:** Top-level outcomes defined globally.
    - *Examples:* Collision (Severe), Collision (PDO), Congestion (Level 1).
- **Consequence Categories:** The dimensions of impact.
    - *Examples:* Safety (Lives/Injuries), Congestion (Time), Financial (USD).
- **Consequence Mapping Matrix:** A logic table defining the severity of an End State within a Consequence Category.

Requirement Satisfied: DR-09, DR-10; NFR-01; FR-16.

The "Use Case" (Template Class)

The Use Case is referred to as a model “blueprint”. These blueprints are created by the system developers/administrations and are pre-defined for users. The blueprints are not tied to a location until instantiated, and have the following structure:

- **HCL Model:** The combination of the Event Sequence Diagram (ESD), Fault Trees (FT), and Bayesian Networks (BBN).
- **Variable Registry:**
    1. **Historic Variables (Static Inputs):** Model inputs mapped to external data sources for each segment.
    2. **V2X Variables (Dynamic Inputs):** Model inputs mapped to V2X technology and automation toggles.
- **End State Mapping:** Defines which end states in the ESD belong to the Global End State Categories.

Requirement Satisfied: FR-11 to FR-13; DR-01 to DR-10; supports NFR-03.

The "Segment" (Geospatial Instance)

This corresponds to a specific stretch of road geometry, referred to as a road link.

- **Attributes:** GIS Data (ID, Length, Coordinates).
- **Historic Data Cache:** Stores the retrieved values for this location (Traffic Volume, Avg Speed, Weather History).
- **Assigned Use Cases:** A list of Use Case IDs applicable to this segment.

Requirement Satisfied: DR-01 through DR-05; FR-07 and FR-08.

4.2.2 Development Tools and Architecture

This section summarizes the planned data ingestion approach, storage strategy, service layer, frontend components, and DevOps workflow for the V2X Safety Evaluation Tool. The descriptions are intentionally high-level and focus on the conceptual architecture rather than implementation details.

Data Ingest (ETL)

Pipelines for acquiring, cleaning, enriching, and standardizing all external datasets. The tool integrates multiple external datasets required for the Environment BBN, HCL/ESD instantiation, and segment-level risk calculations.

- Functions: Imports roadway and metadata (e.g., OpenStreetMap, StreetLight), segmentizes roadways into analysis links suitable for safety modeling, and enriches links with roadway features relevant to the HCL use cases, including roadway geometry, traffic (AADT%), average vehicle speed, average weather, and optional incident data.
- Objective: Establishes the canonical data foundation used by all risk models and scenario evaluations. These attributes support scenario reasoning and define base conditions for the Environment BBN.
- Requirements Supported: DR-01 to DR-04, DR-07, DR-08, DR-09; EIR-02; PR-03.

Note: All ETL processes ultimately populate a unified segment-level data store in PostGIS, which becomes the canonical reference for all downstream computations.

Core storage

The backend maintains a centralized geospatial database that stores all roadway, traffic, and environmental data, as well as risk outputs.

- Functions:
  - Use PostgreSQL + PostGIS to store all road geometry, enriched attributes,traffic and weather time series, segmented crash history, and computed risk scores.
  - Support HCL model instantiation, scenario building, and delta-risk calculations through a canonical “segments” table.
- Objective: Ensures consistency, reproducibility, and spatial alignment across all backend services.
- Requirements Supported: DR-01 to DR-04, DR-09, DR-10; EIR-02; supports PR-01, PR-03, NFR-02, and NFR-03.

Note: Time-varying datasets (traffic, weather) may be partitioned by date or managed via TimescaleDB if volume increases in later phases.

Service Layer

The application layer exposes APIs for retrieving segment data, computing scenario-specific risks, and delivering map tiles to the frontend.

- Functions:

    - Implement Django REST framework to expose endpoints for segment attributes, risk computation under scenario parameters, and map metadata for vector tile rendering.
    - Use Task Runner Celery + Redis to manage ETL schedules and batch risk recomputations, and asynchronous execution of scenario models.
    - Generate vector tiles to enable fast, scalable map rendering directly from PostGIS, producing risk and other thematic layers.
- Objective: Separates interactive user requests from heavy computation and supports responsive, scalable operations.
- Requirements Supported: FR-05, FR-06, FR-09, FR-10; PR-01, PR-02, PR-07, and PR-08; EIR-01; supports SEC-03 and SEC-04.

Frontend (React)

The web interface provides an interactive visualization of roadway segments, scenario inputs, and modeled safety benefits.

- Functions: Use MapLibre GL JS or Mapbox GL JS to provide base road network, segment attributors, and risk layers via vector tiles. This implementation supports interactive exploration, e.g., layer toggles, per-segment details, and A/B scenario comparison.
- Objective: Acts as the primary technology-transfer surface for communicating model results. Designed to support both expert users and non-technical stakeholders through intuitive visualization and controls.
- Requirements Supported: FR-01 to FR-10 and FR-18; PR-02 and PR-08; NFR-03 and NFR-07; supports SEC-01, SEC-02, and SEC-05.

DevOps

The development environment supports reliable deployment, replicability, and collaboration.

- Functions:
    - Docker Compose defines all services (database, API, tiles, worker) for reproducible and portable deployments. It provides isolated services for the PostGIS database, Django backend, vector tile server, frontend development services, and Celery worker and Redis broker.
    - Continuous integration is implemented through GitLab CI/CD, performing automated testing, building, and deployment, as well as seed fixtures to allow consistent initialization of test databases.
- Objective: Simplifies onboarding, ensures consistent environments, and prepares the system for agency or partner deployment.
- Requirements Supported: PR-01 and PR-02; supports NFR-02, NFR-05, and NFR-06; enables repeatable performance verification per VR-05.

4.3 User Interfaces

The interface of the V2XPRA tool is a GIS-based visualization dashboard. The dashboard will provide the estimated safety benefits at road segment level and hosts the toggles for CV market penetration, and RSU availability. Additional user configuration options may be implemented

during the development stage. A conceptual design of this interface is presented in Figure 5, while Figure 6 provides an early implemented version.

Requirements Supported: Implements FR-01 to FR-10 and FR-18; supports PR-02 and PR-08; satisfies VR-03; and contributes to NFR-03, NFR-07, SEC-01, SEC-02, and SEC-05.

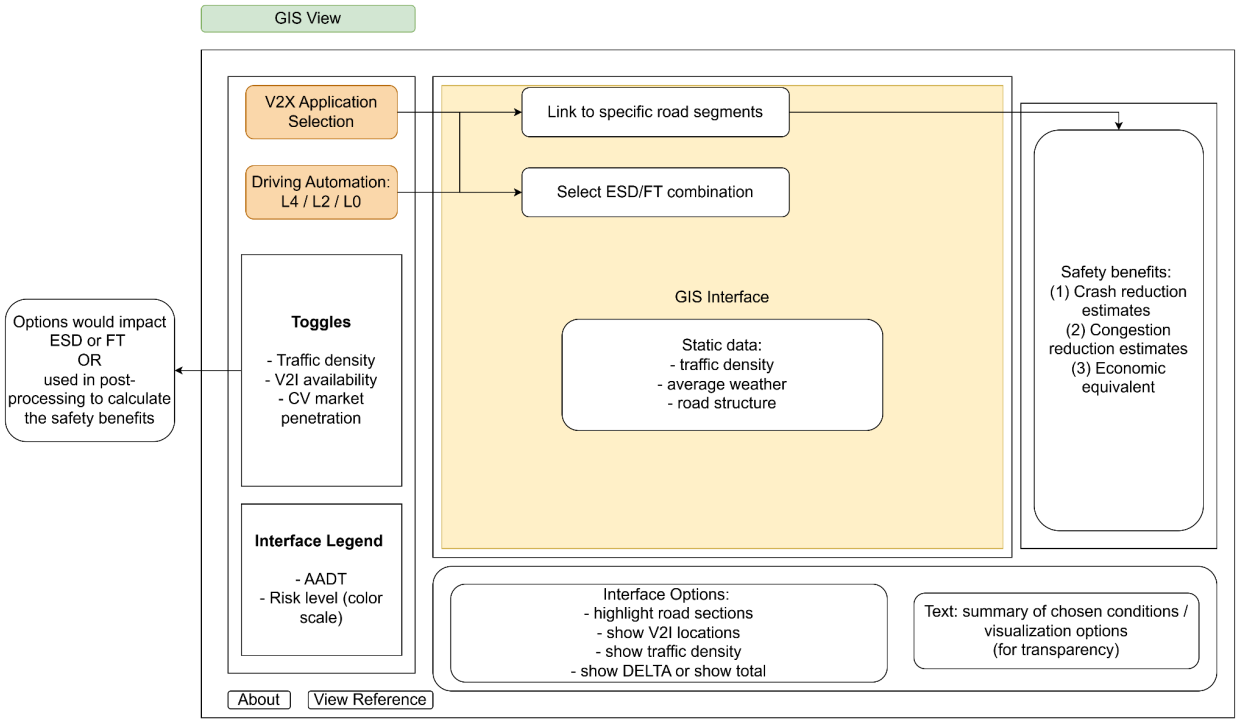

Figure 5: Conceptual interface design. Version 12/2025.

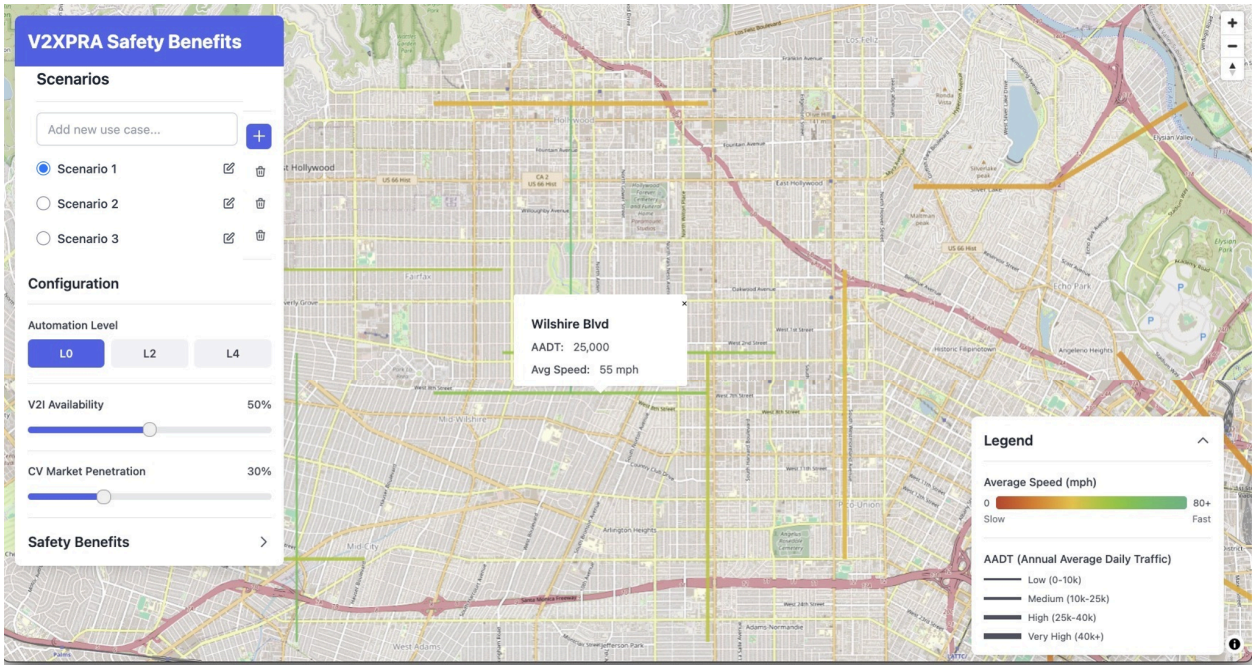

Figure 6: Early interface implementation with sample scenarios. Version 12/2025.

4.4 Data Flow and Timing

The V2XPRA consumes different types of data and integrates them at different calculation stages. This section describes the types and their main purposes in the tool.

4.4.1 GIS Data Inputs

GIS (Geographic Information System) data types represent spatially referenced attributes used to contextualize road segments, model exposure, and parameterize HCL risk models. In the V2XPRA prototype, these data types fall into several categories: road geometry, traffic characteristics (e.g., AADT and average speed), weather and environmental (e.g., lighting, road surface) conditions, and historical incident data. The temporal granularity of the data expected to be collected is at annual average level.

Road Geometry Data

Spatial data describing the physical attributes, layout, and structural properties of roadway segments. Its main use is segment classification and model selection, i.e., every HCL blueprint is associated with a specific road segment based on its specific attributes (FR-11; DR-01, DR-03).

Typical Format:

- Polyline or polygon shapefiles.
- GeoJSON.
- Segment-level attributes stored in tabular format linked by segment ID.

Example Attributes:

- Road type (urban street, arterial, freeway, intersection).
- Intersection type (signalized, stop-controlled, yield).
- Lane count and lane configuration.
- Turn lane availability (left-turn pocket, protected turn lanes).
- Curvature / horizontal alignment.
- Grade / vertical alignment.
- Speed limit.
- Presence of bike lanes or pedestrian crossings.
- Signal infrastructure (if available).

Use in V2XPRA:

- Determines appropriate use case and blueprint HCL model structure (FR-11).
- Determines potential locations for deployed RSUs. This information is used for scenario scaling (Subsystem 2).
- Sets static model parameters affecting baseline risk (FR-13).

- Helps determine exposure conditions (e.g., more conflict points at intersections).

Candidate sources: Open Street Map, StreetLight Data.

Traffic Information

GIS-linked traffic data describing vehicle activity, operational conditions, and traffic density on each road segment. Its main use is as a factor influencing "exposure" to risk, i.e., the initiating event frequency of potential conflicts between vehicles and other road users.

Typical Format:

- Segment-level values from transportation agencies or vendors.
- Time-aggregated values (daily averages, annual averages).

Example Attributes:

- AADT (Annual Average Daily Traffic).
- Average vehicle speed per segment.
- Traffic density (vehicles per mile).
- Vehicle Miles Traveled (VMT) estimates.

Use in V2XPRA:

- Traffic volume used as an exposure modifier for initiating event likelihoods (FR-13).
- Average speeds affect collision probability through BBN environmental nodes.

Candidate sources: Open Street Map, StreetLight Data.

Weather and Environmental Data

Segment-linked or region-level climatic and lighting condition data affecting road safety and crash likelihood. Its main use is to construct safety benefits as a function of the average weather at local level.

Typical Format:

- Raster or vector layers.
- Annual or monthly aggregated weather summaries.
- Derived attributes stored per segment.

Example Attributes:

- Cloud cover (% frequency of low visibility).
- Precipitation type (rain/snow) and rate.
- Temperature ranges (optional).
- Lighting condition bands (daylight, night, dawn/dusk).
- Seasonal averages (optional).

Use in V2XPRA:

- Affects failure probabilities or event likelihoods in BBN environmental nodes (FR-13).
- Contributes to baseline condition modeling for each segment (DR-02).

Candidate sources: Open Weather Map, National Weather Service, FHWA Weather Data Environment.

Historical Crash and Incident Data

GIS-linked historical records of crashes or incidents occurring on a segment or at an intersection. Historical incident data can provide key information to determine baseline risk exposure and severity classes. Purpose: baseline risk characterization and validation (DR-04)

Typical Format:

- Point or segment-level crash records.
- Frequency and severity counts.
- Agency or State DOT crash databases.

Example Attributes:

- Crash count (per year or multi-year total).
- Severity breakdown (PDO, injury, fatal).
- Crash type (rear-end, side-impact, pedestrian).
- Temporal attributes (time of day).

Use in V2XPRA:

- Used to calibrate baseline incident likelihoods (DR-04).
- Validates exposure assumptions (weather, geometry, behavior).
- Provides input to initial conditions for event likelihoods in ESDs and BBN models.

Requirements Supported: DR-01, DR-02, DR-04 and DR-07; supports FR-13, FR-15 and VR-04 (baseline test case validation).

4.4.2 Reliability and Performance Data Inputs

Reliability and performance data inputs represent the foundational parameters used to construct the HCL model blueprints. These inputs define how software, hardware, human behavior, ADS performance, and V2X communication systems interact to influence the likelihood of safety-critical events.

At a high level, reliability data shape both the *structure* and *quantitative behavior* of the HCL models by providing conditional probability values, basic event probabilities, and event-decomposition logic for scenario modeling.

Software Reliability

Includes failure rates, timing delays, message processing errors, perception/planning failures, and unexpected software states.

Used to:

- Populate FT basic event probabilities for software malfunctions.
- Define BBN dependencies related to detection, classification, or communication logic.
- Represent software-based barriers within ESD sequences.

Hardware Reliability

Covers reliability of sensors (camera, radar, lidar), communication modules, GNSS, and computing hardware (vehicle and infrastructure side).

Used to:

- Define hardware failure nodes in FTs and corresponding probabilities.
- Parameterize BBN nodes associated with degradation or intermittent failures.
- Model detection and actuation failures within ESD pathways.

Human Behavior Inputs

Includes reaction times, situational awareness, compliance with warnings, distraction levels, and response variability under different conditions.

Used to:

- Create BBN behavioral nodes representing driver response likelihood.
- Populate ESD branches representing successful vs. unsuccessful human mitigation actions.
- Feed sensitivity analyses exploring human-system interaction effects.

ADS Performance Inputs

Describe capabilities and limitations of SAE Level 2–Level 4 ADS, including perception reliability, fallback performance, and takeover behavior.

Used to:

- Model ADS response pathways in ESDs.
- Define conditional probabilities in BBNs representing ADS detection or classification errors.
- Represent system-level barriers that reduce crash likelihood depending on automation level.

V2X Performance Inputs

Include communication reliability, latency, packet delivery ratio, range, and message reception probability under different conditions.

Used to:

- Represent communication-related failure modes in FTs.
- Quantify BBN conditional probabilities for message success/failure.
- Influence ESD branches that rely on timely V2X warnings or shared situational awareness.

Requirements Supported: DR-05, DR-06, and DR-07; supports FR-12 and FR-13.

4.4.3 Level of Detail and Data Availability in Model Development

The V2XPRA HCL models will be constructed to reflect the level of detail supported by available and reliable data sources. While the HCL framework can model failures at granular levels (e.g., distinguishing specific hardware, software, communication, or human-performance failure modes), the prototype will adopt a data-informed abstraction strategy to ensure that all modeled probabilities are defensible and empirically grounded.

When detailed reliability data are available–for example, separate failure rates for sensing hardware, communication modules, perception software, or ADS control components–these will be incorporated as distinct nodes in the BBN, FT, or ESD structures. However, if reliable data do not exist at that resolution, the model will collapse lower-level components into a single functional failure event (e.g., “Sensor subsystem unavailable,” “V2X message not received,” “Driver failed to respond”) to preserve model validity.

This functional-level modeling approach aligns with the objectives of the V2XPRA tool, which emphasizes system performance in terms of whether key safety functions succeed or fail, such as:

- Whether a V2X message is delivered successfully.
- Whether the message triggers the intended driver or ADS action.
- Whether the available time and conditions allow the recommended action to prevent the crash.
- Whether the mitigation successfully avoids or reduces crash severity.

To support this approach, academic literature, industry data, and relevant standards (e.g., SAE, IEEE, NHTSA documentation, and connected-vehicle performance studies) will be used to determine representative probabilities and default parameter values. These sources will guide both the structure of the models and the assignment of failure likelihoods at the appropriate level of abstraction, ensuring that the resulting HCL blueprints remain both technically credible and aligned with the available evidence base.

Requirements Supported: DR-09 and DR-10; supports FR-13 and NFR-01/NFR-03 by enforcing data-informed abstraction and traceable parameterization.

4.4.4. Calculation Engine Logic

The HCL calculation engine operates in two passes: The Base Case Pass (Pre-computation) and the Intervention Pass (Real-time User Interaction).

Phase 1: Base Case Instantiation (Pre-computation)

Objective: Establish the baseline risk profile for every segment based on historic conditions without V2X intervention.

Algorithm:

1. **Iterate** through all Geographic Segments.
2. **Fetch** historic data (GIS/Weather API) for the segment.
3. **Load** assigned Use Case Template(s).
4. **Instantiate HCL Model:**
    - Create a copy of the generic HCL graph.
    - **Injection:** Find all *Historic Variables* in the ESD/FT and inject the segment's specific data.
5. **Compute Probability:**
    - Calculate Probability of each End State Category (P_{base}).
6. **Store Results:** Save P_{base} vector to the Segment database.

Requirement Links: FR-11 to FR-15; DR-01 to DR-10; supports PR-01, PR-03, and PR-06; contributes to VR-01, VR-02, and VR-04.

Phase 2: V2X Intervention (Real-time)

Objective: Calculate the difference in risk (*risk delta*) when the user toggles different technology options.

Algorithm:

1. **User Input:** User toggles a Use Case, e.g, "V2X Intersection Assist".
2. **Identify Scope:** Query database for Use Cases sensitive to "V2X Intersection Assist". Identify all Segments using these Use Cases.
3. **Delta Calculation Loop (For each affected segment):**
    - Retrieve the Instantiated HCL Model.
    - **Update V2X Variables:** Update specific BBN nodes associated with the tech.
    - **Re-Compute:** Run the HCL solver to get P_{V2X}.
    - **Calculate Delta:** Delta Risk $\Delta R = P_{base} - P_{V2X}$.
4. **Visualization:** Render Delta on the map using a color choropleth.

Requirement Links: FR-05, FR-06, FR-14, FR-16, FR-17, and FR-18; supports FR-10; satisfies PR-07 and PR-08 and contributes to PR-01 and PR-02; contributes to VR-01 and VR-04.

User Experience Workflow

The user experience in V2XPRA follows a structured progression from initial configuration to interactive exploration and scenario-based analysis. The workflow integrates user selections with model instantiation steps, as conceptually illustrated in Figure 7.

Configuration Phase:

- The admin user defines global End States and Use Cases blueprints.
- The admin user assigns one or more use cases to each road segment based on roadway characteristics.
- When the system initializes, it performs the Base Cases quantification for the target geographic region:
    - Segments associated with each selected Use Case are retrieved.
    - The corresponding ESD/FT model combination is identified (per predefined templates).
    - Roadway attributes, average traffic, weather, and incident history are extracted and used to populate the environment portion of the BBN.
    - The HCL engine computes baseline end-state outcomes (e.g., severe crash, PDO crash).
- Base case results are stored for use in subsequent “delta risk” evaluation.

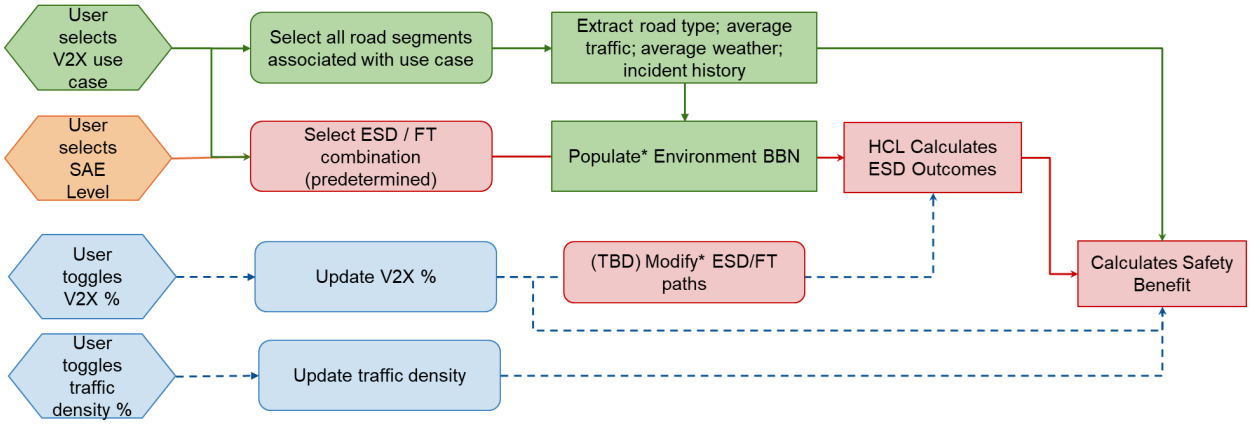

Figure 7: Conceptual mapping of user inputs to HCL models and safety benefit calculations.

Exploration Phase (The Map):

- The user sees a map shaded according to baseline crash risk for each road segment included in the sample area.
- The sidebar displays available V2X technologies and V2X-enabled use cases relevant to the road segments (e.g., “Red-Light Violation Warning,” “Emergency Vehicle Preemption”).
- The sidebar displays additional configuration options related to the traffic volume in terms of AADT (“low”, “average”, “high”), CV market penetration and RSU deployment rate.

Analysis Phase (Dynamic Scenario Interaction):

- When the user selects a V2X use case (e.g., “Red-Light Violation Warning”) the system:
  - Identifies all road segments associated with that use case (e.g., “Red-Light Violation Warning” occurs at “Signalized Intersection”).
  - Loads the predetermined ESD/FT combination for those road segments depending on the selected level of driving automation (Level 0, Level 2, or Level 4) and CV market penetration rate.
  - Backend quickly recalculates risk for segments containing "Signalized Intersection" Use Cases, defined as the difference between baseline probabilities and V2X-adjusted probabilities.
  - Safety impacts, i.e., consequences, are calculated based on the end-state probabilities, depending on traffic density (AADT%) and RSU deployment rate.
- The system updates the interface display:
  - The calculated safety benefit (crash reduction counts and economic impact) is displayed on the map.
  - Depending on the visualization mode, the safety impact is shown as “Total” or "Delta Risk" (Visualizing the benefit).
  - Displays V2I site locations (if applicable based on RSU deployment rate).
  - (Optional) When the user changes visualization mode (e.g., “Safety” to “Financial Consequence”), the legend and color scale update accordingly (USD per segment).

Requirements Supported: The Configuration, Exploration, and Analysis phases together implement FR-01 to FR-10 and FR-11 to FR-17; support PR-02 and PR-06 to PR-08; and provide the basis for verification activities VR-01 and VR-05.

Part II. Market Analysis and Technology Transfer Opportunities

This chapter focuses on identifying similar platforms, opportunities for future improvements, and technology transfer opportunities.

5.1 Market Context and Segmentation

The market for safety-oriented analytics and decision-support tools spans multiple domains and can be grouped into four broad segments:

1. **Commercial safety analytics and mobility data platforms** (e.g., INRIX, StreetLight, Rekor, Miovision) that fuse probe data, crashes, and other feeds to highlight high-risk locations.
2. **Public-sector safety management tools** (e.g., AASHTOWare Safety Analyst, RITIS Probe Data Analytics) that support performance management using archived data for Highway Safety Manual (HSM) and Highway Safety Improvement Program (HSIP) programs.
3. **Research and simulation environments for AV/CAV safety** (e.g., TeraSim[1], OpenCDA[2], and related digital twins) that target AV/ADS safety evaluation via scenario generation and simulation-based metrics.

Beyond road traffic, there is now a mature ecosystem of hazard and risk dashboards in domains such as wildfire, flooding, and earthquakes. Examples include:

- USFS Wildfire Risk to Communities, which provides interactive, community-level maps of wildfire hazard, exposure and potential impacts to homes.
- FEMA's Hazus, a GIS-based loss-estimation platform used to quantify multi-hazard risk (flood, hurricane, earthquake, tsunami) and associated economic and social losses.
- CAL FIRE Fire Hazard Severity Zone (FHSZ) maps and Defensible Space dashboards, which classify long-term fire hazard (Moderate/High/Very High) and provide parcel-level defensible-space inspection status reflecting fire behavior.

[1] H. Sun et al., "TeraSim: Uncovering Unknown Unsafe Events for Autonomous Vehicles through Generative Simulation," Mar. 2025, Accessed: Dec. 08, 2025. [Online]. Available: https://arxiv.org/pdf/2503.03629

[2] R. Xu, Y. Guo, X. Han, X. Xia, H. Xiang, and J. Ma, "OpenCDA: An Open Cooperative Driving Automation Framework Integrated with Co-Simulation," IEEE Conf. Intell. Transp. Syst. Proceedings, ITSC, vol. 2021-Septe, pp. 1155–1162, 2021, doi: 10.1109/ITSC48978.2021.9564825.

- USGS National Seismic Hazard Model and Earthquake Hazard Toolbox, which expose long-horizon seismic probabilities and map-based tools for planners and engineers.

These cross-domain tools provide important design precedents for V2XPRA's role as a probabilistic, map-based, long-horizon risk viewer. In addition, it combines formal probabilistic risk assessment (HCL) with road-link-level GIS visualization and scenario-based evaluation of V2X/CAV deployment strategies. This strategy is distinct from similar traffic safety platforms that focus on real-time traffic data, or extrapolate from historical crash counts or operational KPIs to provide safety estimates.

5.2 Existing Traffic Safety and Mobility Analytics Platforms

5.2.1 Commercial Safety Analytics & Mobility Data Platforms

INRIX Safety Analytics

INRIX Safety Analytics is a cloud-based platform that lets agencies view crash locations, segment-level crash history, and filter by severity, mode, type, or contributing factors. It integrates crash data with traffic volumes, speeding locations, and vulnerable road user concentrations to identify high-risk segments and hotspots, and can support equity-focused safety analysis by combining movement and demographic data.

Relevance to V2XPRA:

- Strong overlap in segment-level visualization and crash hotspot prioritization.
- Safety indicators are primarily reactive (historical crash-based) and empirically driven; safety risk is inferred from historical crashes and exposure.
- Integration opportunity: INRIX can supply baseline crash and exposure layers, while V2XPRA overlays HCL-derived risk deltas for specific V2X/CAV scenarios (e.g., added RSUs, higher CAV penetration). V2XPRA workflow could be integrated as a layer in the INRIX Safety Analytics platform.

StreetLight InSight & Safety Solutions

StreetLight InSight and Safety Solutions provide self-service analytics through a web-based platform that uses connected device and IoT data to estimate traffic volumes, origin-destination patterns, and multimodal activity (vehicles, transit, bikes, pedestrians). StreetLight's dedicated Safety Solutions link these mobility metrics to road safety needs, giving agencies a consistent exposure baseline for crash and risk analysis.

Relevance to V2XPRA:

- Provides high-value exposure metrics (traffic volumes, modes, flows) that can parameterize the traffic and contextual layer of V2XPRA at the road-link level.
- Safety functions focus on empirical indicators (crash and surrogate overlays).
- Integration opportunity: StreetLight data can serve to populate baseline demand and multimodal exposure for V2XPRA's road-link-level risk estimates.

Rekor One (formerly Waycare)

Rekor One provides collaborative tools for traffic management centers. Rekor's suite integrates data from multiple sources (e.g., sensors, probe data, video analytics) to provide real-time incident detection, irregular congestion alerts, and crash forecasting tools through ATMS-style dashboards.

Relevance to V2XPRA:

- Focused on real-time operations and short-horizon incident management (minutes to hours), with predictive analytics for crash likelihood.
- Emphasizes cloud-based ATMS-style integration and real-time dashboards.
- Integration opportunity: V2XPRA could link to Rekor's real-time incident risk signals with V2XPRA's longer-term deployment scenarios (e.g., "if RSUs and CAV penetration reach X%, incident patterns like these are expected to reduce by Y%").

Miovision Continuous Safety Monitoring

Miovision uses video analytics to derive near-miss events and conflict-based safety indicators (e.g., conflicts, speeds, non-compliance). Miovision's platform hosts severity-based dashboards, enables root-cause investigation through video, supporting proactive safety management beyond crash history.

Relevance to V2XPRA:

- Provides near-miss and conflict-based surrogate safety indicators, VRU behavior patterns, and video-derived measures such as speeds and non-compliance events.
- Currently focused on camera-based local analytics to identify safety hotspots.
- Integration opportunity: V2XPRA can benefit from the real-time conflict-based safety indicators to update baseline risk estimates and prioritize RSU deployment sites.

Other Commercial Platforms

Several vision- or lidar-based conflict detection systems (e.g., Ouster Bluecity, Derq Insight) and probe-based mobility datasets (e.g., TomTom) now serve as upstream inputs to safety-related decision-making. These tools provide high-resolution exposure metrics, VRU movement patterns, and surrogate safety indicators that enrich agencies' understanding of safety conditions before crashes occur. For future V2XPRA development, such platforms represent reliable, operationally deployed data sources that can support calibration or validation of V2XPRA's HCL-based baseline risk profiles.

5.2.2 Public-Sector Safety Management Tools

AASHTOWare Safety Analyst

Safety Analyst implements HSM procedures to support state and local agencies in identifying and managing a systemwide program of site-specific safety improvements. It uses statistically calibrated safety performance functions, empirical Bayes methods, and economic appraisal to prioritize countermeasures and HSIP investments.

Relevance to V2XPRA:

- Widely adopted for network-screening and HSIP prioritization using historical crash data.
- Current HSM-based methodologies treat emerging technologies as generic countermeasures or CMFs.
- Integration opportunity: V2XPRA can provide advanced crash modification factors (CMFs) or risk-reduction estimates for CAV/V2X interventions that can be fed into Safety Analyst workflows.

RITIS Probe Data Analytics

The Regional Integrated Transportation Information System (RITIS) and its Probe Data Analytics Suite provide multi-agency data fusion and visualizations for travel time, reliability indices, congestion patterns, incident analysis, and performance reports.

Relevance to V2XPRA:

- Focuses on data fusion and visualization of mobility performance; agencies already rely on RITIS for congestion and reliability studies.
- Safety capabilities are indirect (e.g., bottleneck identification, performance during incidents) rather than explicit risk modeling.
- RITIS is designed as an archived and near-real-time performance dashboard.
- Potential integration: RITIS can serve as key input (e.g., congestion profiles, incident distributions) to V2XPRA's safety estimates (via APIs to RITIS-style dashboards).

Other Public-Sector Platforms

Several mature public-sector tools constitute the foundational upstream safety workflow used by agencies nationwide, including: FHWA's Systemic Safety Project Selection Tool, CMF Clearinghouse, state DOT crash analytics systems, and NHTSA's FARS/CRSS interfaces. These resources provide calibrated crash functions, systemic prioritization logic, and standardized severity distributions that agencies use to justify investments and undertake HSIP programming. V2XPRA can complement these established tools by producing V2X-aware, CMF-like safety impacts that integrate directly with existing workflows, supporting adoption without requiring institutional or methodological disruption.

5.2.3 Research and Simulation Platforms for AV/CAV Safety

TeraSim Traffic Simulation Environment

TeraSim is an emerging research-oriented high-fidelity traffic simulation environment designed to generate diverse safety-critical scenarios and evaluate autonomous vehicle safety performance. It uses generative simulation to create diverse, realistic traffic environments and safety-critical events, and integrates with digital twin environments, including a Mcity digital twin.

Relevance to V2XPRA:

- Focuses on simulating low likelihood, safety-critical events and quantifying resulting AV/ADS risk.
- Currently oriented toward research users, not planners or safety program managers.

- Integration opportunity: V2XPRA could use TeraSim as a scenario generator and statistics source for high-risk interaction patterns (e.g., specific intersection or work-zone scenarios), feeding those into V2XPRA's HCL models and informing parameter ranges.

OpenCDA (UCLA Mobility Lab)

OpenCDA is an open-source cooperative driving automation (CDA) framework developed by the UCLA Mobility Lab in collaboration with U.S. DOT CDA Research and the FHWA CARMA program. It provides a full-stack CDA software platform (perception, localization, planning, control, and V2X communication) integrated with a CARLA+SUMO co-simulation environment, enabling flexible prototyping and evaluation of CDA features such as platooning, cooperative perception, and cooperative merging.

Relevance to V2XPRA:

- Offers a co-simulation testbed where specific V2X/ADS behaviors (e.g., message latency, packet loss, cooperative perception failures, ADS fallback behaviors) can be incorporated and studied under controlled scenarios, producing quantitative performance and failure data.
- OpenCDA emphasizes cooperative behaviors and V2X interaction mechanisms, but at the algorithm and stack level rather than at the policy or planning level.
- Integration opportunity:
  - V2XPRA can benefit from OpenCDA to generate scenario-level reliability and performance parameters (e.g., probability of timely message delivery, ADS takeover success under certain visibility and traffic conditions) that can be mapped into V2XPRA's HCL nodes.
  - OpenCDA can benefit from V2XPRA's sensitivity analyses (which parameters most influence segment-level risk) to prioritize which cooperative behaviors and operating conditions should be explored in OpenCDA simulations.

Other Research Platforms

A diverse ecosystem of mature research and simulation platforms now supports ADS and V2X system evaluation at varying levels of fidelity, including CARMA, CARLA, SUMO, Vissim/SSAM, Autoware, Mcity's digital twin, and industry-grade simulators (e.g., NVIDIA DRIVE Sim, dSPACE). These environments operate upstream of V2XPRA by generating scenario data, performance distributions, message-level reliability metrics, and failure modes that can populate or validate HCL nodes within V2XPRA's modeling framework.

5.3 Cross-Domain Hazard and Risk Dashboards

Recent advances in wildfire, flood, and seismic risk communication provide templates for how complex probabilistic models can be translated into simple, GIS-based views for policymakers and the public:

- Wildfire Risk to Communities offers interactive maps, charts, and downloadable data describing wildfire hazard, exposure, and potential impacts to homes at community scales, emphasizing long-horizon risk and mitigation levers.

- FEMA Hazus uses standardized GIS workflows and multi-hazard loss models to produce maps, tables, and reports summarizing physical, economic, and social impacts for predefined scenario events.
- CAL FIRE FHSZ maps and defensible-space dashboards distinguish hazard (likelihood and intensity over decades) from risk (likelihood × consequences) and tie maps to regulatory requirements and mitigation actions.
- USGS National Seismic Hazard Toolbox exposes probabilistic seismic hazard models and clearly explains what users can and cannot infer from the maps, including treatment of uncertainty and appropriate use cases.

These tools demonstrate that:

- Probabilistic risk models can be operationalized as public-facing dashboards with clear legend definitions and risk categories.
- Scenario-based and long-horizon views (e.g., "chance of damaging shaking over 100 years," "30–50 year wildfire hazard") can coexist with simple user interactions.
- There is value in explicitly distinguishing hazard, exposure, and vulnerability, and in showing how mitigation actions shift those dimensions.

V2XPRA can adopt similar patterns, e.g., separate "baseline risk" and "delta risk," multiple consequence dimensions (crash counts, congestion hours, economic loss), and clear explanations of what the tool does and does not represent, and introduce a V2X/ADS-focused PRA engine to the transportation domain.

5.4 Technology Transfer Options

5.4.1 Cross-Cutting Observations and Gaps

Based on this analysis, several consistent gaps emerge relative to the goals of V2XPRA:

- **Historical vs. Prospective:** Most tools rely on historical crash data or observed surrogates (near-misses, congestion), with limited capability for forward-looking, scenario-based evaluation of V2X/CAV deployment strategies.
- **Limited representation of V2X and ADS internals:** Existing platforms rarely model the behavior of V2X communication systems, ADS stacks, or human-autonomy interactions explicitly; instead they treat interventions as generic countermeasures or infer risk from observed outcomes.
- **Fragmentation between safety, mobility, and operations:** Safety analytics, ATMS platforms, and simulation environments are often siloed, making it difficult for agencies to trace how a change in RSU deployment, CAV penetration, or cooperative maneuvers translates into road-link-level risk reductions.
- **Explainability and probabilistic reasoning:** There is growing interest in explainable safety metrics, but few tools expose underlying causal structures, uncertainty, and sensitivity in a transparent way suitable for both technical and non-technical stakeholders.
- **Missing representation of message-level reliability:** Existing tools do not incorporate specific V2X performance models, i.e., how V2X communication reliability, latency, or packet loss influence safety outcomes or driver/ADS response effectiveness.

These gaps define the niche where V2XPRA can provide unique value: as a probabilistic, scenario-based risk engine that sits between existing data providers, operational platforms, and agency decision processes.

5.4.2 Technology Transfer Strategies

Given the prototype's current design, technology transfer options should focus on ways to integrate the HCL risk engine and GIS components. Initial strategies include:

Plug-In Risk Engine for Commercial Analytics Platforms

- **Concept:** Package the HCL-based risk modeling layer as a modular service that commercial platforms (e.g., INRIX, StreetLight) can call to obtain scenario-based risk deltas for specific segments.
- **Function:** These upstream platforms provide crash history, exposure metrics, and real-time incident flags. V2XPRA receives road-link attributes, baseline conditions, and scenario parameters to compute incremental risk reductions for user-defined scenarios (e.g., "20% CAV penetration with RSUs at every other signalized intersection").
- **Benefit:** Leverages existing user bases and data pipelines while adding explainable "what-if" capability. Risk deltas would appear as additional layers on familiar maps and dashboards.

Enhanced Inputs to Public-Sector Safety Management Workflows

- **Concept:** Align V2XPRA outputs with HSM and AASHTOWare Safety Analyst workflows by producing CMF-like risk reduction factors or scenario-specific crash modification curves for V2X/CAV countermeasures.
- **Function:** Agencies could import these derived factors into their existing Safety Analyst configurations to evaluate V2X interventions alongside traditional infrastructure countermeasures.
- **Benefit:** Minimizes process disruption while embedding V2X-aware safety science into standard HSIP project selection and benefit-cost analysis.

Integration with Archived Data and Digital Infrastructure Platforms

- **Concept:** Design the V2XPRA traffic and contextual layer to interface with platforms such as RITIS/CATT's Probe Data Analytics Suite and USDOT/state digital infrastructure initiatives.
- **Function:** Use probe data, congestion profiles, and incident archives as inputs, and expose V2XPRA outputs through GIS-based dashboards that agencies already use for performance management.
- **Benefit:** Positions V2XPRA as a backend analytics module feeding broader performance management ecosystems.

Research and Co-Simulation Partnerships

- **Concept:** Establish technical integration pathways with academic simulation environments such as TeraSim and OpenCDA.

- **Function:** Use simulation platforms to generate high-risk interaction scenarios and estimate ADS performance, feeding these statistics into V2XPRA's risk models; conversely, use V2XPRA's sensitivity analyses to suggest which scenarios simulators should emphasize.
- **Benefit:** Creates a feedback loop between research-grade simulation and policy-facing decision support, supporting continuous improvement and validation.

Conclusion

V2XPRA is a geospatial, probabilistic risk assessment tool that quantifies the safety impacts of V2X and CAV technologies at the road-segment level. Built on Hybrid Causal Logic (HCL), the system integrates roadway context, traffic conditions, human/ADS behavior, and V2X performance into formal risk models that estimate baseline crash likelihood and changes under user-defined scenarios. Its three-layer architecture (a user-facing dashboard, a contextual data-processing layer, and a core HCL engine) supports interactive “what-if” exploration of RSU deployments, CAV penetration, and automation levels.

This document provides the system requirements defining how V2XPRA manages use-case selection, scenario configuration, geospatial visualization, and risk computation. Performance criteria ensure fast recalculation and scalable analysis, while data requirements specify GIS, traffic, weather, crash, and reliability inputs needed for HCL model instantiation. Security, documentation, and verification requirements guarantee transparency, reproducibility, and correct mapping of inputs to risk outputs, establishing a solid foundation for prototype demonstration and future expansion.

At the current stage of development, V2XPRA fills a key gap between historical crash-based tools, and research-grade AV/CAV simulators by offering scenario-based, probabilistic evaluation of V2X benefits. Technology transfer pathways include integrating V2XPRA as a plug-in risk engine for commercial analytics platforms, generating CMF-like safety adjustments for public-sector tools, linking outputs into dashboards like RITIS, and collaborating with simulation environments such as OpenCDA or TeraSim. These opportunities position V2XPRA as a modular component that strengthens agency planning, investment prioritization, and V2X deployment strategies.

Appendix

Table A1: Functional Requirements Mapping (FR).

Req. ID	Chapter 4 Section	Design Implementation
FR-01	4.1.1, 4.2.2 (Frontend), 4.3, 4.4.4 (Config/Exploration)	Dashboard + React UI provide intuitive access to predefined V2X/CAV use cases and their safety outputs.
FR-02	4.1.1, 4.2.2 (Frontend), 4.3	Dashboard limits and presents 3–4 demo use cases in sidebar controls.
FR-03	4.1.1, 4.2.2 (Frontend), 4.4.4 (Analysis)	UI toggles support selecting L0, L2/ADAS, L4/ADS, passed to HCL templates.
FR-04	4.1.1, 4.1.2, 4.2.2 (Frontend, Services), 4.4.1 (Traffic), 4.4.4	Dashboard controls and intermediate layer compute scenario scaling factors for AADT%, RSU deployment rate, and CAV penetration.
FR-05	4.1.1, 4.2.2 (Frontend, Services), 4.3, 4.4.4 (Phase 2, Analysis)	Side-by-side scenario comparison supported by UI, map layers, and scenario A/B retrieval via API.
FR-06	4.1.1, 4.2.2 (Services, Frontend), 4.4.4 (Phase 2, UX workflow)	“What-if” analyses implemented as real-time re-runs of HCL with updated V2X/traffic parameters.
FR-07	4.1.1, 4.2.2 (Frontend, Services), 4.3, 4.4.1 (GIS)	Heat-map visualization of link-level safety impacts via vector tiles and Mapbox/Leaflet.
FR-08	4.1.1, 4.2.1 (“Segment”), 4.2.2 (Frontend), 4.3, 4.4.1	Segment data structure and GIS inputs supply AADT, weather, roadway type, and speed for display in UI tooltips/panels.
FR-09	4.1.1, 4.1.2, 4.1.3, 4.2.2 (Services), 4.3, 4.4.4	HCL engine + contextual layer compute, and dashboard visualizes, link-level and area-level safety impacts (crash + congestion).
FR-10	4.1.1, 4.1.2, 4.1.3, 4.2.1 (Global Definitions), 4.2.2 (Frontend, Services), 4.4.4 (Phase 2)	Consequence mapping matrix converts probabilities to absolute/relative measures and economic equivalents; UI switches between modes.
FR-11	4.1.3, 4.2.1 (“Use Case” template), 4.4.1 (Road Geometry), 4.4.4 (Phase 1)	HCL blueprint instantiation per segment is defined via Use Case templates and Base Case algorithm.

Req. ID	Chapter 4 Section	Design Implementation
FR-12	4.1.3 (Core HCL Components), 4.2.1 (“Use Case” blueprint)	HCL models explicitly composed of ESDs, FTs, and BBNs as described in Core HCL component details.
FR-13	4.1.2, 4.1.3, 4.2.1 (“Use Case” variable registry), 4.4.1, 4.4.2, 4.4.3, 4.4.4	Static vs dynamic inputs distinguished via historic GIS/HCL variables vs V2X variables; ETL, reliability inputs, and abstraction strategy enforce this.
FR-14	4.1.3, 4.2.2 (Services), 4.4.4 (Phase 2, UX Analysis)	Local HCL instances are updated based on user-supplied V2X/traffic parameters in the intervention pass.
FR-15	4.1.3, 4.2.1 (Global Definitions), 4.4.2, 4.4.4 (Phase 1 & 2)	HCL computes probabilities for severe crash, PDO crash, avoided crash for each segment.
FR-16	4.1.2, 4.1.3, 4.2.1 (Global Definitions), 4.4.1 (Economic parameters), 4.4.4 (Phase 2)	Consequence mapping matrix converts probabilities into avoided crashes, avoided delays, and economic benefit values.
FR-17	4.1.2, 4.1.3 (aggregation bullet), 4.4.4 (Phase 2, Analysis)	Risk deltas and benefits aggregated over segments into area-level summaries under independence assumption.
FR-18	4.1.1, 4.2.2 (Frontend, Services), 4.3, 4.4.4 (UX workflow)	Scenario input validation and feedback (invalid ranges/incompatible combos) handled in dashboard and API layer.

Table A2: Performance Requirements Mapping (PR).

Req. ID	Chapter 4 Section	Design Implementation
PR-01	4.1.2, 4.1.3, 4.2.2 (Core Storage, Services, DevOps), 4.4.4	Segment-based HCL pre-computation, PostGIS, and Celery support horizontal scaling over many segments/scenarios.
PR-02	4.1, 4.1.1, 4.2.2 (Services, Frontend, DevOps), 4.3	Modular web architecture (API + React UI) deployable on local or cloud infrastructure.
PR-03	4.1.2, 4.2.1 (“Use Case”), 4.2.2 (ETL, Core Storage), 4.4.3	ETL + canonical segment schema + template blueprints allow updated datasets/models to be plugged in without redesign.
PR-04	4.1.1 (1-sq-mile sample area reference), 4.3 (map extent), 4.4.1	Design assumes and describes a representative 1-sq-mile urban test area for visualization and computation.

Req. ID	Chapter 4 Section	Design Implementation
PR-05	4.1.2 (RSU deployment rate), 4.4.1 (Road Geometry/RSU locations), 4.4.4 (Analysis Phase)	Predefined RSU sites in GIS feed scenario scaling and map rendering (e.g., V2I site locations).
PR-06	4.1.3, 4.4.4 (Phase 1), 4.4.4 (UX Configuration Phase), 4.1.1	Base Case initialization described as a distinct computation phase with progress feedback exposed via the UI.
PR-07	4.1.3, 4.2.2 (Services), 4.4.4 (Phase 2)	Dynamic intervention processing loop adapts calculation to volume of segments and scenario scope.
PR-08	4.1.1, 4.2.2 (Frontend, Services), 4.3, 4.4.4 (Phase 2, UX)	Asynchronous updates (no page reload) implemented through React + API calls and background HCL recomputations.

Table A3: External Interface Requirements Mapping (EIR).

Req. ID	Chapter 4 Section	Design Implementation
EIR-01	4.1, 4.2.2 (ETL, Services), 4.4.1	Architecture and ETL design assume offline ingests and no real-time external data feeds at runtime.
EIR-02	4.1.2, 4.2.2 (Core Storage), 4.4.1, 4.4.4	All GIS-type inputs are stored in the backend PostGIS database, which is the data source for the HCL engine.

Table A4: Data Requirements Mapping (DR).

Req. ID	Chapter 4 Section	Design Implementation
DR-01	4.2.1 (“Segment”), 4.2.2 (ETL, Core Storage), 4.4.1 (Road Geometry, Traffic)	Segment schema and ETL ingest AADT and roadway attributes into canonical PostGIS store.
DR-02	4.2.2 (ETL, Core Storage), 4.4.1 (Weather)	Weather summaries ingested, mapped to segments, and used as static inputs for HCL environmental nodes.
DR-03	4.2.1 (“Segment”), 4.2.2 (ETL), 4.4.1 (Road Geometry)	Road geometry and classification data define segment instances and drive blueprint/model assignment.

Req. ID	Chapter 4 Section	Design Implementation
DR-04	4.2.2 (ETL, Core Storage), 4.4.1 (Historical Crash), 4.4.4 (Phase 1)	Historical crash data ingested and used to calibrate baseline risk and validate exposure assumptions.
DR-05	4.4.2 (Software/Hardware Reliability), 4.2.1 ("Use Case" blueprint), 4.1.3	Reliability data for hardware/software populate FT and BBN nodes in HCL templates.
DR-06	4.4.2 (Human Behavior Inputs), 4.2.1 ("Use Case" blueprint), 4.1.3	Human driver performance data shape behavioral nodes and ESD branches for mitigation actions.
DR-07	4.4.1 (Traffic, Weather), 4.4.2 (Behavioral/Environmental Inputs), 4.1.2	Behavioral and environmental contributors modeled via GIS layers and HCL causal structures.
DR-08	4.2.1 (Global Definitions & Consequence Matrix), 4.4.1 (Economic parameters), 4.4.4 (Phase 2)	Economic valuation parameters feed the consequence categories and mapping from end states to monetized benefits.
DR-09	4.2.1 (Global Definitions), 4.2.2 (ETL/Core Storage), 4.4.3	Metadata fields and abstraction strategy ensure sources, years, and preprocessing are captured.
DR-10	4.2.1 (Global Definitions, "Use Case" variable registry), 4.2.2 (Core Storage), 4.4.3	Data dictionary and variable registry establish traceability from HCL inputs back to original data sources.

Table A5: Non-Functional Requirements Mapping (NFR).

Req. ID	Chapter 4 Section	Design Implementation
NFR-01	4.2.1 (Global Definitions, data structures), 4.4.3	Design defines documentation artifacts (data dictionary, end-state/ consequence language) to be included in project documentation.
NFR-02	4.1.3 (model versioning), 4.2.2 (DevOps, Core Storage)	Explicit model versioning and containerized source code support transparency and reproducibility.
NFR-03	4.2.1 (Global Definitions, Use Case & Segment), 4.2.2 (Core Storage, Services), 4.3, 4.4.3, 4.4.4	Traceability from user inputs → model computations → outputs maintained via data structures, logs, and UI presentation.

Req. ID	Chapter 4 Section	Design Implementation
NFR-04	4.1 (overall architecture), 4.2.2 (Frontend, Services, DevOps), 4.3	Architecture supports controlled stakeholder viewing (web dashboard) after project completion.
NFR-05	4.2.2 (Services, DevOps), 4.1.3	Use of standard frameworks, role separation, and containerization support secure and maintainable prototype practices.
NFR-06	4.2.2 (Django REST, React, PostGIS, Docker, Celery)	Design explicitly leverages widely adopted, industry-standard libraries and frameworks.
NFR-07	4.2.2 (Frontend), 4.3	React/Web-standards UI ensures operation on current major browsers (Chrome, Edge, Firefox).

Table A6: Security, Access Control, and Data Integrity Requirements Mapping (SEC).

Req. ID	Chapter 4 Section	Design Implementation
SEC-01	4.1.1, 4.2.2 (Frontend, Services), 4.3	UI and API design distinguish end-user dashboard role from developer/administrator capabilities.
SEC-02	4.2.2 (Frontend, Services), 4.3	Role-based behavior in UI/API aligns with documented permissions in the user guide.
SEC-03	4.1.3, 4.2.2 (Core Storage, Services, DevOps)	Access control around databases and HCL templates preserves integrity of datasets and risk logic.
SEC-04	4.1.3, 4.2.2 (Core Storage, Services)	Write access to underlying datasets and HCL model templates constrained to developer/admin paths.
SEC-05	4.1.1, 4.2.2 (Frontend), 4.3	Dashboard is read-only for end users; they can view but not modify underlying datasets or HCL templates.

Table A7: Verification Requirements Mapping (VR).

Req. ID	Chapter 4 Section	Design Implementation
VR-01	4.1 (Subsystems), 4.2.1–4.2.2, 4.4.4 (Phase 1 & 2, UX workflow)	Mapping of each FR to specific components supports verification by inspection/demonstration at prototype review.

Req. ID	Chapter 4 Section	Design Implementation
VR-02	4.1.3, 4.2.1 (“Use Case” & “Segment”), 4.4.2, 4.4.4 (Phase 1)	HCL instantiation steps and template structures enable analytical review of model correctness.
VR-03	4.3, 4.4.1 (GIS Inputs), 4.2.2 (Frontend/Services)	Geospatial visualization design allows visual inspection to confirm correct mapping of attributes to links.
VR-04	4.1.3, 4.2.1 (Global Definitions, consequence mapping), 4.4.1–4.4.4	Known test cases can be reproduced via defined calculation engine and summary output logic.
VR-05	4.2.2 (DevOps), 4.4.4 (Phase 2, UX), 4.1.3	Containerized deployment and defined intervention workflow support timed demonstrations of PR-06–PR-08.

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