Quantifying Safety Impacts of V2X-Enabled Traffic Systems

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16. Abstract

This study explores the safety impacts of vehicle-to-everything (V2X) communication systems using probabilistic risk assessment (PRA) frameworks. Case studies on V2X interactions with Forward Collision Warning (FCW) and Automated Emergency Braking (AEB) in collision avoidance scenarios are developed using a web-based tool, Mobility PRA (MoPRA). Findings suggest that V2X-enhanced driver warnings improve crash modification factors (CMFs) by 7-8% beyond FCW and AEB functions. Future work aims to develop generic PRA models to capture other safety-relevant V2X applications.

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About the Center of Excellence on New Mobility and Automated Vehicles

The Center of Excellence on New Mobility and Automated Vehicles focuses on the impacts of new mobility technologies and highly automated vehicles on the evolving transportation system when deployed at scale. Launched in 2023, the center studies the anticipated long-term impacts of increased new mobility technologies and services on land use, real estate and urban design; transportation system optimization including resilience, security and reliability; access to mobility and job participation; and municipal budget and cost-effective allocation of public resources. Funded by the Federal Highway Administration, the Mobility Center of Excellence is housed at UCLA and made up of five core partners and a community of practice from academia, public and private sectors.

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The Mobility Center of Excellence at UCLA acknowledges the Gabrielino/Tongva peoples as the traditional land caretakers of Tovaangar (the Los Angeles basin and So. Channel Islands). As a land grant institution, we pay our respects to the Honuukvetam (Ancestors), 'Ahiihirom (Elders) and 'Eyoohiinkem (our relatives/relations) past, present and emerging.

Disclaimer

Quantifying Safety Impacts of V2X-Enabled Traffic Systems

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Executive Summary

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, supporting functions like driver warnings, dynamic speed advisories, and incident alerts. These technologies, while promising, remain in the research phase and lack comprehensive methods to quantify their safety benefits when deployed at scale. To address this, the Mobility COE conducted a project to assess the safety impacts of V2X technologies using model-based risk assessments (PRA), a method common in industries like nuclear, space, and defense.

As a starting point, this project focused on the interaction between V2X, Forward Collision Warning (FCW), and Automated Emergency Braking (AEB). FCW provides warnings based on a vehicle's sensors detecting potential collisions, while AEB intervenes if the driver does not act after an FCW warning. V2X is expected to enhance these functions by providing earlier warnings through communications with other vehicles and infrastructure. Studying the interactions between these technologies is crucial, as AEB will become a standard feature in vehicles by 2029, and understanding the interaction of V2X with these safety systems is key to maximizing its benefits. In addition, as the potential impact of V2X will depend on the proportion of vehicles and infrastructure equipped with V2X capabilities, providing reliable estimates of potential safety benefits to infrastructure owners and operators (IOO) is key to supporting the efficient resource allocation and deployment of V2X-enabling technologies.

The study used probabilistic risk assessments (PRAs) to model potential hazards, their likelihood, and consequences. The PRAs incorporated various analysis techniques, including Event Sequence Diagrams, Fault Tree Analysis, and Bayesian Belief Networks, to simulate how V2X, FCW, and AEB might reduce crashes. These models also considered factors such as hardware/software reliability, weather, lighting, road conditions, and driver behavior. More importantly, these models flexibly incorporate data from academic studies, limited pilot deployments, and general hardware and software failure rates and can be updated as more real-world deployment data is collected.

Using a scenario where a driver encounters a slow or stopped vehicle on a straight road and must take action to avoid a collision, initial baseline probabilities of collision outcomes (no collision, property damage, injury) were established without driver assistance systems. These were then compared to scenarios where FCW and AEB were available. Introducing V2X-enhanced warnings further improved safety, with a predicted additional reduction in crash probabilities by 7-8%. This amounts to an estimated crash modification factor of 0.24 (from 0.16) for V2X-enhanced FCW and 0.55 (from 0.49) for V2X-enhanced FCW+AEB for all crash severities. The project developed an online tool, MoPRA, which allows users to explore these scenarios, assess risks, and conduct uncertainty analysis. The tool also highlights which subsystem failures most impact safety, thus providing insights for future data collection initiatives and reliability requirement derivation.

Future research could expand to include metrics beyond crash data, such as driving behaviors like tailgating, harsh braking, and lane changes, as well as the impact of preventive measures such as speed advisories. Larger-scale studies are also needed to assess driver compliance with warnings and the real-world effectiveness of V2X technologies in different environments. Furthermore, it is essential to

incorporate realistic deployment and performance assumptions into V2X reliability estimations. The ultimate goal is to develop generalizable models that can represent the impact of V2X on safety and driving behavior in various scenarios, including crash avoidance applications and broader driving behaviors.

Introduction

Vehicle-to-Everything (V2X) communication paradigms have been developed to address the limitations single-vehicle perception and decision-making capabilities across different Levels of Driving Automation (*1*, *2*). V2X refers to a combination of technologies embedded into vehicles, infrastructure, and other road users, relying on a combination of sensor data, wireless connectivity networks, and real-time calculations to increase the situational awareness of the driver or the Automated Driving System (ADS), enhancing perception, localization, and planning tasks (*3*). While significant research efforts have been made towards designing and implementing V2X-enabled functions for advanced driver assistance systems (ADAS) and cooperative driving automation (CDA) technologies, several challenges must still be addressed to quantify their safety benefits and provide reliable information for technology adopters.

Many academic and industry-led research studies have focused on the reliability and security challenges to V2X-reliant functions. In recent years, several pilot projects have sought to quantify the safety benefits of different V2X technologies, providing the first estimations of real road safety improvement. These studies have mostly focused on V2X-enabled driver warnings providing basic traffic, weather, and safety information. As more real-world driving condition data is collected, it is of interest to provide a systematic approach to incorporating new evidence and fairly assessing the effect of these technologies on driver behavior and road safety. There is a need for systematic methods and approaches to determine the traffic and safety impacts of V2X technologies, including key aspects of hardware, software, and human reliability, as well as connectivity, and improved methods to assess traffic and safety impacts.

This work presents an initial approach to perform probabilistic risk assessments (PRA) of V2X technologies based on the Hybrid Causal Logic (HCL) framework which contains a multi-layer structure that integrates event sequence diagrams (ESDs), fault trees (FTs), and Bayesian belief networks (BBNs) providing a model-based approach to system analysis. This approach draws from novel hazard identification methodologies to define agents, critical events, and key tasks, failures, and errors. The methodology incorporates the effect driver-system team models (*4*, *5*) on the overall system's safety, as well as enhancing context representation to consider effects of road types, weather conditions, traffic levels, and technology effectiveness under limited data availability.

The developed HCL models are packaged in an online web-based application *Mobility PRA* (MoPRA) that enables users to explore the selected scenarios, key importance metrics, and perform uncertainty analysis. The development of MoPRA is centered around a case study on V2X-enhanced collision avoidance functionalities. This report comprises a description of the methodologies, assumptions, data sources and processing steps implemented, as well as the scenario models developed. Initial estimations of the safety benefits of V2X-enhanced driver warnings is presented together with a discussion on data sources and potential data collection efforts to strengthen PRA-based analysis of V2X technologies.

Research Gaps and Objectives

Vehicles equipped with automated driving assistance functions (SAE Levels 0-2) – frequently referred to as ADAS – will become increasingly common, introducing more safety-oriented features in public roads, such as Forward Collision Warning (FCW) and Automated Emergency Braking (AEB) (*6*). While these features have a high potential to increase driver's awareness and reduce the occurrence or severity of incidents (*7*, *8*), these focus on emergency situations that require short reaction times (*9*). In an effort to provide earlier warnings to drivers, vehicle communication-related technologies have been explored as a method to provide timely information on road infrastructure and traffic status, aiming to increase the time available to drivers to safely react to dynamic road conditions. Similarly, providing redundancy to the host vehicle is crucial to address limitations of single-vehicle perception at higher Levels of Driving Automation (SAE Levels 3-5) (*10*).

V2X is a broad term that encompasses a combination of technologies situated on both the vehicle side (On-Board Units – OBUs), on the infrastructure side (Road-Side Units – RSUs), and even configurations with Vehicle-to-Pedestrian (V2P) information sharing. The content and format of messages transmitted between vehicles and infrastructure has been detailed through different standards, such as SAE J2735 (*11*). Safety applications in Vehicle-to-Vehicle (V2V) or Vehicle-to-Infrastructure (V2I) schemes consider the use of messages such as Basic Safety Messages (BSM) detailing the state of the vehicle, 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, the adoption of these technologies has been slower than expected due to a number of factors, including the expected transition from Dedicated Short-Range Communications (DSRC) to Cellular Vehicle-to-Everything (C-V2X) communication standards.

Developing robust V2X cost-benefit analysis tools is key to support different stakeholders' decision to deploy infrastructure-side technologies, in order to take advantage of and further increase the benefits of communication-based vehicle safety functions. The objective of this project is to develop a risk-informed tool for V2X deployment focused on hardware and software reliability, connectivity, driver behavior and the impact of road and weather conditions. This tool is a first step towards developing probabilistic risk assessment methodologies to derive safety, risk, and reliability requirements for V2X technology deployments. This approach relies on four main pillars: (1) focus on scenario-based analysis, (2) provide relevant risk-reduction importance metrics, (3) embed context and other user inputs in the scenario development, and (4) provide means to conduct uncertainty analysis on the model's parameters and technology reliability, connectivity, or deployment assumptions.

Phase I: Development of V2X Risk Assessment Tool

The initial phase of this project aimed to develop a PRA-based tool featuring V2X technologies. This tool is envisioned as a web-based application where users may choose from different parameters, assumptions, and metrics to estimate risk-reduction benefits. The development of this phase is summarized as follows:

- Task 1.1: A case study was selected to demonstrate the risk assessment methodology for V2X related technology. This case study involves the use of V2X-enhanced driver warnings for collision avoidance scenarios and its interaction with emergency warnings and automated braking functions (i.e., FCW and AEB).

- Task 1.2: The crash reduction benefits of the selected technologies were characterized based on available crash databases, industry-reported crash modification factors, V2X technology characteristics, and other contextual factors (e.g., road geometry, weather conditions, driver condition).

- Task 1.3: The HCL framework was employed to develop models representing multiple scenarios targeting the use case, representing the system at different levels. These models focus on subsystem functions and interactions, including hardware, software, connectivity, and driver-related elements.
- Task 1.4: The HCL models developed for V2X-enhanced FCW and AEB technologies were hosted on an online web application "Mobility PRA" (MoPRA) that enables the user to obtain collision risk estimations.
- Task 1.5: The MoPRA tool and the underlying HCL models were used to provide initial risk reduction estimations for the selected use cases based on available data, model assumptions, and technology effectiveness estimations. The HCL framework was employed to perform uncertainty and sensitivity analysis of technology effectiveness.
- Task 1.6: Data collection initiatives were proposed based on the models' development process and analysis. This focuses on data sources, safety metrics, and other information relevant to reducing the risk reduction estimation uncertainties and improving the models developed.

The structure of the report is as follows. First, the overall risk-informed assessment methodology is presented, introducing the HCL tools capabilities and the modeling approach of this work. Then the modeling assumption, data sources, developed scenarios are described, and the initial estimates of V2X impacts benefits are discussed. Following this, identified data collection priorities and future model improvements are discussed. Finally, the implementation of the MoPRA tool is presented.

Challenges and Limitations

Assessing the safety impacts vehicle communication technologies introduced to public roads faces multiple technical and data-related challenges. The effectiveness of functions enabled or enhanced through V2V or V2I applications to reduce incident risks (either frequency or severity) depends on multiple factors, including technology deployment, communication, and market penetration assumptions.

Current data limitations represent one of the most important challenges. Frequently, studies rely on analyzing crash statistics specific to a function ("target crashes") and estimating the risk-reduction impact based on quasi-exposure methods, for instance, the role of FCW in front-rear vehicle collisions. However, the impact of contextual information, such as weather, road, and driver conditions, can significantly alter the function's effectiveness and are usually not reported in these studies. As vehicles with advanced safety functions increasingly participate in public roads, more information can be collected and used to determine the real-word benefits. However, as V2X technologies have not been deployed at scale, this information is not readily available, and in general, consist of simulation or closed-track testing. Model- and scenario-based approaches provide strategies towards identifying the role critical system functions or components play in risk scenario development even under limited data regimes. Probabilistic risk assessment frameworks provide a path to estimate and propagate uncertainty from component- to system-level effects, considering hardware, software, environment, and human factors. In addition, these models provide a flexible path towards identifying the highest contributors to system uncertainty and incorporating new evidence as it is collected.

The scope of this initial work phase is limited to collision avoidance scenarios for rear-end collisions between two vehicles. Further analysis is required to extend analysis to the surrounding traffic-level effects as well as pre-crash scenario driver behavior. Currently, the MoPRA web application provides inputs to Crash Modification Factor (CMF) calculations for V2X-enhanced FCW and AEB functions.

Risk-Informed Assessment Methodology

This work leverages multiple PRA methods and tools to estimate the risk reduction benefits of V2X-enhanced safety functions. This section briefly introduces the framework structure, modeling, and quantification approach.

Hybrid Causal Logic Methodology

PRA approaches can provide a comprehensive sensitivity analysis for technology adoption, effectiveness, and risk reduction, relying on a series of tools to estimate the risk of complex systems, providing both qualitative and quantitative insights to risk management (*12*). The HCL framework consists of a model-based approach to system analysis, containing a multi-layer structure that integrates event sequence diagrams (ESDs), fault trees (FTs), and Bayesian belief networks (BBNs. These modeling approaches, employed in both research and industry, have provided a basis for many industry standards (*13*).

An effective approach to modeling risks in complex systems involves employing ESDs to capture abnormal system behaviors and then utilizing FTs to analyze the contributing causes of the functional events identified in the ESDs. Both ESD and FT events can be linked to BBN structures, which are well-suited for representing common cause failures and the 'soft' causal dependencies arising from human, socio-economic, regulatory, or physical factors. Furthermore, BBNs provide a framework for linking these dependencies to quantification models that incorporate incomplete information and *soft* factors. Based on the framework developed in (*14*), this work presents an early implementation of HCL to model high-level collision avoidance scenarios (*15*). In addition, when coupled to probabilistic simulation capabilities, these methods allow for uncertainty propagation analysis in low-data regimes. Probability-based approaches such as Monte Carlo simulations are typically used for uncertainty propagation through system models. This technique requires empirical input data or expert judgement in the form of probability density functions of relevant parameters (*16*). Thus, even in low-data regimes, different importance metrics can be used to identify the relevance of model parameters and prioritize future data collection initiatives.

Modeling Methods

This section briefly describes the modeling methods involved in the HCL methodology.

Event Sequence Diagrams (ESD)

ESDs can be defined as generalized event trees (ETs), allowing them to represent better dynamic systems. ESDs depict a flowchart diagram (Figure 1) 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. Thus, ESDs allow a graphical representation of the risk R, is defined as the set of triplets:

$$R = \{s_i, p_i, x_i\}, i = 1, 2, \dots, N \quad (1)$$

where s_i is a scenario identification or description; p_i is the probability of that scenario; and x_i is the consequence or evaluation measure of that scenario, i.e., the measure of damage (*17*).

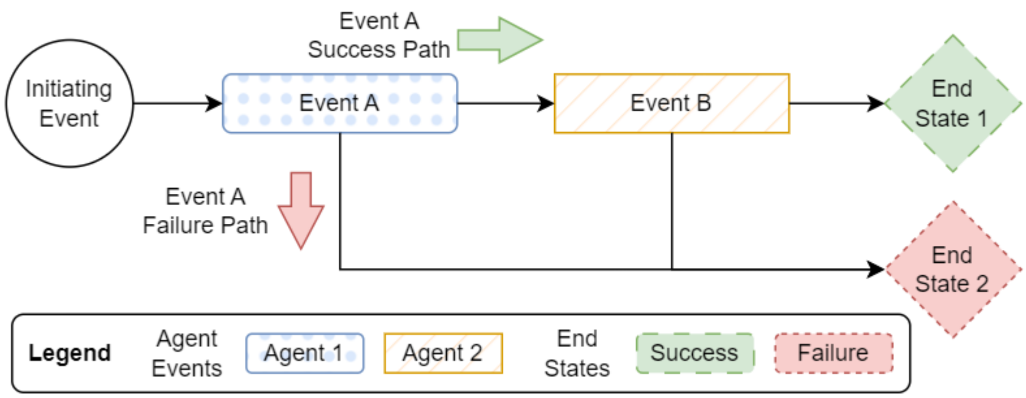


Figure 1: Event Sequence Diagram sample model.

The probability of success or failure of each event may be associated with a known probability distribution, or obtained through other models, such as FTs or BBNs.

Fault Trees (FT)

These 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 (Figure 2).

The probability of success or failure of each basic event may be associated with a known probability distribution, or obtained through other models, such as other FTs or BBNs.

Bayesian Belief Networks (BBN)

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.

In HCL, the conditional probability tables for dependent nodes can be defined in terms of their parent nodes (Figure 3). 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.

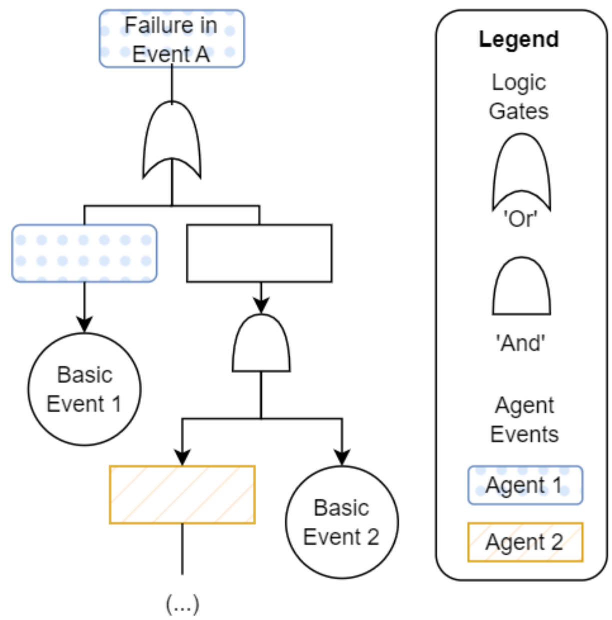


Figure 2: Fault Tree sample model.

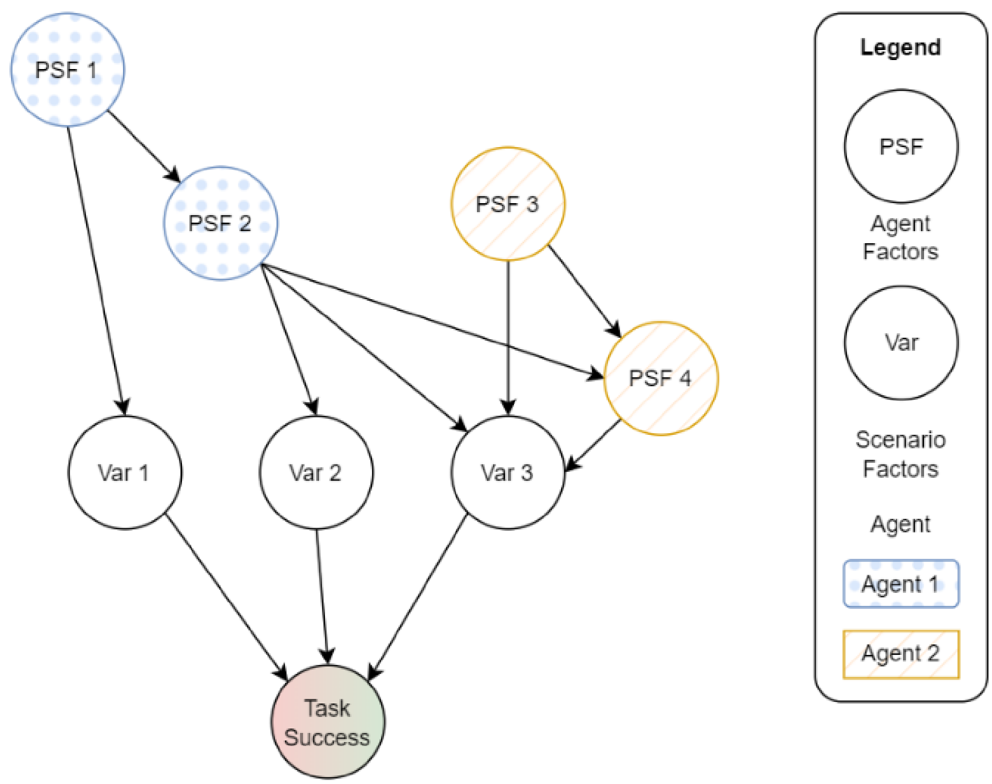


Figure 3: Bayesian Network sample model.

These models combine probability theory with graph theory to construct directed acyclic graphs (DAG), where the network structure is embedded with the system's operational and failure causal logic (*18*), (*19*). It provides a method for explicit quantitative treatment of uncertainty and partial information, where inferences are made through Bayesian updating methods:

$$\pi(x|x') = \frac{L(x'|x)\,\pi_0(x)}{\int L(x'|x)\,\pi_0(x)dx} \tag{2}$$

where $\pi_0(x)$ represents the prior belief about the behavior of x, $L(x'|x)$ likelihood of evidence x' given the model of x, and $\pi(x|x')$ the resulting posterior distribution.

Model Development Logic

The construction of the ESD, FT, and BBN models are based on the Information, Decision and Action (IDA) cognitive model (*20*). This framework was originally developed to assess the role of nuclear power plant operators in response to emergencies. It 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). This framework has also been extended to studying autonomous system operations through Concurrent Task Analysis (CoTA) (*21*, *22*). These methods can improve the robustness of the hazard analysis prior to the quantitative risk modeling (*23*), as well as aiding the identification of the most critical data needs. Modeling human and machine agents at the same level of detail, such as the driver and the vehicle, allows for a more comprehensive analysis of functional interfaces and task dependencies (*14*).

Figure 4 presents a high-level diagram of the I-D-A tasks associated with each agent – the driver and the vehicle –dependent of the level of driving automation (*24*).

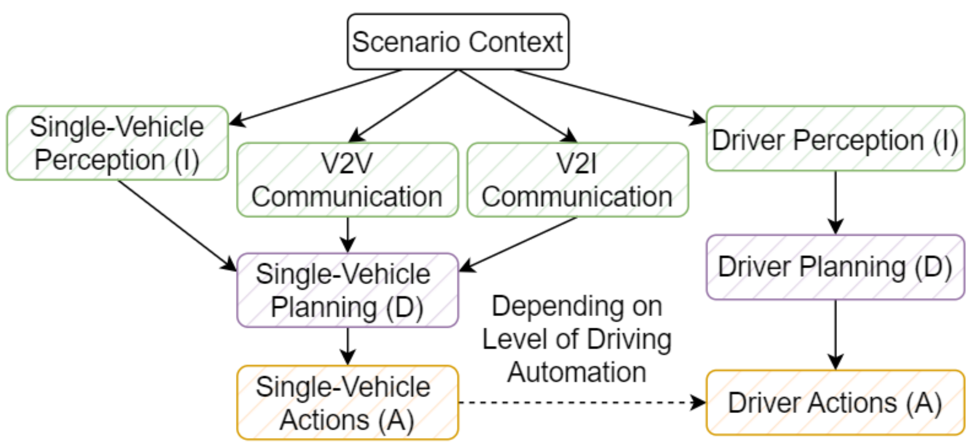


Figure 4: IDA functional flow chart.

Vehicle actions (A-Stage) may include transmitting FCWs to the driver, implementing AEB to avoid or mitigate a collision, emitting a takeover request (TOR) to the driver, or autonomously implementing Dynamic Driving Tasks (DDTs) based on a combination of data-driven and rule-based decision-making algorithms (D-Stage). In this context, 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. A crucial aspect to consider is how different contextual factors play in the development of driving scenarios. This includes elements such as road types, weather conditions and traffic levels. These elements would contribute to the scenario exposure (expressed as the ESD's initiating event) and the driving task complexity estimations.

HCL Software and Quantification

The HCL software 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 and provides risk importance metrics at component level. Different 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 logic, structure, and reliability values. Some relevant measures to identify critical components are:

- Conditional Importance Measure: The conditional probability of system failure given that a specific component has already failed. A high value may indicate that the reliability of this component significantly contributes to the overall system reliability.
- Marginal Importance Measure: The sensitivity of the system's reliability with respect to changes to the reliability of the specific component. Components with high marginal importance are critical to system reliability and more efforts should be invested into improving their reliability or changing the structure of the system to reduce their relative importance.
- Improvement Potential: Measure that indicates the extent to which system reliability improves when the failure probability of a specific component is reduced to zero.
- Criticality: Measure that indicates which component is more likely to have led to a system failure.
- Diagnostic Importance Measure (Fussell-Vesely): Measures the probability that a failure path including a specific component leads to a system failure.

- 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 an increase in the component's reliability is negligible towards system reliability.
- Risk Reduction Worth (RRW): Quantifies the relative decrease in the system failure probability given that a specific component is functioning.

The HCL software also provides tools to conduct uncertainty analysis through different simulation methods. Uncertainty is defined in the form of a distribution, expression, or uncertain BBN link in a basic event in the developed FTs and ESDs representing the system. Different sampling methods are implemented in the software, including Monte Carlo and three variants of Latin Hypercube sampling.

Please review the HCL documentation for more details[1].

Modeling and Quantification Approach

This work leverages the HCL framework to represent critical collision avoidance scenarios by decomposing them into event sequences (ESD), where the probability of each event occurring can be expressed through failure-oriented logic trees (FTs) or through partial causal relationships (BBNs), and each sequence leads to outcomes with varying degrees of severity (based on crash severity classifications). Basic events in each of these models are related to hardware and software failures, as well as human errors and other external events. The probability of occurrence of each basic event is propagated through the model's logic (represented by its structure) such that the probability of occurrence of each end-state is estimated, e.g., the probability of a property-damage only (PDO) crash.

The safety evaluation of vehicle technologies typically relies on crash statistics, naturalistic driving studies, and simulations, with the effectiveness of these technologies often characterized by Crash Modification Factors (CMFs). CMFs represent the ratio of crash likelihoods with and without the implementation of a given safety intervention, quantifying the impact of the technology on reducing or increasing crash risk. The HCL-based approach underlines the importance of estimating collision probabilities under various conditions to assess performance differences. By comparing the end-state probabilities of collisions across technologies, CMFs can be derived, providing a standardized measure to evaluate and compare their safety benefits.

Crash probabilities are estimated for five different cases to assess the effectiveness of different driving assistance and vehicle communication technologies. The first case serves as the baseline, representing a driver exposed to a rear-end collision scenario without any driver warning assistance. The second case introduces FCW technology, while the third includes AEB. The fourth case enhances FCW with V2X communication, and the fifth case additional incorporates AEB functionalities. Once the crash probabilities for these scenarios are estimated, the corresponding CMFs are derived for each case (FCW, AEB, and V2X-enabled warnings), quantifying their relative impact on reducing collision risk.

Different types of data are required to support the safety benefit estimation of V2X-enabled collision avoidance features. The main sources of data used to establish the baseline crash rates and the crash rate reduction estimations include national traffic incident databases, industry-led ADAS effectiveness

[1] The Hybrid Causal Logic (HCL) software is hosted by The B. John Garrick Institute for the Risk Sciences. Available [online] at: https://apps.risksciences.ucla.edu/

studies using real-world data, pilot deployments of V2X-related technologies, and relevant academic publications. Figure 5 presents an overview of the data-informed modeling and integration approach, briefly described as follows:

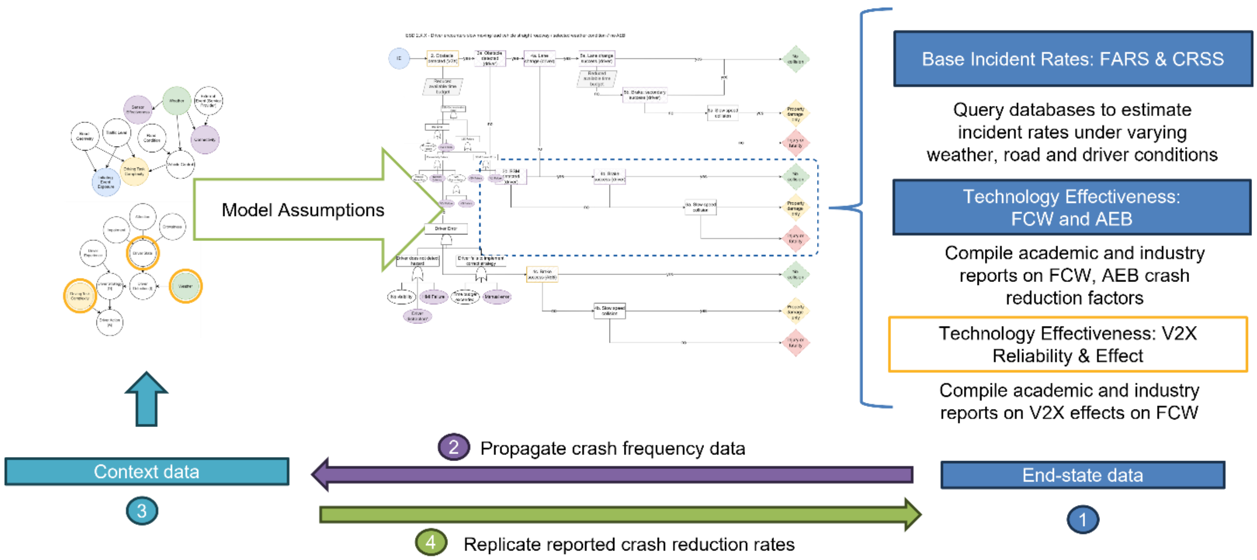


Figure 5: HCL-based quantification approach.

1. **Estimate end-state probabilities**: End-state data is collected from different transport and incident databases to obtain estimations of the (a) base crash rates and the (b) crash reduction effect of supporting technologies (FCW, AEB and V2X). This step outputs estimated crash probabilities under varying driving conditions.

    a. Base incident rates: Databases providing the number and characteristics of police-reportable crashes are queried to obtain a sub-sample representative of the selected use case. For this sub-sample, the relative frequency of different contextual factors (e.g., weather, road surface conditions, driver distraction) is calculated.

    Additional vehicle usage information is required to estimate the probability of a crash occurrence, e.g., annual vehicle miles traveled (VMT), the average number of trips, and average trip lengths. Combining the general exposure data with the information provided by the crash datasets enables the estimation of both the likelihood of crashes and the contextual conditions under which they occur.

    b. Technology effectiveness (FCW, AEB): This step involves compiling academic and industry sources reporting crash reduction rates for vehicles equipped with FCW and AEB under varying driving conditions. These crash reduction rates are applied to the base rate estimated in (a) to obtain modified crash probabilities.

    c. Technology effectiveness (V2X): This step involves compiling academic and industry sources reporting the effectiveness of V2X-enhanced driver warnings, including real-world data collected from V2X pilot deployments and reported efficiencies in academic literature. The estimated efficiencies are applied to the base rate estimated in (a) to obtain an initial estimate of crash probabilities.

2. **Propagate crash rates to basic event probabilities**: The end-state base crash rates are then propagated to the lower-levels of the HCL model. The contribution of each contextual factor (e.g., weather, lighting conditions) towards an incident is estimated through Bayesian methods. This step outputs the prior probabilities of an incident occurring given the presence of contextual factors.

3. **Represent factors leading to crashes**: A model representing the causal relationship between the contextual factors and the occurrence of an incident is populated with the values calculated in step (2). This model aims to represent how the presence of contextual factors affects the probability of an incident occurring.

4. **Model calibration**: The objective of this stage is to adjust model structure, assumptions, and parameters to recreate the end-state probabilities derived in steps (1a, 1b). This involves compiling academic and industry sources reporting component-level failure rates related to hardware, software, and connectivity elements in the system, as well as driver behavior data. Base incident rates and reported CMF for FCW and AEB functionalities are used to validate model parameters and assumptions.

5. **Safety benefit estimation**: After the model is calibrated, it is employed to estimate the crash reduction rates for V2X-enhanced driver warnings. These crash reduction rates are applied to the base rate estimated in (1a) to obtain the technology effectiveness and modified crash rates. Obtained end-state probabilities are compiled and the crash modification factors are calculated in a post-processing.

Developed Collision Avoidance Scenarios

System Characteristics and Data Sources

This section briefly describes the main characteristics of the technologies involved and the data sources supporting risk scenario quantification.

Crash incident databases

The Fatality Analysis Reporting System (FARS)[2] provides nationwide statistics from every fatal traffic crash on public roads. This database provides information about fatal crashes, including weather and road conditions, road geometry and speed, and related driver factors, among other elements, per vehicle, incident, and road type. Similarly, the Crash Report Sampling System (CRSS)[3] provides estimations of crash numbers based on a compilation of police-reported crashes involving all types of motor vehicles, pedestrians, and cyclists, ranging from property damage-only (PDO) crashes to those that result in injuries or fatalities. This database provides contextual information for each crash, including weather conditions, road geometry, and other crash-related factors, among other elements.

To address collision avoidance scenarios, the FARS and CRSS databases were queried to estimate baseline crash rates. The query criteria were aligned with the filters commonly reported in the literature for rear-end collisions, as this crash type is the primary target for FCW and AEB technologies. The FARS dataset was queried under the following conditions:

- Incidents occurred between 2019-2021 on the non-junction roadways, excluding special jurisdictions and work zone areas. This date range was selected based on more than 65% of new vehicle models across eight vehicle Original Equipment Manufacturers (OEMs) were equipped with AEB functions (*6*).
- Incidents where only two vehicles were involved in front-to-rear collisions, excluding other road user-related incidents, such as those involving pedestrians and pedal cyclists, as well as those involving hit-and-run events.
- Incidents where injuries/fatalities are recorded for drivers of motor vehicles in-transport.

[2] 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
[3] 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

Based on this selection, the data extracted for the crashes is summarized in Table 1. These variables were selected to represent the contextual conditions under which the crash developed (e.g., light and weather conditions). However, some variables identified as relevant were removed from the current analysis given the limited samples available (e.g., roadway alignment, attempted avoidance maneuver). Additional variables may be extracted to support an additional severity assessment (e.g., number of fatalities, vehicle damage).

Table 1: Variables of interest selected from FARS database.

Variable	Description	FARS File	Type	Implemented
Light Conditions	The level of light that existed at the time of the crash.	Accident	Categorical	Yes
Weather	The prevailing atmospheric conditions that existed at the time of the crash	Accident	Categorical	Yes
Speeding Related	Whether the driver was speeding, and it was related to the crash.	Vehicle	Categorical	Yes
Speed Limit	The speed limit just prior to this vehicle's critical precrash event	Vehicle	Numerical	Yes
Roadway Alignment	The roadway alignment prior to this vehicle's critical precrash event	Vehicle	Categorical	No
Roadway Surface	The roadway surface condition prior to this vehicle's critical precrash event	Vehicle	Categorical	Yes
Attempted Avoidance Maneuver	The movements/actions taken by this driver, within a critical crash envelope, in response to the "Critical Precrash Event."	Vehicle	Categorical	No
Age	The person's age in years on the date of the crash.	Person	Numerical	No
Injury Severity	The severity of the injury to this person in the crash using the KABCO scale[4].	Person	Categorical	Yes
Drinking	Whether alcohol was involved for this person and reflects the judgment of law enforcement.	Person	Categorical	Yes

[4] KABCO scale: No Apparent Injury (O), Possible injury (C), Suspected Minor In jury (B), Suspected Serious Injury (A), Fatal Injury (K), Injured, Severity Unknown (U), Died Prior to Crash, Unknown/Not Reported.

Variable	Description	FARS File	Type	Implemented
Drugs	Whether drugs were involved for this person and reflects the judgment of law enforcement.	Person	Categorical	Yes
Driver Distraction	The driver's attention to driving prior to the driver's realization of an impending critical event or just prior to impact if realization of an impending critical event does not occur.	Driver Distraction	Categorical	Yes

The FARS dataset provides information regarding injury severity resulting from each vehicle collision. To complement this information with lower severity crashes (i.e., PDO crashes), the CRSS dataset was queried under the following conditions:

- Incidents occurred between 2019-2021 on the non-junction roadways, excluding special jurisdictions and work zone areas.
- Incidents where only two vehicles were involved in front-to-rear collisions, excluding other road user-related incidents, such as those involving pedestrians and pedal cyclists, as well as those involving hit-and-run events.

Based on this selection, the data extracted for the crashes is summarized in Table 2. This dataset was mainly used to estimate the proportion of crashes by severity.

Table 2: Variables of interest selected from CRSS database.

Variable	Description	Type	Implemented
Severity	The reported severity of Motor Vehicle Crashes (PPO, Injury Only, or Fatal).	Categorical	Yes
Light Conditions	The level of light that existed at the time of the crash.	Categorical	Yes
Weather	The prevailing atmospheric conditions that existed at the time of the crash	Categorical	Yes

Driver assistance technologies

Automated driving technology is currently organized into a six-level scale by the Society of Automotive Engineers (SAE) (*24*). These levels are broadly divided into driver support features (Levels 0-2), commonly referred to as ADAS, and ADS (Levels 3-5). This division is based on the allocation of DDTs between humans and automated driving technology. While the driver is responsible for all DDTs at Level 2 (L2), from Level 3 (L3) onwards, these are progressively transferred to the ADS while within its Operational Design Domain (ODD). This continues up to Level 5 (L5), which represents a theoretical fully self-driving vehicle, unrestricted in its operational range. Even if a vehicle operate within constrained

ODDs, scenarios may develop in which the automation performing specific portions of the DDTs may not be capable of reliably maintaining or reaching a safe state.

At lower levels of driving automation, driver assistance features (≤L2), such as FCW and AEB, are expected to increase traffic safety by supporting the driver's situational awareness or provide automated response to emergency conditions (*25*). However, recent studies suggest that more evidence is required to demonstrate automation benefits on traffic safety (*26*). FCW rely on vehicle sensors (e.g., radars, cameras) to detect and track the distance between the vehicle and objects on the road[5]. Driver warnings are triggered if the current vehicle speed leads to an imminent collision. Most algorithms rely on fixed time-to-collision (TTC) thresholds and driver reaction models, although implementations may differ significantly across vehicle OEMs (*27*, *28*). Different modalities of driver warnings have been developed, employing visual (e.g., dashboards alerts), audible (alarms), and/or tactile (e.g., steering wheel, seat belt or seat vibrations), with the aim of 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 (*29*‑*31*).

FCW functionalities have been combined with other technologies for collision avoidance support, such as AEB and other brake-assist functions, to assist or supply contingency braking, in an effort to reduce the severity of potential collisions[6]. Multiple elements can affect the efficiency of these collision 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 (*7*, *8*, *32*). Several academic and industry-led studies have shown that AEB could reduce rear-end collisions by 25% to 50% (*8*, *26*, *32*‑*35*). Many of these studies rely on driving simulator experiments, naturalistic driving data and crash statistics analysis. Studies based on crash datasets frequently rely on the quasi-induced exposure method, where vehicles equipped or unequipped with certain features are compared based on the rate of target crashes to total crashes to account for the lack of traditional exposure data in crash datasets (*34*).

An early study relying on crash statistics reported that the effectiveness of FCW alone, low-speed AEB, and FCW with AEB reduced rear-end striking crash involvement (Table 3) (*33*). A more recent study (2021) focused on specific vehicle models from 2013-2019 (Table 4) (*34*) and heavy-duty (Class 8) trucks incidents recorded during 2017-2019 (Table 5) (*36*). This study noted that driver warnings were issued in only 31% of rear-end crashes for FCW-equipped trucks, and that AEB intervened in 43% of rear-end crashes (where 26% involved autobrake activation). Note that these analyses do not report the effect varying driving conditions may have on the effectiveness of the FCW or AEB features.

[5]ISO 22839:2013 Intelligent transport systems — Forward vehicle collision mitigation systems — Operation, performance, and verification requirements. This document specifies the concept of operation, minimum functionality, system requirements, system interfaces, and test methods for Forward Vehicle Collision Mitigation Systems (FVCMS).

[6] ISO 22733-1:2022 Road vehicles — Test method to evaluate the performance of autonomous emergency braking systems. This document specifies a method to evaluate the behavior of a vehicle equipped with an autonomous emergency braking system (AEBS), or dynamic brake support (DBS) during several accident scenarios.

Table 3: Reported rear-end striking crash involvement rates by Cicchino (2017).

ADAS Feature/ Crash Type	All Crashes	Injury Crashes	Third-party Injury Crashes
FCW	27% (19%, 34%)	20% (2%, 34%)	18% (-1%, 33%)
Low-speed AEB	43% (39%, 47%)	45% (40%, 48%)	44% (40%, 49%)
FCW + AEB	50% (34%, 62%)	56% (24%, 74%)	59% (26%, 77%)

Table 4: Reported reduction in the rate of police-reportable crashes for GM models by Leslie (2021).

ADAS Feature/ Crash Type	All Crashes	Injury Crashes
FCW	20% (17%, 23%)	31% (24%, 37%)
FCW + AEB (camera)	38% (34%, 41%)	53% (46%, 59%)
FCW + AEB (fusion/radar)	45% (40%, 49%)	58% (49%, 65%)
Overall FCW + AEB	60% (57%, 63%)	45% (40%, 51%)

Table 5: Reported reduction in the rate of police-reportable crashes by Teoh (2021).

ADAS Feature/ Crash Type	All Crashes	Rear-end Crashes
FCW	22% (9%, 33%)	44% (2%, 68%)
FCW + AEB	12% (4%, 20%)	41% (18%, 57%)

A recent study published by the Partnership for Analytics Research in Traffic Safety (PARTS)[7] provided the largest government-automaker study to date about the real-world effectiveness of ADAS technologies in passenger vehicles in 2022 (*7*, *8*). This study assessed the effectiveness of ADAS functions to reduce crashes, focusing on FCW and AEB, in addition to other applications such as pedestrian automatic emergency braking (PAEB), lane departure warning (LDW), lane keeping assistance (LKA), and lane centering assistance (LCA).

The data sample analyzed covered incidents recorded between 2016-2021, combining data from eight participating industry partners[8] and police-reported state-level crash data. Each ADAS function was assessed in relation to specific crash types ("system-relevant crashes") compared to the control group. The system-relevant crashes for FCW and AEB applications were defined as those where:

[7] Partnership for Analytics Research in Traffic Safety (PARTS) - National Highway Traffic Safety Administration, part of the U.S. Department of Transportation. Available [online] at https://www.nhtsa.gov/parts-partnership-for-analytics-research-in-traffic-safety

[8] Eight automakers are currently participating: American Honda Motor Co., Inc., General Motors LLC, Mazda North American Operations, Mitsubishi Motors R&D of America, Inc., Nissan North America, Inc., Stellantis (Fiat Chrysler Automobiles US LLC), Subaru Corporation, and Toyota Motor North America, Inc.

- The manner of crash was identified as front-to-rear.
- Initial point of contact on the rear end of the vehicle.
- Not a non-standard front-to-rear crash, such as vehicles that were reported to be backing up or parked (to remove these edge cases).
- No crashes where more than two vehicles were reported (to reduce the potential for misattribution of striking and struck vehicles).

The ADAS effectiveness for each crash type was assessed across three severity groups: (1) All Crashes: Crashes involving property damage, unknown injury level, or any injury severity; (2) Injury Crashes: Crashes involving any injury severity, including fatality; and (3) Serious Crashes: Crashes involving a serious injury or fatality (Table 6).

Table 6: Crash reduction rates for FCW and AEB in front-to-rear collisions reported by PARTS study.

ADAS Feature	Crash Severity	Point Estimate	Lower Bound (5%)	Upper Bound (95%)
FCW	All Crashes	16%	13%	20%
	Injury Crashes	19%	13%	25%
	Serious Crashes	21%	-7%	41%
FCW + AEB	All Crashes	49%	48%	50%
	Injury Crashes	53%	51%	54%
	Serious Crashes	42%	33%	50%

The study also attempted to estimate the contribution of different contextual factors influencing the effectiveness of ADAS (e.g., driver, vehicle, environmental, crash characteristics). Significant interactions between some driving conditions and FCW and AEB functionalities were reported for different crash severities (Table 7,Table 8).

To address the uncertainty of driving conditions reported in the data, authors either removed sets of incidents from the overall analysis or considered certain conditions to be not present. The changes reported are:

- Presence of alcohol or drugs: Unknown values were set to False.
- Driver distraction: Unknown values were set to False.
- Weather: Unknown and “Not Reported” values were removed. Only “Good” and “Bad” categories were used to describe weather, with the latter accounting for all adverse weather conditions reported (e.g., rainy, fog, snow, smoke, hail, sleet, severe crosswinds).
- Road surface: Unknown and “Not Reported” values were removed. Only “Wet” and “Dry” categories were used to describe road surface conditions.

- Light conditions: Unknown values were removed. Only "Daylight", "Dawn/Dusk" and "Dark" categories were used to describe light conditions, with the latter including lighted, unlighted, or unknown dark conditions.

- Road alignment: Unknown and "Other" values were removed. Only "Intersection", "Curved" or "Straight" were used as categories to describe road alignment.

Note that no significant interactions were reported for driver states.

Table 7: Reported FCW + AEB factor interactions on effectiveness for all crashes.

Covariate	Category	Point Estimate	Lower Bound (5%)	Upper Bound (95%)
Light Condition	Daylight	50%	49%	52%
	Dawn/Dusk	44%	36%	48%
	Dark	42%	39%	44%
Road Surface Weather	Wet Roads	44%	42%	47%
	Dry Roads	49%	48%	51%
Weather	Good	49%	48%	51%
	Bad	42%	39%	45%
Roadway Alignment	Intersection	45%	43%	46%
	Curved Road	34%	29%	38%
	Straight Road	50%	48%	51%
Sales Type	Fleet Vehicles	43%	40%	45%
	Retail Vehicles	50%	48%	51%
Driver Age	14-24	52%	49%	54%
	25-34	52%	49%	54%
	35-54	50%	48%	51%
	55-64	44%	40%	47%
	65-74	42%	38%	46%
	75+	34%	27%	40%

Covariate	Category	Point Estimate	Lower Bound (5%)	Upper Bound (95%)
Speed Limit	<25mph	24%	16%	32%
	25-34mph	44%	42%	47%
	35-44mph	51%	49%	53%
	45-54mph	51%	49%	52%
	55-64 mph	50%	47%	53%
	>65mph	48%	45%	51%

While no significant interactions were found for serious front-to-rear crashes, the study noted this may be related to the small sample size. Similarly, this study estimated the reduction in system-relevant crashes based on the presence of vehicles equipped with ADAS. However, this analysis does not account for variability of ADAS across manufacturers (e.g., ODD, driver warning implementation), whether the ADAS features were enabled by the driver at the time of the crash, nor the state of the driver prior to the crash, elements which are key to attribute the technologies' contribution to collision avoidance scenarios.

Table 8: Reported FCW + AEB factor interactions on effectiveness for injury crashes.

Covariate	Category	Point Estimate	Lower Bound (5%)	Upper Bound (95%)
Light Condition	Daylight	55%	53%	57%
	Dawn/Dusk	49%	39%	56%
	Dark	45%	40%	49%
Road Surface Weather	Wet Roads	46%	41%	50%
	Dry Roads	54%	52%	56%
Weather	Good	54%	52%	56%
	Bad	44%	39%	49%
Roadway Alignment	Curved Road	38%	30%	45%
	Straight Road	54%	52%	55%
Sales Type	Fleet Vehicles	45%	41%	49%
	Retail Vehicles	54%	52%	56%

V2X technologies and applications

In vehicle communication contexts, V2X refers to different information-sharing schemes between vehicles and their environment to improve road safety. This consists of a combination of V2V, V2I, and V2P, among other paradigms. At the current level of development, two approaches can be identified:

(1) **Driver Assistance Functions:** This approach focuses on supporting human drivers by providing critical information to enhance safety and decision-making. These vehicle communications aim to complement and expand the current capabilities of driver assistance functions (ADAS), for instance, by providing reliable early warnings to drivers. Examples include alerts for blind spots and collision warnings (V2V), and real-time updates on traffic signals and speed limits (V2I).

(2) **Automated Driving Functions:** This approach focuses on enhancing the single-vehicle perception capabilities of ADS-equipped vehicles. These functions are enabled by more data-sharing schemes of varying complexity and detail (i.e., early vs late fusion). More complex cooperative driving automation (CDA) functionalities, such as platooning, rely on these communication schemes.

V2X applications are supported by two primary network technologies. Initial developments relied on Dedicated Short-Range Communications (DSRC), facilitating direct local communication between vehicles (V2V) and traffic infrastructure (V2I). Table 9 provides an overview of the communication technologies defined in the standard SAE J2735 (*11*), identifying the main sender and receiver roles of vehicles (OBUs) and infrastructure (RSUs).

Table 9: SAE J2735 DSRC Message Set Dictionary.

Technology	Sender	Receiver	Example Application
Basic Safety Message (BSM)	OBU	OBU	Forward Collision Warning (FCW), Blind Spot Warning (BSW)
Signal Phase and Timing (SPaT)	RSU	OBU	Red Light Violation Warning (RLVW)
Map Data Message (MAP)	RSU	OBU	Intersection Movement Assist (IMA)
Radio Technical Commission for Maritime Services (RTCM)	RSU	OBU	Automated Vehicle Navigation
Traveler Information Message (TIM)	RSU	OBU	Location-based travel advisory information, e.g., Work Zone Safety
Signal Request Message (SRM)	OBU	RSU	Emergency Vehicle Preemption (EVP)
Signal Status Message (SSM)	RSU	OBU	Emergency Vehicle Preemption (EVP)
Road Safety Message (RSM)	RSU	OBU	Dynamic Speed Limit Notifications

In recent years, there has been a shift from DSRC to Cellular V2X (C-V2X) communications which can provide superior network performance, longer range, and increased reliability (*37*). While this transition is expected to significantly enhance V2X-enabled functions by providing faster, it has also raised compatibility concerns regarding existing infrastructure and deployed DSRC-based vehicle safety functions.

At lower levels of driving automation, the purpose of V2X communication technologies is to increase the information available for drivers to support real-time decision-making. Many of the technologies described in Table 9 provide information regarding driving conditions, i.e., weather events, with the objective of changing strategic-level decisions which may be better captured by surrogate safety metrics, such as headway and average speeds, rather than analyzing crash statistics. Other messages, such as BSM, can directly impact time-sensitive safety functions, such as FCW and AEB. In this regard, this work seeks to explore methods to determine how effective V2X-enhanced driver warnings can (1) extend the time available to the driver to perform an action, and (2) reduce the response time to external conditions in time-sensitive scenarios.

Although data on the effectiveness of V2X technologies in reducing incident rates is still scarce, different methods can be leveraged to populate models such as the BBN presented in Figure 6 to provide a baseline, which may be further updated as more information is collected.

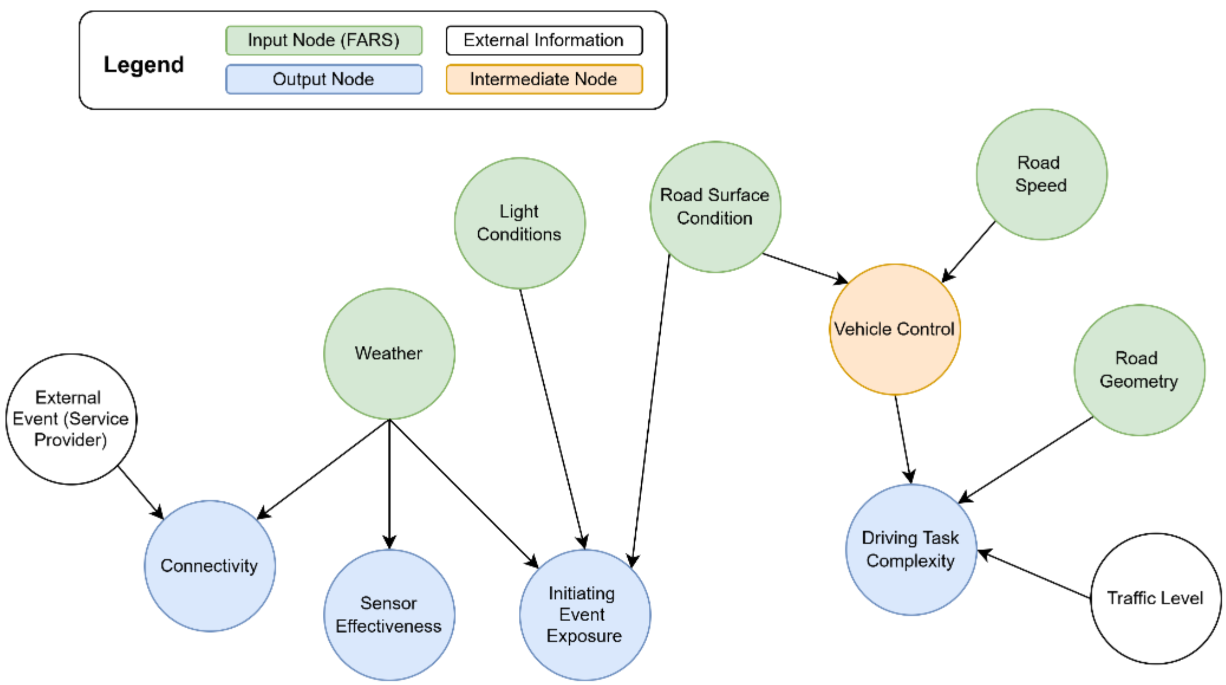


Figure 6: Example of context representation BBN model.

Findings from Connected Vehicle Pilot Deployment Program (*38*) provide some insights on incident reduction and driver behavior changes based on real driving conditions. However, the evidence of safety benefits remains inconclusive, partly due to the limited applicability of these studies and limited technological readiness, in particular for V2X-enhanced FCW functionalities. Accessible information on the safety impact of these technologies, as well as data on bandwidth capacities, and component or software reliability, remains primarily at research level, often collected through virtual simulations and driving simulator-based experiments (*39*). When assuming ideal communication-related conditions (i.e., when packets are sized properly, latency is kept low, and broadcast power is sufficiently high), rear-end collision avoidance drive warnings are highly effective – up to a 99% incident reduction in some simulations (*40*). However, obtaining reliable estimations of the warning's effectiveness under real driving conditions, such as varying weather conditions and traveling speeds, is still a challenge. In addition, many studies rely on driver reaction time models and not account for driver distraction or attitude towards the warnings, an active area of research in higher levels of driving automation technologies (*41*‑*43*).

For instance, the THEA CV Pilot program implemented several V2V and V2I applications deployed on private vehicles, transit, and pedestrian modes in a connected urban environment. Results suggest that driver reactions increased 9.93% when exposed to audio-visual FCW generated by the host vehicle based on remote vehicle information (as opposed to no driver warnings) (*44*). Yet, these estimations do not address the interactions between driver warnings generated from the host vehicle's sensors and those generated from the received BSM.

While studies have extensively examined the effects of traffic congestion on network latency and stability (*45*, *46*), more focus is required to determine the impact of missed warnings and stale information on driver warning generation, the additional resources required to increase reliability (*47*, *48*), and the interplay with higher-level functions like FCW and AEB (*49*, *50*). Moreover, thresholds for latency and communication reliability necessary for functions like driver warnings and AEB activation are not universal; these may heavily depend on environmental factors such as weather, road conditions, and traffic density (*51*). While many V2X studies focus on metrics like packet loss rates and average latency to evaluate communication quality, translating these metrics into tangible traffic safety benefits remains challenging due to the high human behavior and environmental variability. In driving simulator environments, findings suggest that V2X-enabled warnings without visible reasons – in which the cause of warning is beyond the decision sight distance of the driver – did not negatively impact reaction times or behavior. In this regard, designing adequate human-system interface and timing of the warnings is key to the success of the warning (*39*, *44*). While driver's reliance on early warnings enabled by V2X communications (i.e., extended warning lead time than achievable through local vehicle's sensors) may negatively affect their situational awareness in the event the early warnings are not triggered (*52*), warnings targeted at reducing secondary risk crash for incidents beyond the decision distance of the driver may have a positive effect on overall traffic operation and safety (*53*).

Scenario Modeling and Data Processing

This section describes the system and scenario modeling logic, as well as the steps taken to process and analyze available crash datasets and available literature.

Estimating Base Crash Probabilities

A strategy to quantify the risk-reduction benefits of a technology through scenario-based models such as HCL consists of comparing the estimated probabilities of each outcome, where each end-state represents a series of success- and failure-related events. In this regard, it is not only relevant to estimate the probability of an injury crash vs. a property-damage crash or the relative reduction in crashes (e.g., through quasi-induced exposure methods), but also estimating the probability of avoiding a collision, accounting for the overall exposure. The implemented approach seeks to estimate the base crash probabilities from crash databases (such as FARS and CRSS). As the crash probability estimation relies on the reported crash rates, it is key to compare these values relative to all crashes, all rear-end crashes, and all-rear end crashes that satisfy the criteria previously described.

Table 10 and Table 11 provide data related to police-reported crashes between 2019-2022 as summarized in (*54*), containing information on fatal motor vehicle traffic crashes based on data from FARS and non-fatal motor vehicle traffic crashes from CRSS. Note that results from FARS, such as fatal crashes and fatalities, are actual counts, while results from CRSS, such as non-fatal crashes and people injured, are estimates.

Table 10: Fatality and injury rates per licensed drivers and VMT. Adapted from summary of motor vehicle crashes: 2022 data (NHTSA, 2024).

Year	Licensed Drivers	Injury Rate per 100,000 Licensed Drivers	Fatality Rate per 100,000 Licensed Drivers	Vehicle Miles Traveled (Millions)	Injury Rate per 100 million VMT	Fatality Rate per 100 million VMT
2019	228,915,520	1,197	16.19	3,261,772	80.00	1.11
2020	228,195,802	1,000	15.88	2,903,622	79.00	1.34
2021	232,781,797	1,073	17.09	3,132,411	84.00	1.38
Average	229,964,373	1,014	16.39	3,099,268	81.00	1.28

Table 11: Police-reported traffic crashes, by crash severity. Adapted from summary of motor vehicle crashes: 2022 data (NHTSA, 2024).

Crash Severity	Fatal		Injury		PDO		Total
Year	Number	Percent	Number	Percent	Number	Percent	Number
2019	33,487	0.50%	1,916,344	28.40%	4,806,253	71.10%	6,756,084
2020	35,935	0.70%	1,593,390	30.30%	3,621,681	69.00%	5,251,006
2021	39,785	0.70%	1,727,608	28.30%	4,335,820	71.00%	6,103,213
Average	36,402	0.60%	1,745,781	28.92%	4,254,585	70.48%	6,036,768

The crash rates by crash severity presented in Table 12 are calculated based on data extracted from the CRSS databases. While these values underestimate the fatality and injury rates per 100 million VMT when compared to those reported by FARS (by 7.81% and 30.5% respectively, on average), CRSS also provides estimates on PDO crashes.

Table 12: Estimated crash rates by crash severity per 100 million VMT.

Crash Severity	Fatal		Injury		PDO		Total
Year	Estimated	Diff.	Estimated	Diff.	Estimated	Diff.	Estimated
2019	1.03	-25.4%	58.75	-26.6%	147.35	--	207.13
2020	1.24	-7.56%	54.88	-30.5%	124.73	--	180.84
2021	1.27	14.4%	55.15	-34.3%	138.42	--	194.84
Average	1.18	-7.81%	56.26	-30.5%	136.83	--	194.27

Most sources report that rear-end crashes comprise around 29%-30% of all crashes reported in the U.S (*30*). This is consistent with the average of 27.91% obtained from sampled data from CRSS shown in Table 13. On average, rear-end crashes accounted for 7.11% of fatalities, 21.92% of injuries, and 30.56% of PDO crashes. These crash statistics are further filtered to those occurring on non-junction roadways, excluding special jurisdictions and work zone areas, as well as those where only two vehicles were involved in front-to-rear collisions, excluding other road user-related incidents, such as those involving pedestrians and pedal cyclists, as well as those involving hit-and-run events. These values are presented in Table 14, where the sub-sampled rear-end collisions represented, on average, 0.76% of all fatalities, 5.82% of all injuries, and 7.13% of all PDO crashes.

Table 13: Rear-end crashes by crash severity sampled from CRSS.

Crash Severity	Fatal		Injury		PDO		Total	
Year	Number	Percent (Fatalities)	Number	Percent (Injury)	Number	Percent (PDO)	Number	Percent (All)
2019	2,363	7.06%	455,806	23.79%	1,596,903	33.23%	2,055,072	30.42%
2020	2,441	6.79%	329,472	20.68%	1,037,665	28.65%	1,369,578	26.08%
2021	2,971	7.47%	367,846	21.29%	1,291,605	29.79%	1,662,422	27.24%
Average	2,592	7.11%	384,375	21.92%	1,308,724	30.56%	1,695,691	27.91%

Table 15 provides a summary of the crash statistics for all three populations: all crashes, all-rear end crashes, and the sampled rear-end crashes. The proportion of fatality, injury, and PDO crashes for each population (in bold) were found to be statistically similar. Thus, these proportions were applied to the estimated crash rates by severity per 100 million VMT (Table 12) for the sampled rear-end crashes as shown in Table 16.

Table 14: Sub-sample of rear-end crashes by crash severity.

Crash Severity	Fatal		Injury		PDO		Total	
Year	Number	Percent (Fatalities)	Number	Percent (Injury)	Number	Percent (PDO)	Number	Percent (All)
2019	247	0.74%	116,336	6.07%	417,141	8.68%	533,724	7.90%
2020	259	0.72%	86,118	5.40%	253,213	6.99%	339,590	6.47%
2021	321	0.81%	103,402	5.99%	324,860	7.49%	428,583	7.02%
Average	276	0.76%	101,952	5.82%	331,738	7.72%	433,966	7.13%

Table 15: Summary of crash percentages by crash severity.

Crash Severity	All Crashes	Rear-End Crashes		Sample of Rear-End Crashes		
		w/r All Crashes	w/r Rear-End Crashes	w/r All Crashes	w/r Rear-End Crashes	w/r Sample
Fatality	0.60%	7.12%	0.15%	0.76%	0.02%	0.06%
Injury	28.92%	22.02%	22.67%	5.84%	6.01%	23.49%
PDO	70.48%	30.76%	77.18%	7.80%	19.56%	76.44%
Total	100.00%	59.90%	100.00%	14.39%	25.59%	100.00%

Table 16: Estimated rear-end crash rates by crash severity per 100 million VMT.

Crash Severity	Fatal	Injury	PDO	Total
All Crashes	1.18	56.26	136.83	194.27
Rear-End Crashes	0.08	12.39	42.09	54.56
Sampled Rear-End Crashes	0.01	3.29	10.67	13.96

As detailed in Table 10, on average $d = 2.3 \times 10^8$ drivers accumulated $D = 3.1 \times 10^{12}$ VMT per year, resulting in $m = 13{,}477$ VMT per driver. 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:

$$P(C|m,r) = 1 - \exp^{-m \times r} \quad (1)$$

Table 17 presents the estimated annual crash probabilities per driver and the total estimated crashes for each population by crash severity. These estimates produce crash numbers similar to those reported in Table 11, Table 13, and Table 14, and will be used to scale end-state probabilities in the HCL model.

Table 17: Estimated crash probability per crash severity.

Population	All Crashes		Rear-End Crashes		Sampled Rear-End Crashes		Equivalent KABCO Severity Number Percent (All)	
Crash Severity	Probability	Estimated Crashes (Diff.)	Probability	Estimated Crashes (Diff.)	Probability	Estimated Crashes (Diff.)		
Total	2.58E-02	6,020,983 (0.26%)	7.33E-03	1,690,995 (0.28%)	1.88E-03	432,769 (0.28%)	K, A, B, C, O, Unknown	7.90%
Fatal	1.59E-04	36,513 (-0.30%)	1.13E-05	2,600 (-0.30%)	1.20E-06	277 (-0.30%)	K	6.47%
Non-Fatal	2.58E-02	5,984,470 (0.26%)	7.32E-03	1,688,396 (0.28%)	1.88E-03	432,492 (0.28%)	A, B, C, O, Injured (Unknown)	7.02%
Injury	7.55E-03	1,743,651 (0.12%)	1.67E-03	383,906 (0.12%)	4.43E-04	101,828 (0.12%)	A, B, C, Injured (Unknown)	7.13%
PPO	1.83E-02	4,240,819 (0.32%)	5.66E-03	1,304,490 (0.32%)	1.44E-03	330,665 (0.32%)	O	
No Collision	9.74E-01	--	9.93E-01	--	9.98E-01	--	--	

Model Variables and Assumptions

This section discusses the processing steps to populate the HCL models based on data extracted from the databases discussed in the previous section. While data entries of police-reportable incidents (FARS, CRSS) contain detailed information about the crash conditions, potential causes, and consequences, the following analysis relies on a sub-section of variables common to the FCW and AEB studies. The general approach is to select a sample of categorical variables, such as weather or road conditions, to estimate how these conditions affect the probability of a crash occurring.

In general, driving environment statistics reveal that most crashes occur on straight roads, dry surfaces, in clear weather, and during daylight hours (*55*).

FARS Dataset Filtering

FARS data are made available to the public in Statistical Analysis System (SAS) data files as well as comma-separated values (CSV) files. For the current collection year, there are 30 data files containing information collected from police crash reports, death certificates, state vehicle registration files, emergency medical service reports, among others. Four main data files from the FARS dataset were used for this analysis. These consist of the “Accident”, “Vehicle”, “Person” and the “Distract”, as detailed in the FARS manual[9]:

- Accident – (1975-current): This data file contains information about crash characteristics and environmental conditions at the time of the crash. There is one record per crash.
- Vehicle – (1975-current): This data file contains information describing the motor vehicles in-transport and the drivers of motor vehicles in-transport who are involved in the crash. There is one record per motor vehicle in-transport.
- Person – (1975-current): This data file contains information describing all people involved in the crash including motorists (i.e., drivers and passengers of motor vehicles in-transport) and non-motorists (e.g., pedestrians, pedal cyclists, and occupants of motor vehicles not in-transport). It provides information such as age, sex, vehicle occupant restraint use, and injury severity. There is one record per person.
- Distract – (2010-current): This data file contains information about driver distractions. Each distraction is a separate record. There is at least one record for each driver of a motor vehicle in-transport.

Table 18 provides an overview of the selected data elements describing the conditions of a motor vehicle crash. The resulting dataset was merged according to the instructions provided in the FARS manual based on the unique case number (ST_CASE) and vehicle number (VEH_NO). A subset of these data elements were implemented for the current analysis (refer to Table 1). Additional processing was performed to simplify the data entries described in the following sections.

[9] National Center for Statistics and Analysis. (2024, April*). Fatality Analysis Reporting System analytical user’s manual, 1975-2022* (Report No. DOT HS 813 556). National Highway Traffic Safety Administration.

Table 18: Selected FARS data types and scenario filters.

File	Data Element ID	Data Element Name	Filter Applied
Accident	ST_CASE	Consecutive Number (Unique Case Number)	--
	VE_FORMS	Number of Motor Vehicles In-Transport (MVIT)	Two vehicles involved in the crash
	PVH_INVL	Number of Parked/Working Vehicles	No parked or working vehicles
	SP_JUR	Special Jurisdiction	No Special Jurisdiction
	HARM_EV	First Harmful Event	Motor Vehicle In-Transport
	MAN_COLL	Manner of Collision of the First Harmful Event	Front-to-Rear
	RELJCT1	Relation to Junction—Within Interchange Area	Not Within an Interchange Area
	RELJCT2	Relation to Junction—Specific Location	Non-Junction
	TYP_INT	Type of Intersection	Not an Intersection
	REL_ROAD	Relation to Trafficway	On Roadway
	WRK_ZONE	Work Zone	None
	LGT_COND	Light Condition	--
	WEATHER	Atmospheric Conditions	--
Vehicle	ST_CASE	Consecutive Number (Unique Case Number)	--
	VEH_NO	Vehicle Number	--
	HIT_RUN	Hit-and-Run	No Hit-and-Run
	ROLLOVER	Rollover	No Rollover
	SPEEDREL	Speeding Related	--
	VSPD_LIM	Speed Limit	--
	VALIGN	Roadway Alignment	--

File	Data Element ID	Data Element Name	Filter Applied
	VSURCOND	Roadway Surface Conditions	--
	P_CRASH1	Pre-Event Movement (Prior to Recognition of Critical Event)	--
	P_CRASH3	Attempted Avoidance Maneuver	--
Person	ST_CASE	Consecutive Number (Unique Case Number)	--
	VEH_NO	Vehicle Number	--
	PER_NO	Person Number	--
	AGE	Age	--
	PER_TYP	Person Type	Driver of a Motor Vehicle In-Transport
	INJ_SEV	Injury Severity	--
	DRINKING	Police Reported Alcohol Involvement	--
	DRUGS	Police Reported Drug Involvement	--
Distract	ST_CASE	Consecutive Number (Unique Case Number)	--
	VEH_NO	Vehicle Number	--
	DRDISTRACT	Driver Distracted By	--

Light Conditions

Police-reported crashes retrieved from FARS and CRSS provide detailed information regarding the light conditions. Nine categories are defined in FARS: Daylight, Dark (Not Lighted, Lighted, Unknown Lighting), Dawn, Dusk, as well as Other, Not Reported, or Reported as Unknown.

To incorporate the crash reduction rates reported by PARTS, the light condition variable is simplified as:

- Daylight
- Dawn/Dusk
- Dark

Given the sample data queried from FARS (Table 19), "Unknown" light conditions account for 4.3% and are removed from further analysis.

Table 19: Sampled crashes by light condition.

Light Conditions	Crashes	Relative Frequency	Adjusted Relative Frequency
Dark	38,888	0.525	0.526
Daylight	31,895	0.431	0.431
Dusk/Dawn	3,167	0.043	0.043
Unknown	91	0.001	--
Grand Total	74,041	1.000	1.000

Weather Conditions

Police-reported crashes retrieved from FARS and CRSS provide a detailed report about the weather conditions at the moment of the crash. Thirteen categories are defined in FARS, such as: Clear (no adverse atmospheric conditions), Cloudy, Rain (including mist, sleet, hail), Snow (including blowing snow), Fog, Smog, or Smoke, Severe Crosswinds, Blowing Sand, Soil, or Dirt, and Unknown.

To incorporate the crash reduction rates reported by PARTS, the weather variable is simplified as:

- Clear
- Adverse (consisting of all other weather conditions)

Given the sample data queried from FARS (Table 20), "Unknown" weather conditions account for 3.5% and are removed from further analysis.

Table 20: Sampled crashes by weather condition.

Weather Conditions	Crashes	Relative Frequency	Adjusted Relative Frequency
Clear	56,776	0.767	0.795
Adverse	14,667	0.198	0.205
Unknown	2,598	0.035	--
Grand Total	74,041	1.000	1.000

Posted Road Speed Limit

The initial approach was to classify roads by speed, high or low, depending on the reported function of the road, i.e., interstate or local. However, PARTS reports CMF values per posted speed limits of the road (Table 21). Similarly, FARS reports the posted speed limits of the road as a continuous variable (as opposed to categorical). Considering the alternative approaches, a mixed strategy was chosen by categorizing roads by their posted speed limit (Table 22) as:

- High speed (above 45 mph)
- Low speed (below 45 mph)

As these values are taken from road infrastructure information, there are a minimal number of unknowns compared to other police-reported variables. Thus, all data samples were used to estimate the scenario exposure.

Table 21: Sampled crashes by road speed limit.

Road Speed	Crashes	Relative Frequency
Over 65	24,731	0.334
55-64	20,831	0.281
45-54	12,831	0.173
35-44	10,716	0.145
25-34	4,558	0.062
Under 25	374	0.005
Grand Total	74,041	1.000

Table 22: Sampled crashes by adjusted road speed limit.

Road Speed	Crashes	Relative Frequency
High Speed	58,393	0.789
Low Speed	15,648	0.211
Grand Total	74,041	1.000

Road Surface

Police-reported crashes retrieved from FARS and CRSS provide detailed information regarding the road conditions. Twelve categories are defined in FARS: Dry; Wet; Snow; Ice/Frost; Sand; Water (Standing or

Moving); Oil; Other; Slush; Mud, Dirt, or Gravel; as well as those related to a Non-Trafficway Are or Driveway Access, Not Reported, and Reported as Unknown.

To incorporate the crash reduction rates reported by PARTS, only the following two conditions are considered:

- Dry
- Wet

Given the sample data queried from FARS (Table 23), "Unknown" and "Other" road surface conditions account for 2.4% and are removed from further analysis.

Table 23: Sampled crashes by road surface condition.

Road Surface	Crashes	Relative Frequency	Adjusted Relative Frequency
Dry	64,663	0.873	0.894
Wet	7,644	0.103	0.106
Other	1,163	0.016	--
Unknown	571	0.008	--
Grand Total	74,041	1.000	1.000

Injury Severity

The FARS dataset follows the KABCO severity rating scale which includes the following categories: No Apparent Injury (O), Possible injury I, Suspected Minor Injury (B), Suspected Serious Injury (A), Fatal Injury (K), Injured, Severity Unknown (U), Died Prior to Crash, and Unknown/Not Reported. Note that the numbers of crashes in the latter three categories are usually small.

The PARTS analysis considers the following categories of crash severities:

- All crashes (K, A, B, C, O, Unknown)
- Injury Crashes (K, A, B, C)
- Serious Crashes (K, A)

An intermediate approach is adopted in this work. Table 24 presents the distribution of crashes by crash severity present in the sampled rear-end crash scenarios. As the FARS database primarily reports fatalities (as opposed to lower risk crashes), the sample is significantly skewed towards High Severity Crashes (K, A). The number of crashes with unknown severity amount to 2.2% and thus are removed from future analysis. Table 25 and Table 26 present the distribution according to the denominations used in FARS and PARTS, respectively.

Table 24: Sampled crashes by crash severity.

Severity	Crashes	Relative Frequency	Adjusted Relative Frequency
High Severity (K,A)	40,026	0.541	0.553
Moderate Severity (B,C)	11,430	0.154	0.289
Minor Severity (O)	20,955	0.283	0.158
Unknown	1,630	0.022	--
Grand Total	74,041	1.000	1.000

Table 25: Sampled crashes by crash severity (PARTS equivalent).

Severity	Crashes	Relative Frequency
All Crashes	74,041	1.000
Injury Crashes (K, A, B, C)	51,456	0.695
Serious Crashes (K, A)	40,026	0.541
Other Crashes (O, U)	22,585	0.305
Grand Total	74,041	1.000

Table 26: Sampled crashes by crash severity (CRSS equivalent).

Severity	Crashes	Relative Frequency	Adjusted Relative Frequency
PDO Crash	20,955	0.283	0.289
Injury Crash	17,055	0.230	0.235
Fatal Crash	34,546	0.467	0.476
Unknown	1,485	0.020	--
Grand Total	74,041	1.000	1.000

Driver Model

The state of the driver has been incorporated as a major factor contributing to motor vehicle crashes using a variety of methods, for instance, relying on reaction times and the impact of distraction tasks. Given the available granularity of the data, models such as the one presented in Figure 7 can be employed. This represents a conceptual BBN model for driver's state, including the effect of the driver's state impact the probabilities of success in detecting (I-Phase), selecting a strategy (D-Phase), and correcting implementing an action (A-Phase).

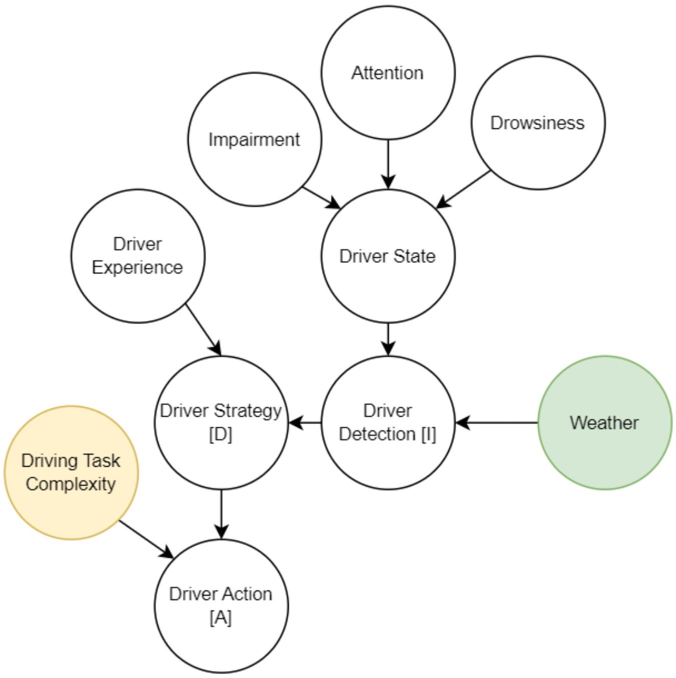


Figure 7: Example of simplified driver BBN model.

While databases such as FARS may be employed to collect data on distracted or impaired driving, more sophisticated discussions on Performance Influencing/Shaping Factors (PIF/PSF) used in Human Reliability Analysis (HRA) may lead to more complex models (*56*). These model-based approaches may play a significant role as means to explain the effect of human-system interactions in the decrease – or increase – of incidents where ADAS features are involved (*26*).

To incorporate police-reported information available in FARS and CRSS databases, variables related to the driver state are extracted and analyzed.

Driver State

Two variables are used to describe the driver's state in PARTS. These are (1) distraction and (2) impairment due to alcohol or drugs. This is a simplified approach compared to the police-reported information available in the FARS dataset, which includes more information about impairment (including drowsiness), and the reported causes of distraction, as well as additional information of the drugs and alcohol.

The police-reported alcohol and drug involvement data elements were combined. The following categories are considered for the initial model implementation:

- Driver Distraction: Yes/No. All data entries except for "Not Distracted" and "Unknown" were considered to indicate that the driver was distracted at the moment of the crash.

- Driver Impaired (Alcohol, Drugs): Yes/No. If either alcohol or drugs were reported, the driver is considered to have been impaired at the moment of the crash. If either alcohol or drug presence was not reported or unknown, then these cases were considered as negative.

However, variables not related to alcohol or drug consumption have a high number of unknowns. As shown in Table 27, the distracted drivers account for only 7.5% of the crashes in the selected sample, while in comparison, the state of the driver was unknown in 62.4% of the cases. Impaired driving (alcohol and/or drugs) data is more reliable, with unknown accounting for 28.9% of the samples (Table 28).

Table 27: Sampled crashes by driver distraction.

Distracted	Crashes	Relative Frequency	Adjusted Relative Frequency
Not Distracted	22,302	0.301	0.801
Distracted	5,548	0.075	0.199
Unknown	46,191	0.624	--
Grand Total	74,041	1.000	1.000

Table 28: Sampled crashes by driver impairment.

Impaired	Crashes	Relative Frequency	Adjusted Relative Frequency
Not Impaired	37,772	0.510	0.718
Impaired	14,867	0.201	0.282
Unknown	21,402	0.289	--
Grand Total	74,041	1.000	1.000

Driver Actions

The initial approach considered two variables reported as precrash characteristics in the FARS datasets. While these variables are not reported in the PARTS study, it is considered that these could provide important contextual information regarding the driver strategy (D) and action implemented to avoid the crash (A). These are:

- Speeding: Whether the driver speeding was related to the crash occurrence as reported by law enforcement. FARS includes detailed information about whether the speeding was related to the driver exceeding the speed limit or driving too fast for the road conditions. This was simplified to Yes/No categories. Given the sample data queried from FARS (Table 29), "Unknown" speeding conditions account for 4.4% and are removed from further analysis.

- Avoidance Action: This data element identifies the attribute that best describes the movements or actions taken by the driver in response to a "critical precrash event," i.e., suspected triggering event contributing to the crash. This includes information about whether the driver braked, steered, or accelerated and thus contains key information.

However, due to the high number of unknowns (over 68%) this variable is not considered in the first implementation of the model. These values might be revisited in future ESD models considering the following categories: none (including accelerating), braking, and steering.

Table 29: Sampled crashes by driver speeding.

Speeding	Crashes	Relative Frequency	Adjusted Relative Frequency
No	53,665	0.725	0.758
Yes	17,112	0.231	0.242
Unknown	3,264	0.044	--
Grand Total	74,041	1.000	1.000

Scenario Exposure Derivation

This work implements a BBN model to capture the effect of environmental conditions and other contextual elements over crash scenarios. This corresponds to the lowest level of the HCL models developed and leverages the categorical variables extracted from the FARS dataset. Models such as the one presented in Figure 8 can be constructed, where the relationship between different variables can be justified based on statistically significant interactions found through covariate analysis. Given the current data availability and assumptions, the initial model is simplified as presented in Figure 9.

The node "Scenario Exposure" collects key contextual information from Weather, Light, and Road Surface Conditions. Additional inputs and external events, such as communication service provider failures and traffic levels, may be included to better estimate the impact on V2X communications ("Connectivity"), vehicle's detection capabilities ("Sensor Effectiveness"), driving maneuver complexity ("Vehicle Control"), and overall driver reaction ("Driver Action").

The model in Figure 9 aims to answer the following question: (a) given all these environmental conditions, what is the exposure to a crash scenario? This question is represented by equation (4):

$$P(C_i|S_j) = \frac{P(S_j|C_i)P(C_i)}{P(S_j)} \tag{2}$$

where S_j is the condition j, e.g., weather conditions, and C_i represents a crash of severity i, e.g., an injury crash. However, crash statistics such as those collected in FARS detail the conditions present at the moment of the crash. Thus, this data source provides information on (b) given that there was a crash, what is the probability of having certain conditions present? This question is formulated by $P(S_j|C_i)$ where, as a first approach, the relative frequency of the conditions at the moment of the crash are used to estimate the corresponding conditional probability. The conditional probabilities derived from the FARS dataset are summarized in Table 30.

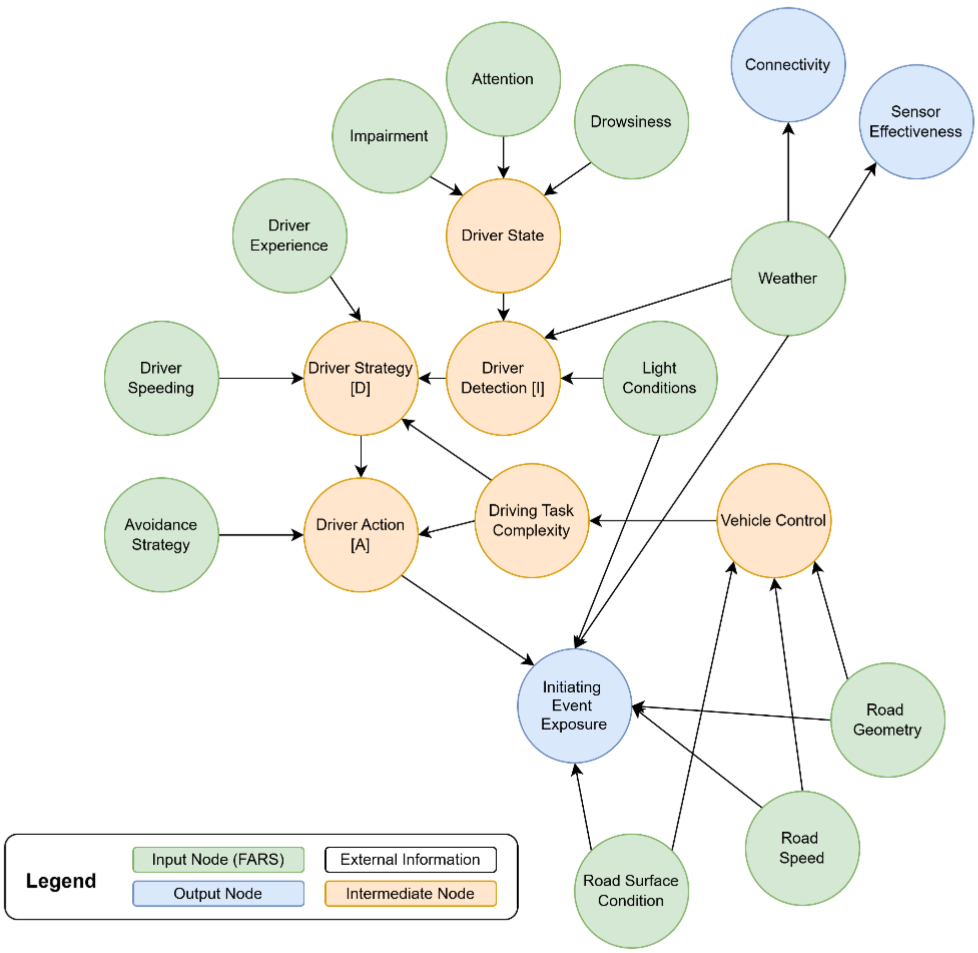


Figure 8: Initial scenario exposure BBN model.

Table 30: Summary of prior conditional probabilities.

Variable	Category	Conditional Probability P(S|C)
Distraction	Distracted	0.199
	Not Distracted	0.801
Impairment	Impaired	0.282
	Not Impaired	0.718
Light Cond	Dark	0.526
	Daylight	0.431
	Dawn/Dusk	0.043
Road Speed	High Speed	0.789
	Low Speed	0.211
Speeding	Speeding	0.242
	Not Speeding	0.758
Weather	Clear	0.795
	Adverse	0.205
Road Surface	Dry	0.894
	Wet	0.106

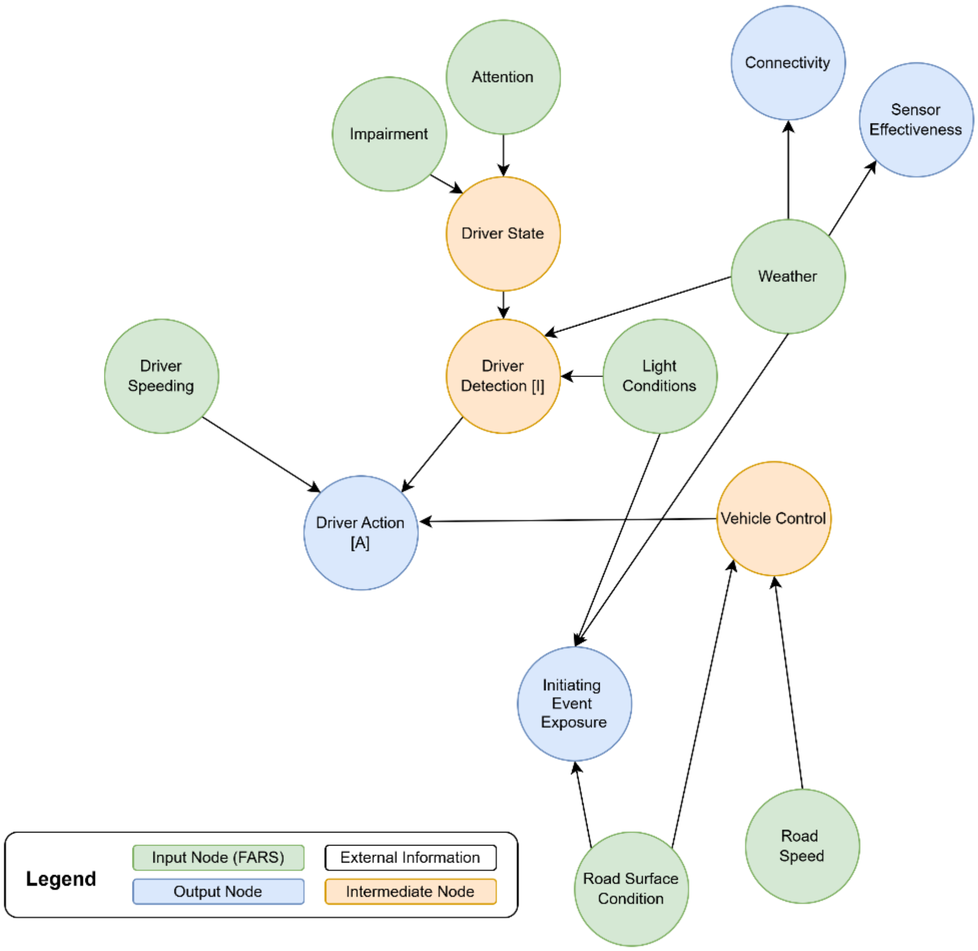


Figure 9: Proposed scenario exposure BBN model.

In order to estimate the probability of a crash occurring given certain conditions, the conditional probability tables of the intermediate and output nodes are derived. Intermediate nodes, such as "Driver State," "Driver Detection Task" and "Vehicle Control" are derived from the FARS dataset described in the previous sections, as are the output nodes "Driver Action Task" and "Scenario Exposure". Note that these probabilities reflect the relative frequency of conditions occurring rather than implying their contribution to the crash occurring. This is a conservative approach, considering the presence of each factor as an indication of a crash occurring.

Conditional probabilities can be further refined by conducting a sensitivity analysis based on the model shown in Figure 10, representing equation (4). By setting the evidence of different nodes, i.e., one of the input node states is known, the distribution of crashes by crash severities may change. An example is presented in Table 31. This procedure is not implemented at the current stage of the model.

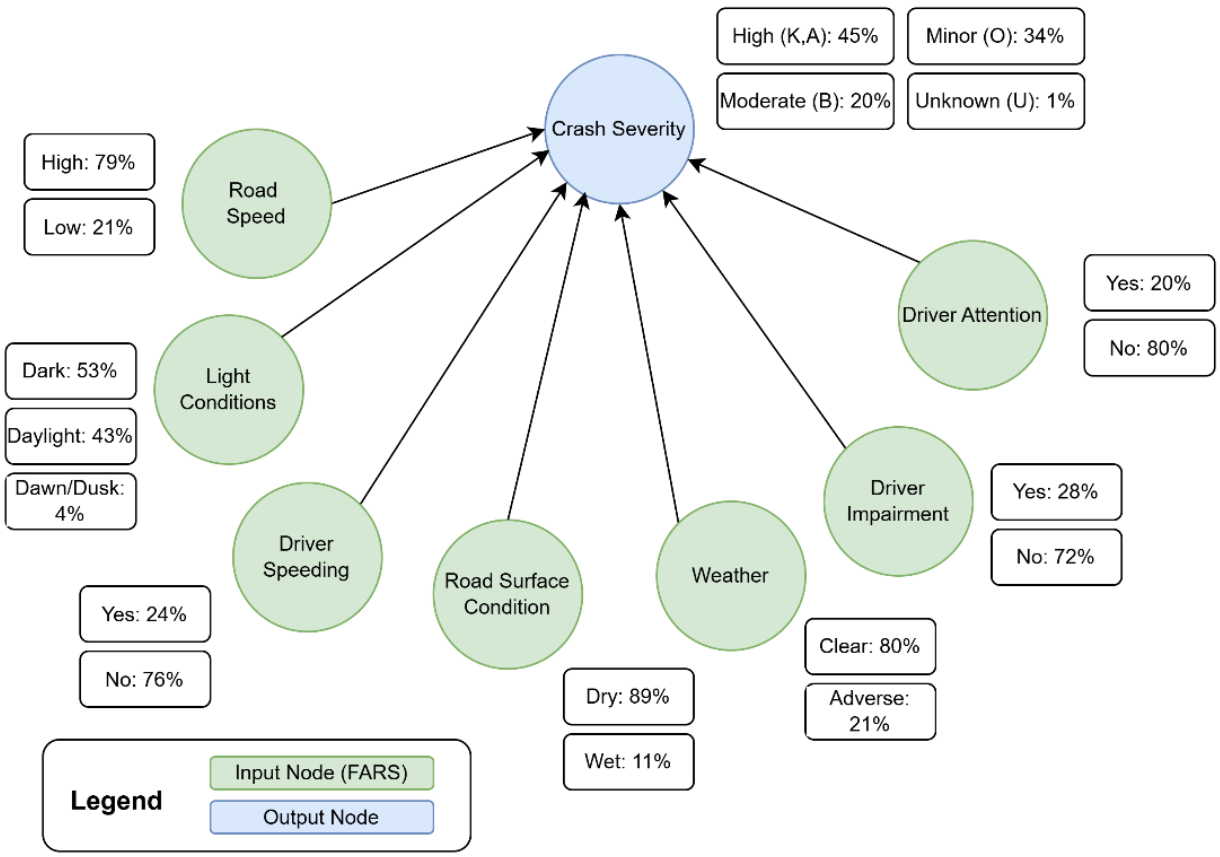


Figure 10: Prior conditional probabilities model.

Table 31: Example of crash contributing factors sensitivity analysis.

Crash Severity	P(Ci|Sj=Driver Impaired, Dark Light Conditions, High Speed Roads)	P(Ci|Sj=Driver Distracted, Dry Surface Conditions, Driver Speeding)	P(Ci|Sj=Driver Distracted, Wet Surface Conditions, Low Speed Roads)
High Severity (K, A)	0.60	0.52	0.30
Moderate Severity (B, C)	0.26	0.30	0.15
Minor Severity (O)	0.14	0.17	0.40
Unknown (U)	0.00	0.01	0.10

Driver State

This node represents the driver's Information Stage, referring to the tasks the driver performs when receiving information from external sources. In this model, it is used to represent the success or failure of the driver to monitor their own state as well as driver warnings (i.e., the environment "internal" to the vehicle). The probability of the driver being available to receive information is dependent on their attention and impairment state.

The relative frequency of the conditions present at the moment of the crash are used to populate the "Not Available" state of the node resulting in the conditional probability Table 32.

Table 32: BBN model - conditional probability table for driver state.

Distracted Year	Impaired	Driver State	
		Not Available	Available
Attentive	No	0.59	0.41
	Yes	0.06	0.94
Distracted	No	0.32	0.68
	Yes	0.03	0.97

Driver Detection Task

This node represents a secondary aspect of the driver's Information Stage, but with respect to the environment "external" to the vehicle. Thus, the probability of success of the driver detecting an obstacle while driving is affected by the driver's state ("Available" vs. "Not Available"), the weather and light conditions.

The relative frequency of the conditions present at the moment of the crash are used to populate the "Failure" state of the node resulting in the conditional probability Table 33.

Table 33: BBN model - conditional probability table for driver detection task.

Driver State	Weather	Light Conditions	Driver Detection Task	
			Success	Failure
Driver Not Available	Clear	Daylight	0.92	0.08
		Dark	0.89	0.11
		Dawn/Dusk	0.99	0.01

Driver State	Weather	Light Conditions	Driver Detection Task	
			Success	Failure
	Adverse	Daylight	0.98	0.02
		Dark	0.97	0.03
		Dawn/Dusk	1.00	0.00
Driver Available	Clear	Daylight	0.74	0.26
		Dark	0.40	0.30
		Dawn/Dusk	0.97	0.03
	Adverse	Daylight	0.93	0.07
		Dark	0.92	0.08
		Dawn/Dusk	0.99	0.01

Vehicle Control

This node is used as a proxy to represent the driving task complexity. The probability of experiencing a high or low driving task complexity is dependent on the road speed (“High Speed” vs. “Low Speed”) and surface (“Dry” vs. “Wet”). Dependent on the data available, many other factors may be included in this node, including additional information on the road’s geometry (e.g., curve vs. straight), function (e.g., intersection vs not an intersection), and traffic density (e.g., high traffic vs low traffic).

The relative frequency of the conditions present at the moment of the crash are used to populate the “High Complexity” state of the node resulting in the conditional probability Table 34.

Table 34: BBN model - conditional probability table for vehicle control.

Road Speed	Road Surface	Vehicle Control	
		High Complexity	Low Complexity
High Speed	Dry	0.70	0.30
	Wet	0.08	0.92
Low Speed	Dry	0.19	0.81
	Wet	0.02	0.98

Driver Action Task

This node represents the driver's Action Stage, referring to the tasks the driver performs in response to external stimuli after selecting a strategy (Decision Stage). As the true state of the "Decision Stage", i.e., the driver selecting a correct strategy given the road conditions requires data not readily available from the crash datasets, the information related to "Speeding" is used to represent the driver's overall strategy prior to the crash. This is combined with the perceived driving task complexity represented by the "Vehicle Control" node, and whether the driver detected the obstacle on the road ("Driver Detection Task").

The relative frequency of the conditions present at the moment of the crash are used to populate the "Failure" state of the node resulting in the conditional probability Table 35.

Table 35: BBN model - conditional probability table for driver action task.

Driver Detection Task	Speeding	Vehicle Control	Driver Action Task	
			Success	Failure
Success	No Speeding	High Complexity	0.94	0.06
		Low Complexity	0.55	0.45
	Speeding	High Complexity	0.99	0.01
		Low Complexity	0.88	0.12
Failure	No Speeding	High Complexity	0.96	0.04
		Low Complexity	0.79	0.21
	Speeding	High Complexity	0.98	0.02
		Low Complexity	0.91	0.09

Initiating Event Exposure

This output node represent the Initiating Event's probability of occurrence, fundamental to the calibration of the ESD models. While many other factors may be included in this node related to road's geometry, road function and traffic density, the weather, light and road surface conditions are used to represent the scenario's exposure.

The relative frequency of the conditions present at the moment of the crash are used to populate the "True" state of the node resulting in the conditional probability Table 36.

Table 36: BBN model - conditional probability table for scenario exposure.

Weather	Light Conditions	Road Surface	Driver Action Task	
			Success	Failure
Clear	Daylight	Dry	0.25	0.75
		Wet	0.02	0.98
	Dark	Dry	0.07	0.93
		Wet	0.01	0.99
	Dawn/Dusk	Dry	0.31	0.69
		Wet	0.02	0.98
Adverse	Daylight	Dry	0.08	0.92
		Wet	0.01	0.99
	Dark	Dry	0.03	0.97
		Wet	0.00	1.00
	Dawn/Dusk	Dry	0.01	0.99
		Wet	0.00	1.00

Estimated Nodes

Additional nodes have been included to represent the effect of weather on hardware and software reliability of vehicle components.

- Connectivity: This output node represents the impact of adverse weather conditions on overall network reliability. The purpose of this node is to quantify the event of adverse weather impacting the Communication Service Providers (CSPs) on the specific corridor where the collision may potentially occur. The high reliability values imply that communication stability is only temporarily and intermittently affected, and that extended network failures are rare events (Table 37).

- Sensor Effectiveness: This output node represents the impact of adverse weather conditions on overall sensor (Table 38). Given the high variety of sensors available, including RGB cameras, radars, LiDARs, etc., the values of this output node are envisioned as a user input in future iterations of the model.

Table 37: BBN model - conditional probability table for v2x connectivity.

Weather	Connectivity	
	Available	Not Available
Clear	0.99	0.01
Adverse	0.93	0.07

Table 38: BBN model - conditional probability table for sensor reliability.

Weather	Sensor Reliability	
	Operational State	Failed State
Clear	0.98	0.02
Adverse	0.75	0.25

Modeled Scenarios and Estimated CMF

To study how V2X can impact scenario development, two high-level collision avoidance applications are selected. Each represents different levels of driving automation, driver roles, and use of V2X information.

The general scenario considers a driver encountering a slow or stopped vehicle on a straight road (non-intersection). The driver must detect the obstacle and take the appropriate action (in this case, breaking) to avoid a collision. The following scenarios are considered:

- Scenario 1: No Driver Assistance Systems. This is the base case which serves to compare all other technologies involved.
- Scenario 2: Driver Assisted by Local FCW System. In this scenario, the driver is assisted by a local FCW system based on host vehicle's sensors.
- Scenario 3: Driver Assisted by Local AEB System. In this scenario, the driver is assisted by a local FCW system based on host vehicle's sensors and supported by AEB features.
- Scenario 4: Driver Assisted by V2X-enhanced FCW. This scenario builds upon Scenario #2, such that the FCW system is enhanced by V2V or V2I communications.
- Scenario 5: Driver Assisted by V2X-enhanced FCW and AEB. This scenario builds upon Scenario #3, such that the FCW system is enhanced by V2V or V2I communications and the driver is supported by AEB features.

Each of these scenarios can lead to the following end-states:

1. No Collision: The driver is successful in avoiding a collision with an obstacle on the road.
2. Property-Damage Only (PDO): A collision occurs, but at a lower speed resulting in property damage.
3. Injury Crash: merges injury from low-to-high severity and fatality crashes.

The logic of each scenario is briefly described in the following sections. Scenarios #4 and #5 are implemented in the MoPRA tool. Details of the model parameters can be found in the Appendix.

Scenario 1: No Driver Assistance Systems

This case is structured around the following high-level events:

- The driver detects an object or obstacle on the road and brakes in response. The success of this event implies that the driver detected the obstacle and braked in response.
- The braking action is sufficient to avoid a collision with the obstacle. The success of this event implies that the driver braked sufficiently given the road conditions and that no failure in the vehicle prevented braking from occurring.

This scenario is depicted in Figure 11, where all end-states are directly related to the driver's actions. Each key event is supported by a simple FT model (Figure 12), depicting potential causes of the driver failing to brake or that after braking, a slow speed collision is not avoided. Model parameters can be found in Table 51. Note that vehicle brake related failure values are estimated from the sampled rear-end crash data retrieved from FARS.

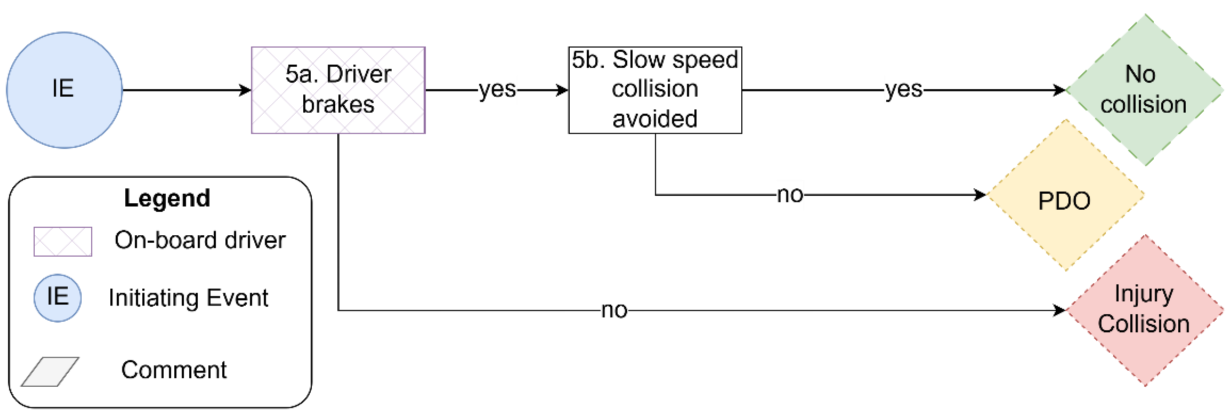
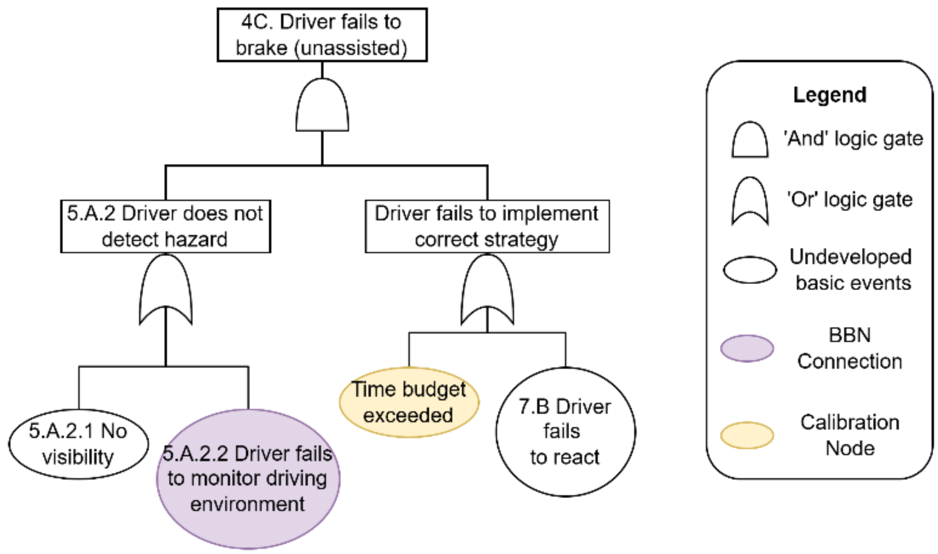
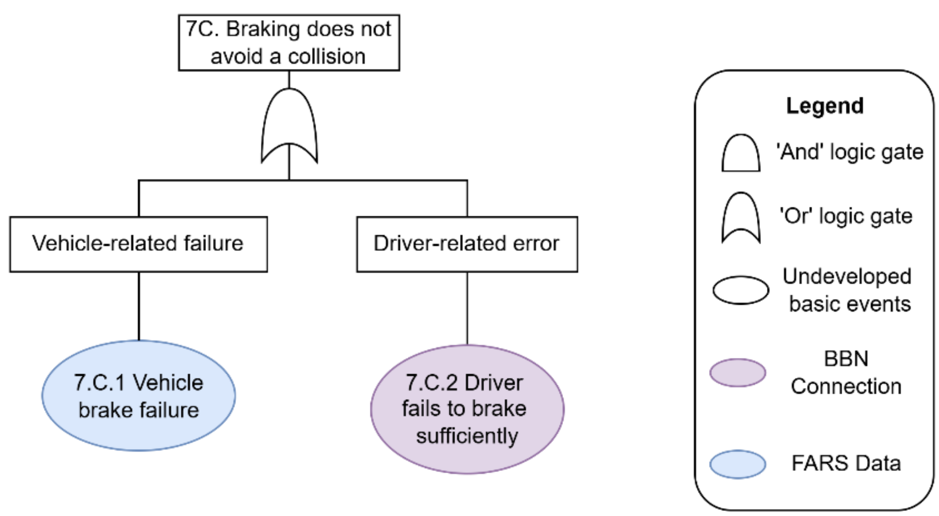


Figure 11: Scenario #1 – no driver assistance systems.

Table 39 provides the point estimate and the 5%-95% confidence intervals for the probabilities for the end-states represented in Scenario #1 (P1). The obtained probabilities are compared to the probabilities of PDO, Injury, and All Crashes for all three populations analyzed: all motor-vehicle crashes (P2), rear-end crashes (P3), and the sub-sample of rear-end crashes (P4) (Table 40). The distribution of obtained crashes severities are, in general, consistent with the populations containing all crashes (1%) and all rear-end crashes (0.18%).



(a) FT#1 – Driver fails to brake (event 5a failure).



(b) FT#2 – Braking does not avoid a collision (event 5b failure).

Figure 12: Scenario #1 - driver related fault trees FT#1-2.

Table 39: Scenario #1 - estimated crash probabilities per crash severity.

End-State	Estimated Prob.					
	P1(C)	Norm.	Mean	Median	5th Percentile	95th Percentile
No Collision (Total)	9.748E-01	--	--	--	--	--
No Collision Scenario	8.788E-01	--	8.764E-01	8.924E-01	7.547E-01	9.634E-01
No Collision (Driver)	9.499E-02	7.837E-01	9.337E-02	7.769E-02	1.569E-02	2.016E-01
PDO Crash (Driver)	1.923E-02	1.587E-01	2.090E-02	1.077E-02	4.700E-04	8.544E-02
Injury Crash (Driver)	7.017E-03	5.790E-02	7.318E-03	6.373E-03	1.524E-03	1.530E-02
All Crashes (Driver)	2.625E-02	2.166E-01	2.822E-02	1.714E-02	1.994E-03	1.007E-01

Table 40: Reference crash probabilities per crash severity.

End-State	All Crashes		Rear-End Crashes		Rear-End Crashes (Sample)	
	P2(C)	Diff.%	P3(C)	Diff.%	P4(C)	Diff.%
No Collision (Total)	0.974	**-0.07%**	0.993	**-1.80%**	0.998	**-2.34%**
No Collision Scenario	--	**--**	--	**--**	--	**--**
No Collision (Driver)	--	**--**	--	**--**	--	**--**
PDO Crash (Driver)	0.018	**5.24%**	0.020	**-4.81%**	0.025	**-23.89%**
Injury Crash (Driver)	0.008	**-9.02%**	0.006	**17.00%**	0.008	**-10.10%**

End-State	All Crashes		Rear-End Crashes		Rear-End Crashes (Sample)	
	P2(C)	Diff.%	P3(C)	Diff.%	P4(C)	Diff.%
All Crashes (Driver)	0.026	**1.01%**	0.026	**0.18%**	0.033	**-20.63%**

However, the model underestimates the number of crashes observed for the sub-sample of rear-end crashes (where higher severity crashes are over-represented in comparison) by up to 20%. Nonetheless, the proportion of PDO-crashes and injury crashes are consistent with the crash numbers estimated for this population (Table 41), thus conclusions related to the relative impact of technologies on end-state probabilities may still be derived. Note that the end-state "No Collision" contains information regarding the exposure to the scenario, as well as the driver's contribution to avoiding a collision based on the modeling parameters. Thus, the normalized crash probabilities per crash severity are also calculated (Norm) and used for further comparisons with Scenarios #2 and #3.

Table 41: Comparison of proportion of crashes by crash severity.

Crash Severity	Estimated Number of Crashes (Sample Population)	Proportion (Sample Population)	Proportion (Scenario #1)
All Crashes	1,301,897		
Fatality Crashes	827	0.06%	--
Injury and Fatality Crashes	305,856	23.56%	26.73%
PDO Crashes	995,214	76.44%	73.27%

Scenario 2: Driver Assisted by Local FCW System

The second scenario consists of a driver supported by an FCW system that relies on the host vehicle's local sensors to detect the presence of an obstacle on the road and determine the probability of an imminent crash given the current vehicle speeds.

This case is structured around the following high-level events:

- The obstacle is detected by vehicle sensors. The detection of the object triggers an alarm for the driver.
- The driver brakes in response to detecting the obstacle. The success of this event implies that the driver detected the alarm and braked in response.

- The braking action is sufficient to avoid a collision with the obstacle. The success of this event implies that the driver braked sufficiently given the road conditions and that no failure in the vehicle prevented braking from occurring.

Depending on system failures, three different branches are distinguished (see Figure 13):

- Branch 1: Collision avoidance is supported by single-vehicle FCW assisted driver warnings.
- Branch 2: No additional collision avoidance assists the driver.

This scenario is depicted in Figure 13, where the end-states can be associated with whether the FCW system was triggered or not. Thus, the new branch of the system is added to the base ESD developed for Scenario #1. The new events depict the effectiveness of the FCW system in assisting the driver to avoid the collision.

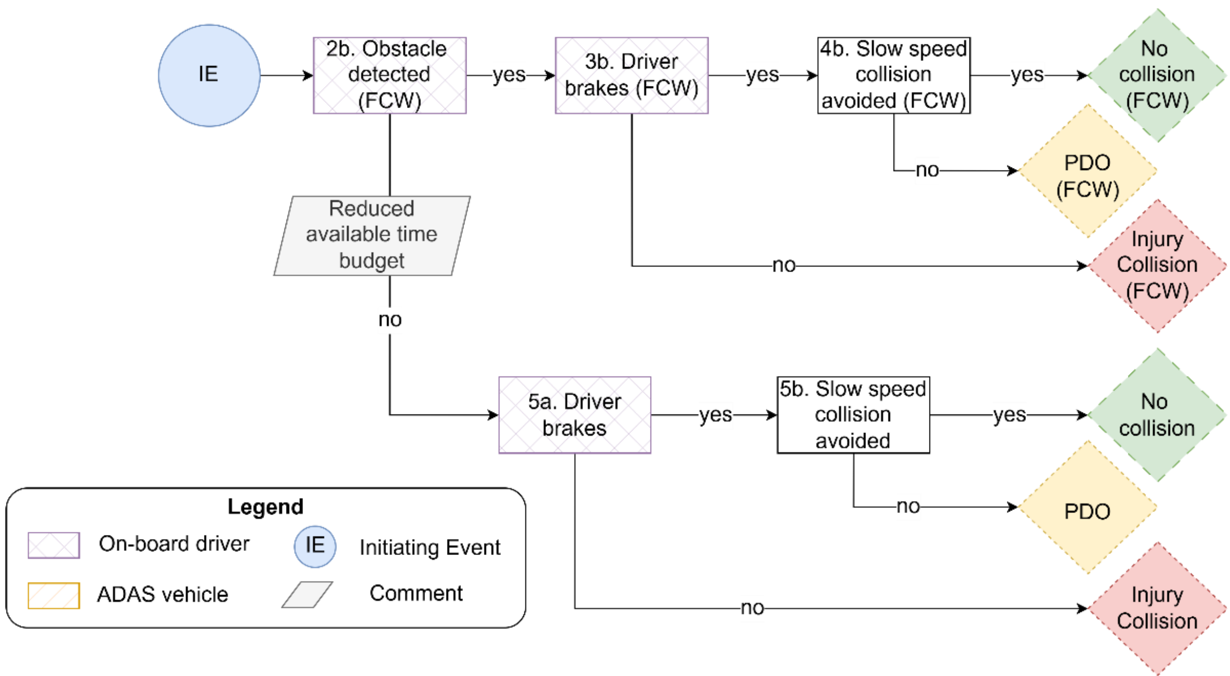


Figure 13: Scenario #2 ‐ driver assisted by local FCW system.

The failure of event “2b. Obstacle detected (FCW)” is described by the FT model presented in Figure 14. As an initial approach, the failure of this event is modeled based on IDA phases described. Thus, whether the driver received the FCW depends on whether the obstacle is detected (I-phase), if the warning is triggered (D-phase), and whether it is communicated to the driver (A-phase). These failures are related to sensor reliability, FCW missed alarm rates, and HMI hardware reliability (either acoustic or visual alarms). While sensor and HMI reliability values have been included for calibration purposes, estimated FCW missed alarm rates (false negatives) between 0.73%-3.72% have been reported in literature (*57*, *58*).

In contrast, the effect of false positives has not been included in the initial development of the model (*59*). Similar to Scenario #1, each event related to the driver’s actions is supported by a simple FT model

(Figure 15), depicting potential causes of the driver failing to brake or that after braking, a slow speed collision is not avoided. Model parameters can be found in Table 52.

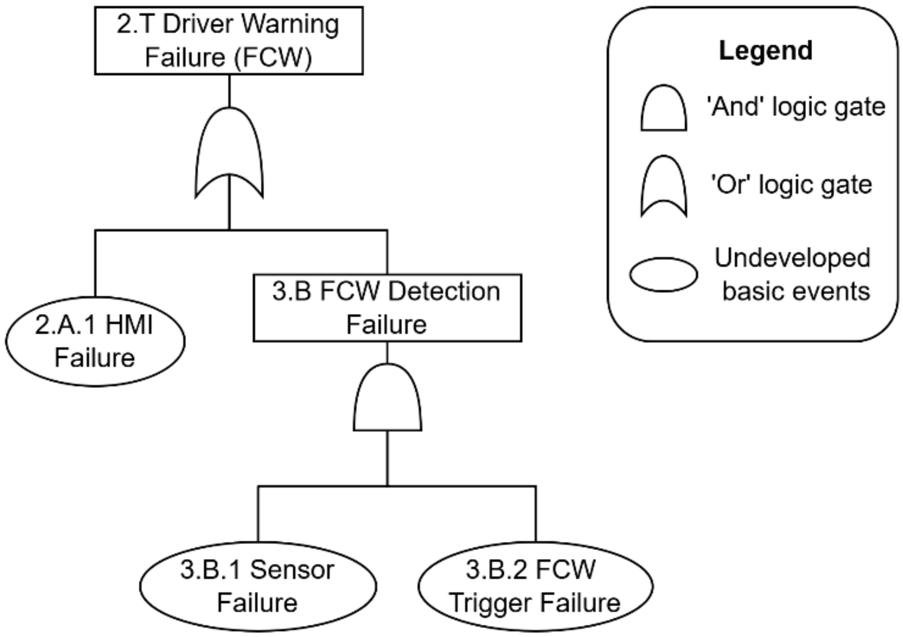
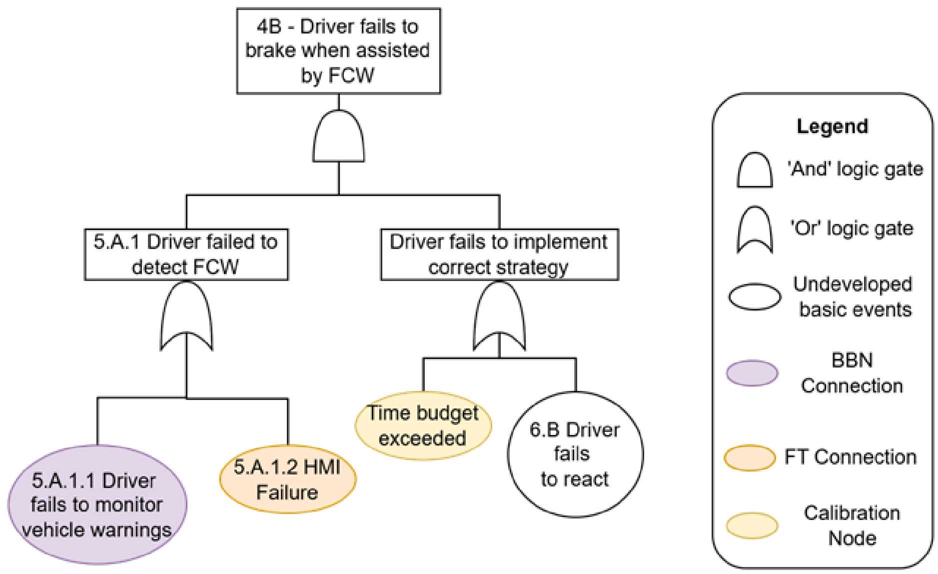


Figure 14: Scenario #2 – FCW related fault tree FT#3.

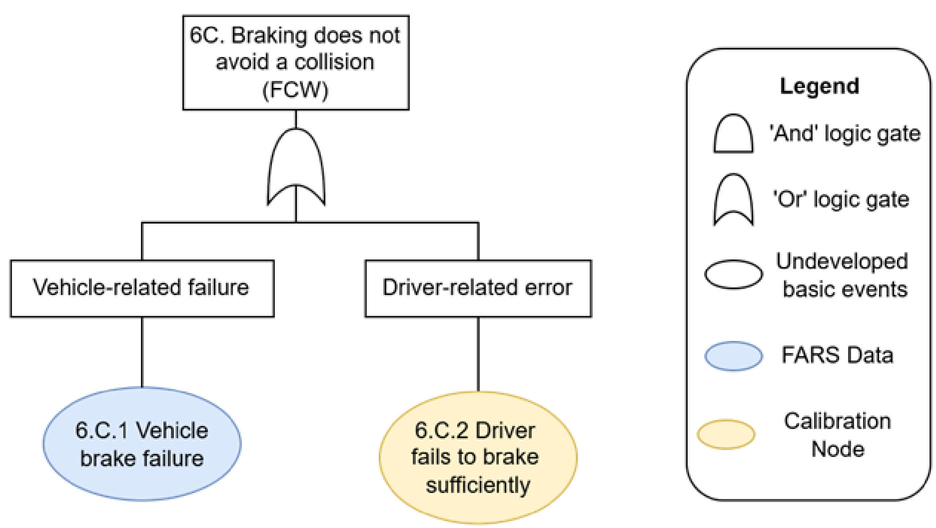
Table 42 provides the point estimates of the end-state probabilities and resulting CMFs for Scenario #2. These values are within 3% of those reported by the PARTS study for all crashes, thus validating the model's parameters for further analysis. Scenario #2 serves as the basis for Scenario #4 which incorporates V2X-enhanced FCWs.

Table 42: Estimated end-state probabilities and crash modification factors for scenario #2.

End-State	Estimated Prob.	Diff.% (PARTS, 2022)	CMF (Scenario #1)
No Collision (Total)	9.721E-01	--	--
No Collision Scenario	8.788E-01	--	--
No Collision	9.886E-02	28.21%	1.0407
PDO Crash	1.558E-02	-4.90%	0.1899
Injury Crash	5.881E-03	3.40%	0.1619
All Crashes	2.146E-02	-2.76%	0.1824



(a) FT#4 – Driver fails to brake when assisted by FCW (Event 3b failure).



(b) FT#5 – Braking does not avoid a collision (Event 4b failure).

Figure 15: Scenario #2 – driver related fault trees FT#4-5.

Scenario 3: Driver Assisted by Local AEB System

The third scenario consists of a driver supported by an FCW system that relies on the host vehicle's local sensors to detect the presence of an obstacle on the road and determine the probability of an imminent crash given the current vehicle speeds. In addition to the FCW system, the vehicle is equipped with AEB features.

This case is structured around the following high-level events:

- The obstacle is detected by vehicle sensors. The detection of the object triggers an alarm for the driver.
- The driver brakes in response to detecting the obstacle. The success of this event implies that the driver detected the alarm, and that the driver braked in response.
- The AEB functionality is triggered in response to the driver not reacting to the alarm within a set time budget.
- The braking action (performed automatedly or by the driver) is sufficient to avoid a collision with the obstacle. The success of this event implies that the driver braked or the AEB was implemented sufficiently given the road conditions and that no failure in the vehicle prevented braking from occurring.

Depending on system failures, three different branches are distinguished (see Figure 16):

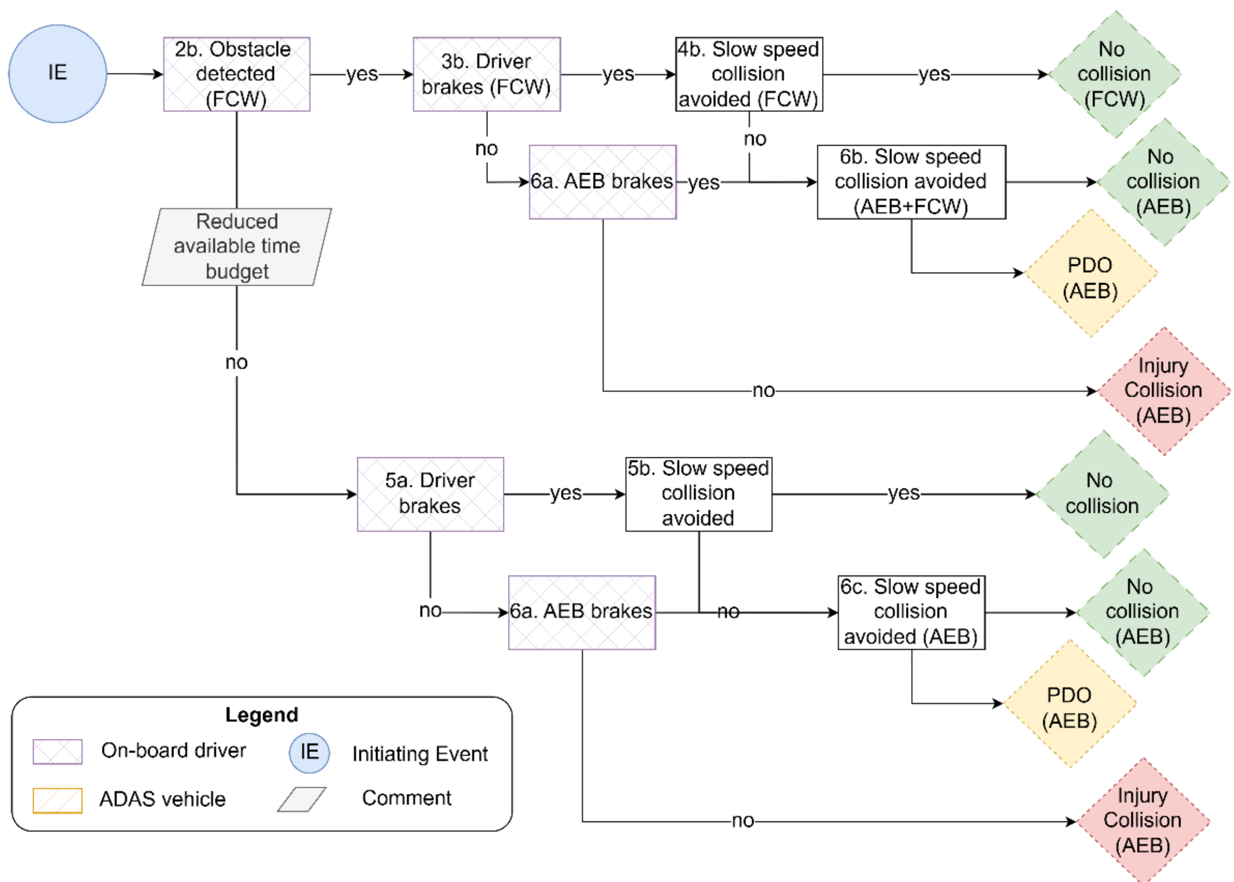


Figure 16: Scenario #3 – driver assisted by local AEB system.

- Branch 1: Collision avoidance is supported by single-vehicle FCW assisted driver warnings. A recovery path is available through the AEB functionality.
- Branch 2: No additional collision avoidance assists the driver. A recovery path is available through the AEB functionality. This assumes the independence between FCW and AEB failures.

This scenario is depicted in Figure 16, where the end-states can be associated with whether the FCW and/or the AEB systems were triggered. The new events depict the effectiveness of the AEB system in assisting the driver to avoid a collision.

The behavior of the AEB system is described by the FT model presented in Figure 17. As an initial approach, this model considers the independence of the FCW and AEB systems, including the sensors and triggering mechanisms. The AEB system's failure is characterized by failing to trigger the braking system even if conditions are met (*36*), and similar to the driver brake models, if the braking implemented is sufficient to avoid a collision based on the road conditions. Note that in this case, the crash end-states are singularly attributed to failures in the AEB system, and that no distinction is made between high-TTC and low-TTC scenarios. Model parameters can be found in Table 53.

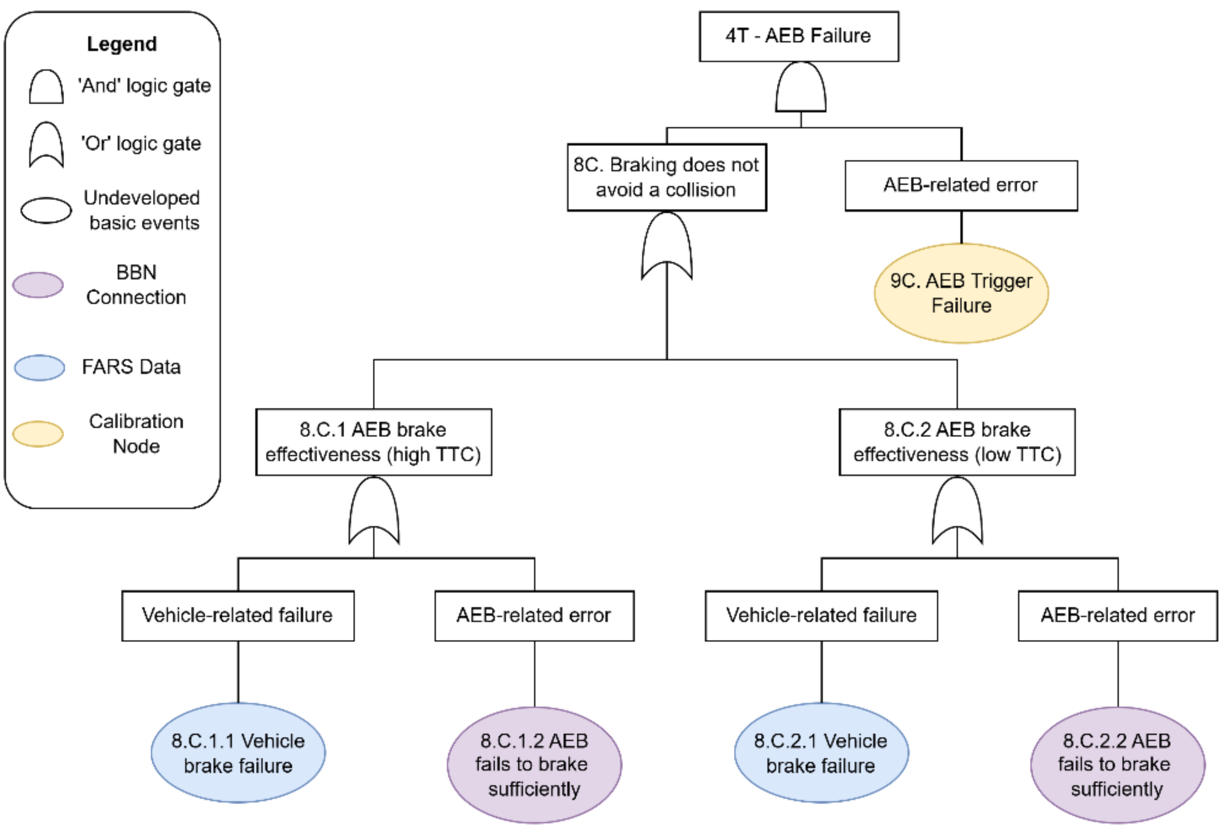


Figure 17: Scenario #3 – AEB related fault tree FT#6.

Table 43 provides the point estimates of the end-state probabilities and resulting CMFs for Scenario #3. These values are within 5% of those reported by the PARTS study for all crashes, thus validating the model's parameters for further analysis. Scenario #3 serves as the basis for Scenario #5 which incorporates V2X-enhanced FCWs supported by AEB.

Table 43: Estimated end-state probabilities and crash modification factors for scenario #3.

End-State	Estimated Prob.	Diff.% (PARTS, 2022)	CMF (Scenario #1)
No Collision (Total)	9.834E-01	--	--
No Collision Scenario	8.788E-01	--	--
No Collision	1.085E-01	14.87%	1.1419
PDO Crash	9.581E-03	-5.03%	0.5018
Injury Crash	3.152E-03	-4.41%	0.5507
All Crashes	1.273E-02	-4.88%	0.5149

Scenario 4: Driver Assisted by V2X-enhanced FCW

The fourth scenario demonstrates the potential impact of V2X-related technologies on driver warnings. In this scenario, a driver is supported by an FCW system that relies on the host vehicle's local sensors. In addition, the FCW is supported by a V2X communication system which receives BSM from remote vehicles equipped with V2V communication on-board devices or infrastructure-based RSUs. The BSMs are received by the host vehicle and communicated to the driver though the same HMI mechanism as the regular FCWs. Thus, the V2X not only does provide an additional redundancy layer to trigger driver warnings but also can provide earlier warnings to the driver. The focus of Scenario #4 is the role of V2X communications in increasing short-TTC driver warnings.

This case is structured around the following high-level events:

- The obstacle is detected by vehicle sensors or through vehicle communications. The detection of the object triggers an alarm for the driver.
- The driver brakes in response to detecting the obstacle. The success of this event implies that the driver detected the alarm and braked in response.
- The braking action is sufficient to avoid a collision with the obstacle. The success of this event implies that the driver braked sufficiently given the road conditions and that no failure in the vehicle prevented braking from occurring.

Depending on system failures, three different branches are distinguished (see Figure 18):

- Branch 1: Collision avoidance is supported by V2X assisted driver warnings.
- Branch 2: Collision avoidance is supported by single-vehicle FCW assisted driver warnings, i.e., the V2X communications do not trigger the FCW driver alerts.
- Branch 3: No additional collision avoidance assists the driver, i.e., neither the V2X communications nor the vehicle sensors trigger the FCW driver alerts.

This scenario is depicted in Figure 18, where the end-states can be associated with whether the FCW system was triggered based on the host vehicle's sensors or through received BSM. The new events depict the effectiveness of the V2X system in providing redundancy to the FCW assisting the driver to avoid the collision.

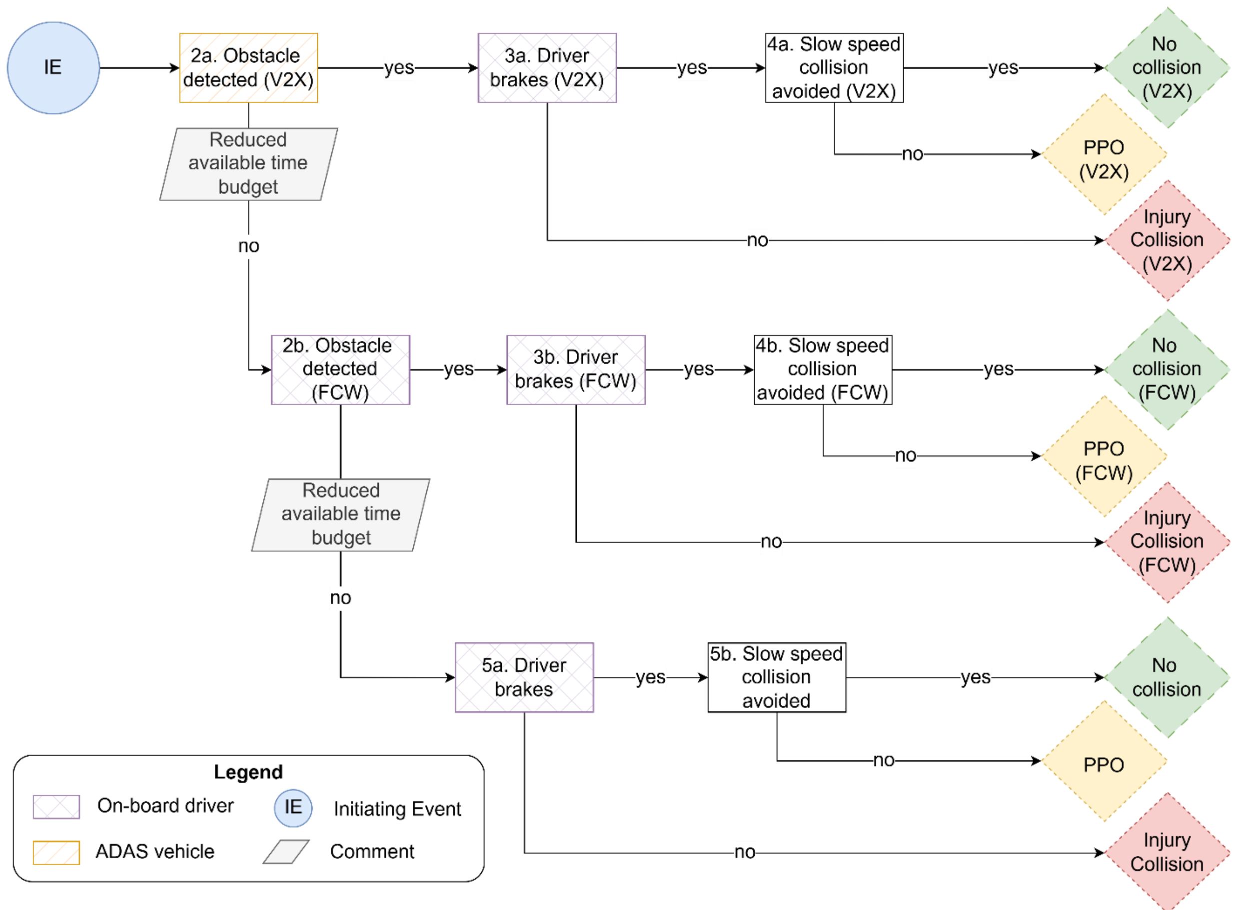


Figure 18: Scenario #4 – driver assisted by V2X-enhanced FCW.

The behavior of the V2X-enhanced FCW system is described by the FT model presented in Figure 19. Despite the limited data available to characterize the impact of vehicle communications on driver warning generation in real road conditions, several academic works have sought to quantify the impact of vehicle speeds and distance to the quality and reliability of vehicle communication. For instance, early works report package loss rates up to 3% across distances between host and remote vehicles from 0-200 m and differences between speeds from 10-50 km/h (50). Other studies focus on the latency and the rate of stale information relayed between different OBUs and RSUs. Further studies are required to establish delay and/or package loss thresholds and corresponding impact on the FCW reliability. Similar to previous scenarios, each event related to the driver's actions is supported by a simple FT model (Figure 20), depicting potential causes of the driver failing to brake or that after braking, a slow speed collision is not avoided. Model parameters can be found in Table 54.

Table 44 provides the point estimates of the end-state probabilities and resulting CMFs for Scenario #4 with respect to Scenario #1 (the base case) and Scenario #2 (FCW relying on the host vehicle's sensors).

The estimated CMF for the V2X-enhanced FCW is 0.24 when compared to no driver warnings and can provide a reduction of 0.07 with respect to traditional FCW functions.

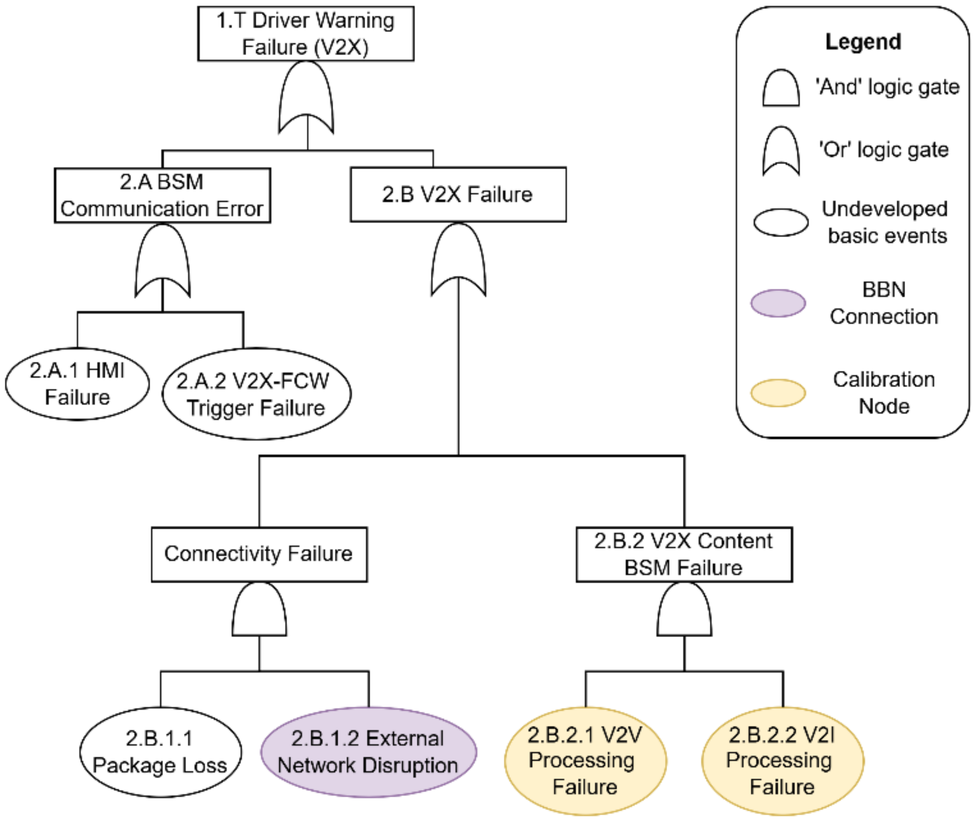
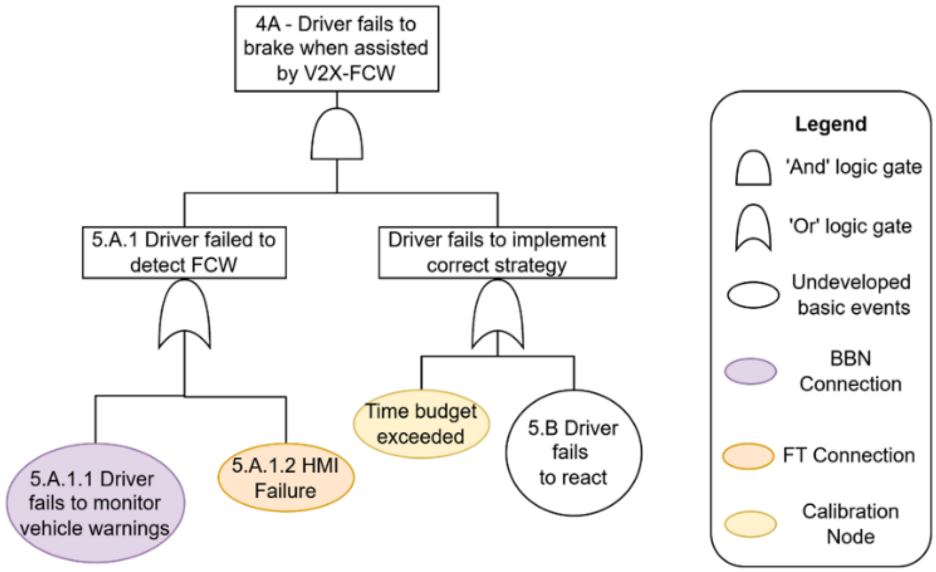


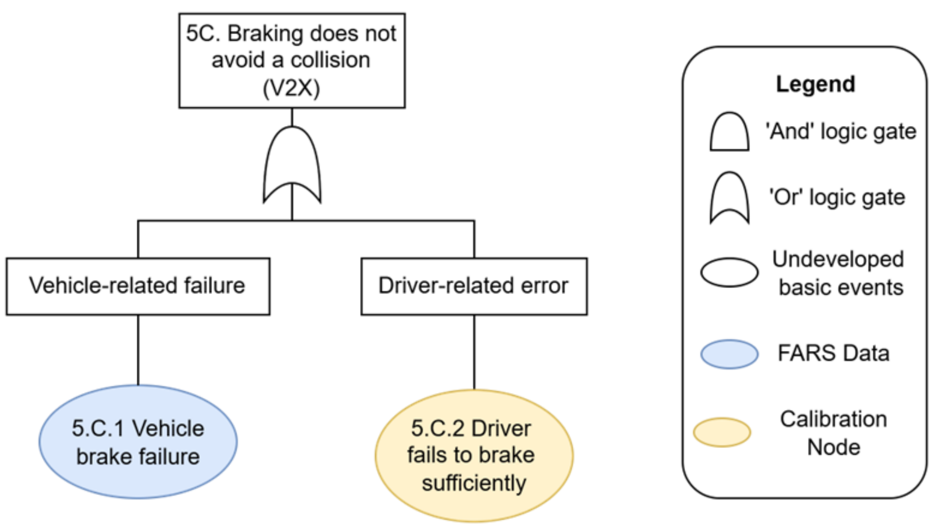
Figure 19: Scenario #4 – V2X related fault tree FT#7.

Table 44: Estimated end-state probabilities and crash modification factors for scenario #4.

End-State	Estimated Prob.	CMF (Scenario #1)	CMF (Scenario #2)
No Collision (Total)	9.801E-01	--	--
No Collision Scenario	8.788E-01	--	--
No Collision	1.014E-01	1.0671	1.0254
PDO Crash	1.389E-02	0.2776	0.1082
Injury Crash	5.978E-03	0.1481	-0.0164
All Crashes	1.987E-02	0.2430	0.0741



(a) FT#8 – Driver fails to brake when assisted by V2X-FCW (Event 3a failure).

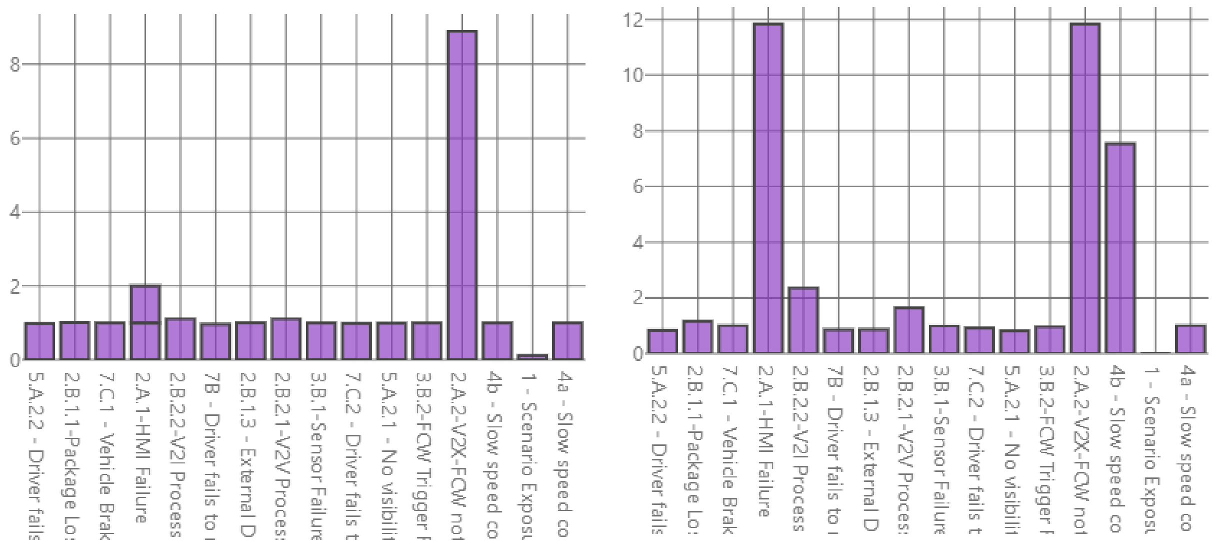


(b) FT#9 – Braking does not avoid a collision (Event 4a failure).

Figure 20: Scenario #4 – driver related fault trees FT#8-9.

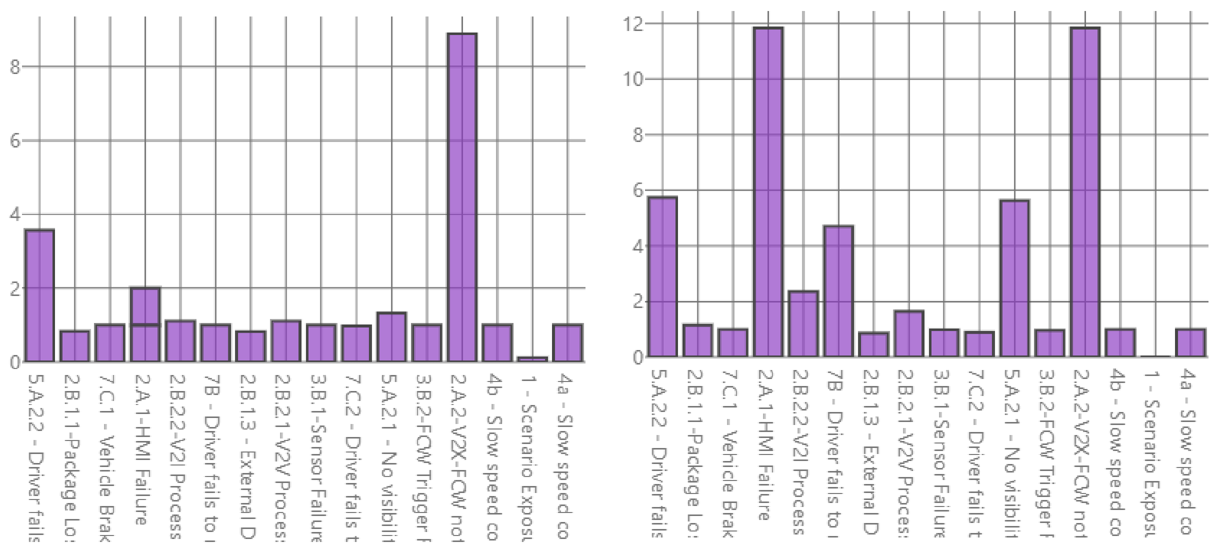
Figure 21 and Figure 22 present selected importance metrics for PDO and Injury crashes, respectively, in the case the V2X-enhanced warning have failed (Branch 2). These figures show the impact of the V2X-related events in the scenario outcome by crash severity. The event 2.A.2 V2X-FCW Trigger failure depicted in Figure 19 exhibits the highest impact on the system-level risk. This event is related to the host vehicle receiving information about an obstacle on the road through V2X but failing to trigger the driver warning on time, potentially related to stale information, excessive network latency, or the FCW's reliability. Other events relevant to PDO crashes refer to failures communicating the driver warnings

(2.A.1) or the driver's insufficient reaction to the warning (4b), while events related to the driver's behavior (5.A.2.2 and 7B) play an important role in injury crashes.



(a) RRW *(b) RAW*

Figure 21: Selected importance metrics, scenario 4 - PDO crashes under V2X failure.



(a) RRW *(b) RAW*

Figure 22: Selected importance metrics, scenario 4 - injury crashes under V2X failure.

Scenario 5: Driver Assisted by V2X-enhanced FCW and AEB

The fifth scenario demonstrates the potential impact of V2X-related technologies on driver warnings, coupled to the AEB features. In this scenario, a driver is supported by an FCW system that relies on the host vehicle's local sensors. The FCW is supported by a V2X communication system which receives BSM from remote vehicles equipped with V2V communication on-board devices or infrastructure-based RSUs, as described in Scenario #4. In addition to the V2X-enhanced FCW system, the vehicle is equipped with AEB features as described in Scenario #3.

This case is structured around the following high-level events:

- The obstacle is detected by vehicle sensors or through vehicle communications. The detection of the object triggers an alarm for the driver.
- The driver brakes in response to detecting the obstacle. The success of this event implies that the driver detected the alarm, and that the driver braked in response.
- The AEB functionality is triggered in response to the driver not reacting to the alarm within a set time budget.
- The braking action (performed automatedly or by the driver) is sufficient to avoid a collision with the obstacle. The success of this event implies that the driver braked or the AEB was implemented sufficiently given the road conditions and that no failure in the vehicle prevented braking from occurring.

Depending on system failures, three different branches are distinguished (see Figure 23):

- Branch 1: Collision avoidance is supported by V2X assisted driver warnings and a recovery path is available through AEB functionality.
- Branch 2: Collision avoidance is supported by single-vehicle FCW assisted driver warnings, i.e., the V2X communications do not trigger the FCW driver alerts. However, a recovery path is available through AEB functionality.
- Branch 3: No additional collision avoidance assists the driver, i.e., neither the V2X communications nor the vehicle sensors trigger the FCW driver alerts. A recovery path is available through the AEB functionality. This assumes the independence between FCW and AEB failures.

Scenario #5 combines the FT models developed for Scenario #3-4. Thus, the behavior of the V2X-enhanced FCW system is described by the FT model presented in Figure 19, while the AEB functionality is described by Figure 17. The driver behavior models are the same as for Scenario #4 (Figure 20). The full model parameters can be found in Table 55.

Table 45 provides the point estimates of the end-state probabilities and resulting CMFs for Scenario #5 with respect to Scenario #1 (the base case) and Scenario #3 (FCW relying on the host vehicle's sensors and AEB as a safety backup function). The estimated CMF for the V2X-enhanced FCW is 0.55 when compared to no driver warnings and can provide a reduction of 0.08 with respect to traditional FCW and AEB functions. These results are consistent with those obtained in Scenario #4, given the assumption that V2X and AEB functions are independent.

Figure 24 and Figure 25 present selected importance metrics for PDO and Injury crashes, respectively, in the case the V2X-enhanced warning have failed (Branch 2) but when AEB functionalities are available. As can be seen in both figures, the role of AEB's reliability is key for PDO and Injury crashes (Figure 17).

Other events relevant to PDO crashes refer to the driver's insufficient reaction to the warning (4a), while events related to the driver's behavior (5.A.2.2 and 7B) and environmental conditions (5.A.2.1) play an important role in injury crashes.

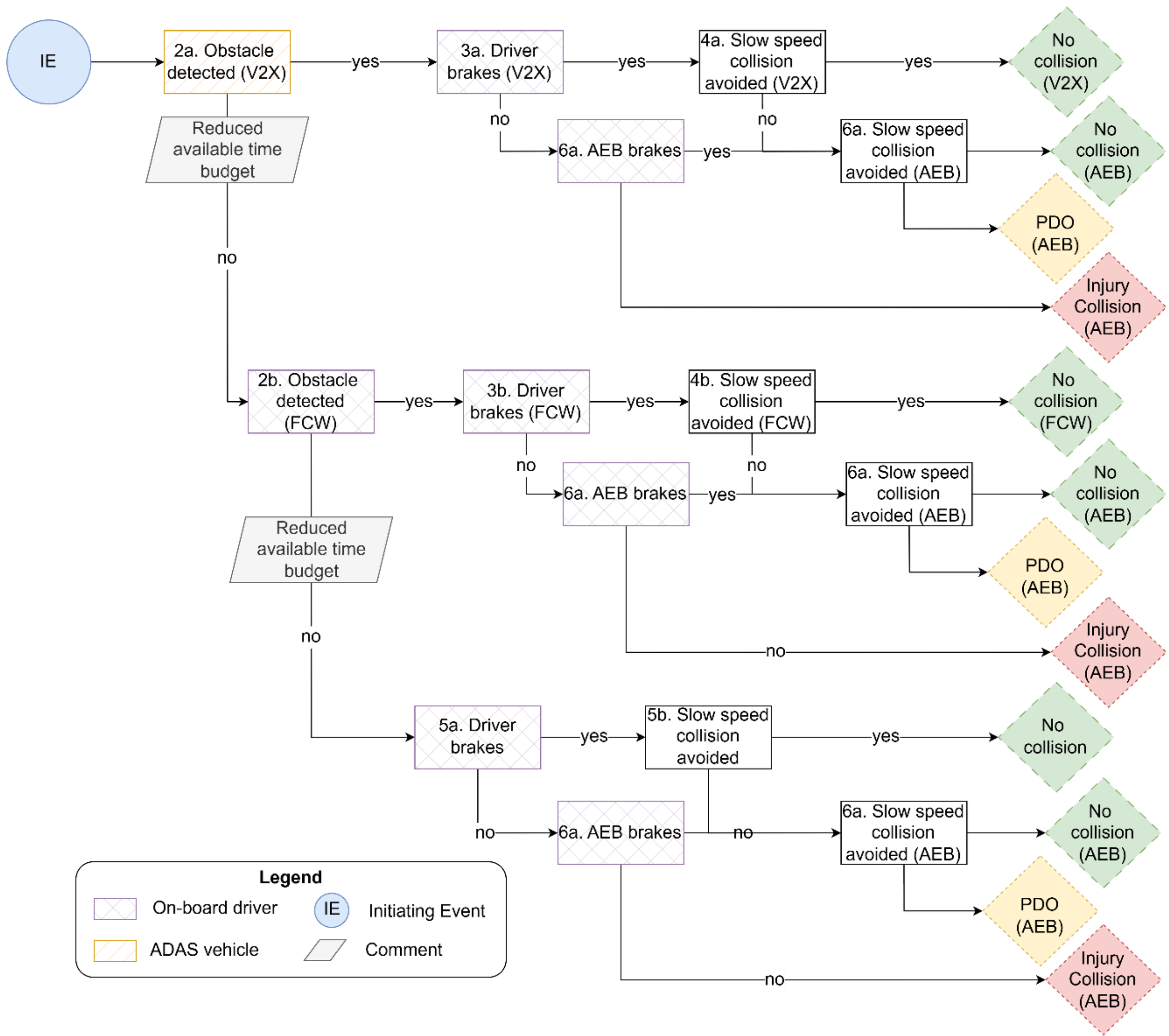
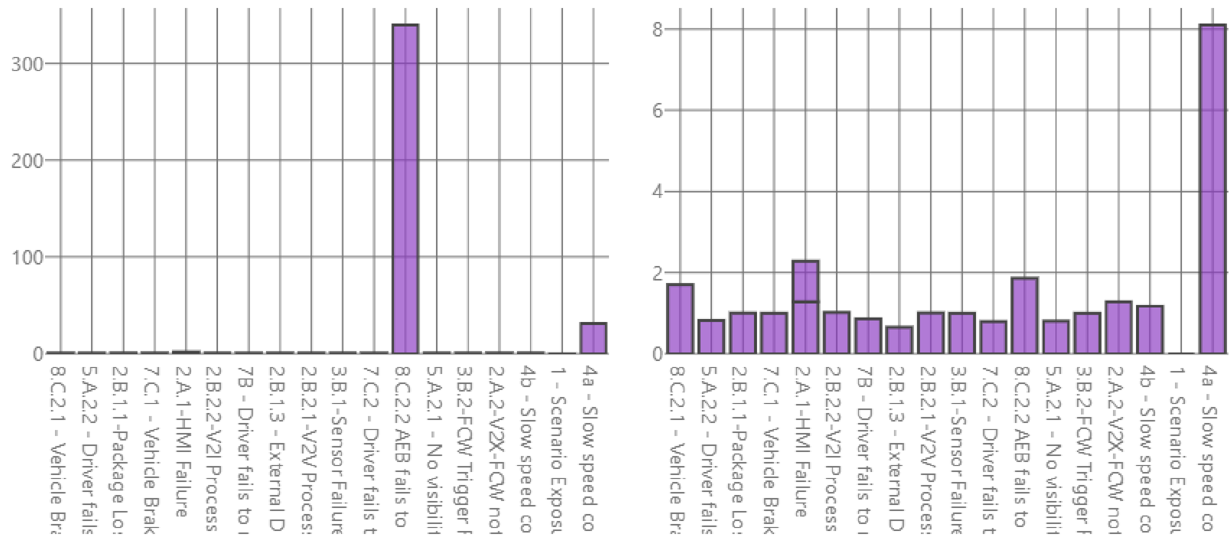


Figure 23: Scenario #5 – driver assisted by V2X-enhanced FCW and AEB.

Table 45: Estimated end-state probabilities and crash modification factors for scenario #5.

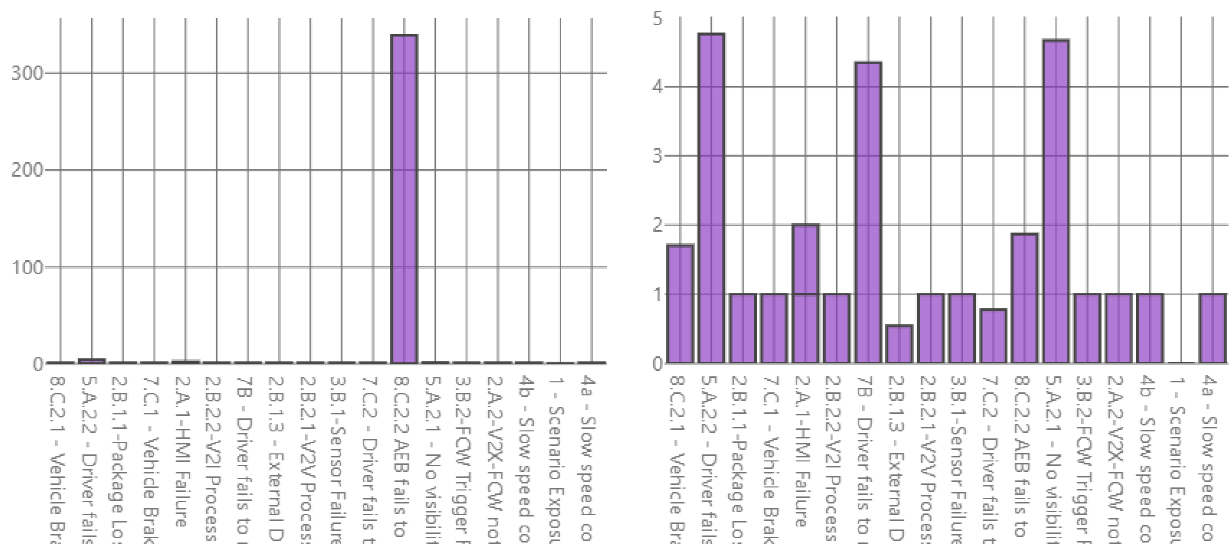
End-State	Estimated Prob.	CMF (Scenario #1)	CMF (Scenario #2)
No Collision (Total)	9.883E-01	--	--
No Collision Scenario	8.788E-01	--	--
No Collision	1.095E-01	1.1529	1.1078

End-State	Estimated Prob.	CMF (Scenario #1)	CMF (Scenario #2)
PDO Crash	8.215E-03	0.5728	0.1426
Injury Crash	3.512E-03	0.4995	-0.1141
All Crashes	1.173E-02	0.5532	0.0790



(a) RRW (b) RAW

Figure 24: Selected importance metrics, scenario 5 - PDO crashes under V2X failure.



(a) RRW (b) RAW

Figure 25: Selected importance metrics, scenario 5 - injury crashes under V2X failure.

Discussion and Concluding Remarks

While driving automation and communication technologies possess significant potential to enhance road safety, there is a critical need for systematic and transparent data collection and model-based risk assessment methods. Further, driver behavior, extensively studied within the field of human factors, will continue to play a role in traffic safety. Thus, it is important to leverage methods capable of representing causal relationships, handling uncertainty and leveraging incomplete data, such as Bayesian modeling and probabilistic simulation. Such methods aim to uncover high-severity, low-frequency events that simulation-based analysis might overlook.

The methods presented in this report offer an initial estimate of the safety benefits of V2X-enhanced driver warnings in collision avoidance scenarios. The results obtained from the developed scenario-based models rely on data extracted from national crash datasets, reported CMF for FCW and AEB technologies, and estimations of V2X communications reliability based on academic literature and limited field tests.

To fairly assess the incremental risk-reduction impact of V2X technologies, many other factors must be assessed in addition to functional safety analysis, for instance, investigating the impact of extending time budgets for driver maneuvers.

Identified Data Requirements

As more vehicles with a combination of ADAS functions are deployed on public roads, collecting supporting evidence to support the safety benefits of specific technologies may become increasingly challenging (*26*). However, accurate information on function activations under varied weather conditions and its impact on driver behavior may only be possible to collect from naturalistic driving studies (*36*).

Relying on crash statistics as the main source of evidence to demonstrate the safety impact of driver assistance technology can hide key can hide the interactions between them. While it has been reported that AEB effectively can reduce rear-end collision rates in emergency situations, relying solely on crash frequency reductions obscures whether driver warnings (FCW) have contributed to the driver’s reaction. While these technologies are expected to function in combination on new motor vehicles, without obtaining information about function activations (and under what conditions) in a pre-crash or near miss scenarios, the contributions of each technology to reducing crash rates are harder to discern. This is partially observed when transitioning between scenarios with vehicles equipped with FCW to those with FCW and AEB functionalities (Scenario #2 vs. Scenario #3, and Scenario #4 vs. Scenario #5). Collecting information on function activations may be important to determine whether early driver warnings (such as those given by V2X) can impact driver behavior in pre-crash scenarios and to what extent.

The results obtained in this initial work indicate that V2X can provide warning redundancy, increasing CMFs between 7-8% when compared to their counterparts with FCW and AEB but without V2X communications (Scenario #5 vs. #3 and #4 vs. #2). The models developed in MoPRA can also enable system requirement analysis. For instance, Figure 26 and Figure 27 provide estimations on how the CMFs would be affected by the V2X module reliability (see fault tree model in Figure 19). Figure 26 compares V2X-enhanced FCW with and without AEB support against no driver assistance functions available (Scenario #5 vs. Scenario #1 and Scenario #4 vs. Scenario #1, respectively). The linear increase behavior may be explained by the independence assumptions in model construction.

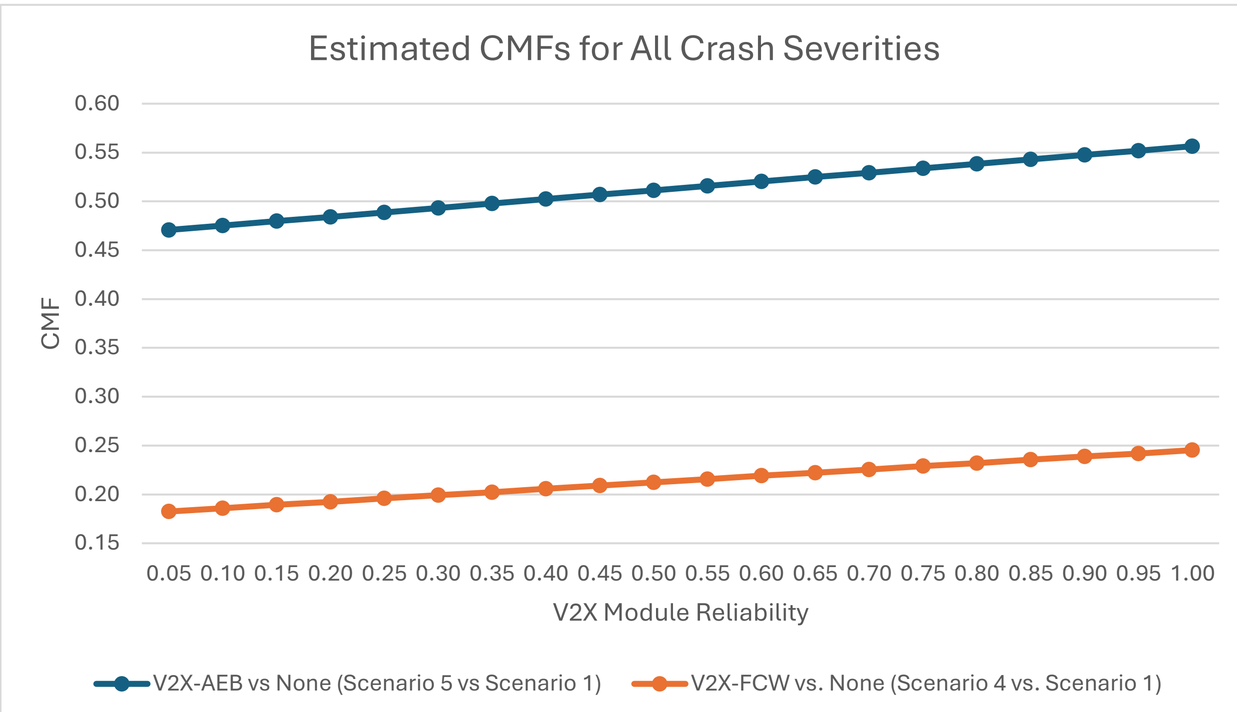


Figure 26: Impact of V2X module reliability on CMFs, considering V2X-enhanced FCW and AEB compared to no driver assistance.

Figure 27, on the other hand, compares the obtained CMFs for V2X-enhanced FCW with and without AEB support against traditional FCW and AEB (Scenario #5 vs. Scenario #3 and Scenario #4 vs. Scenario #2, respectively). It can be observed that for systems combining V2X-enhanced FCW and AEB, the safety impacts are positive starting at around a V2X driver warning reliability of 55%. This can indicate that at lower reliabilities, if the system fails to generate the driver warning, the driver would not have enough time to implement the correct action and thus, the braking success will rely on the AEB system (which may or may not be triggered). These initials findings suggest that for time-sensitive scenarios, such as collision warnings applications, moderate CMF increases can be observed when combining V2X and FCW, but that overall safety impacts are driven mainly by the AEB.

Limitations of the current models include the exclusion of time budgets that extend beyond short to very short time frames, which may inadequately capture the full range of driver decision-making processes. Further study is necessary to refine these model parameters and incorporate longer time scales, enabling a more comprehensive understanding of how drivers respond to V2X communications over extended periods. While this may carry important implications for driver warning and vehicle interface design, it may also imply that the effectiveness of V2X communications may be better observed across other functions that do not require immediate reaction from the driver. Immediate collision warning scenarios may not represent optimal use cases for demonstrating the capabilities of V2X communications due to the fundamental characteristics of the technology.

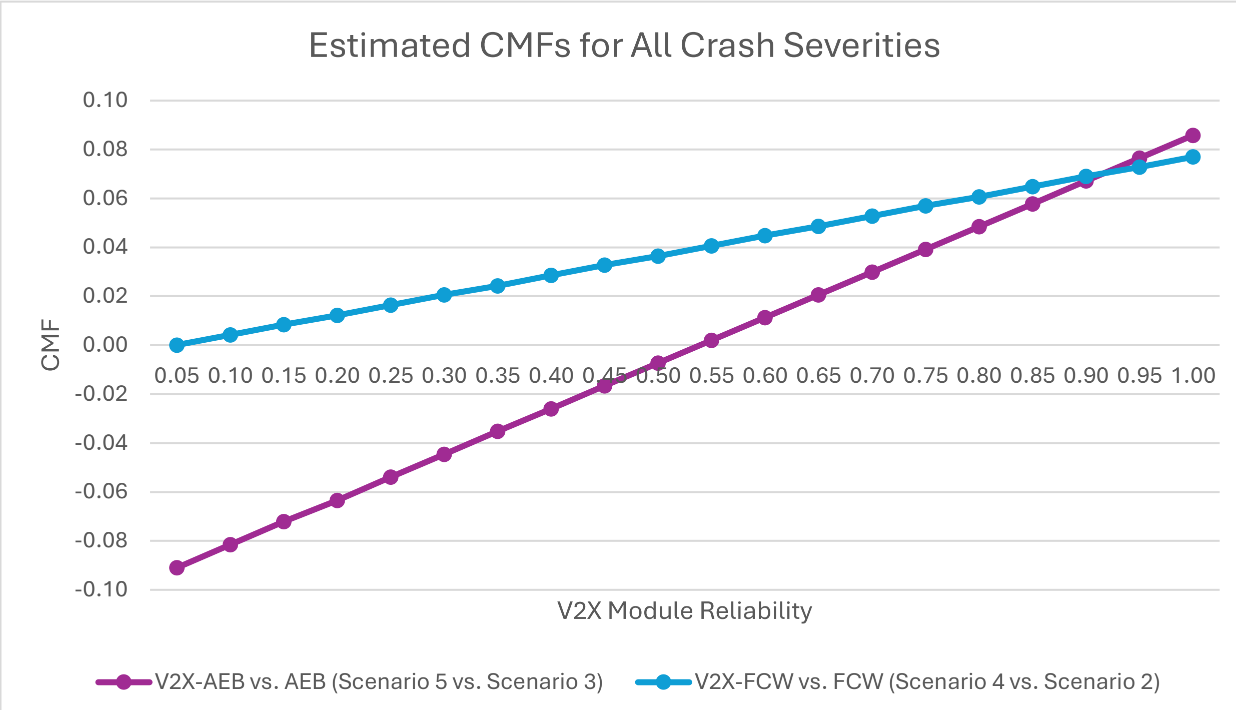


Figure 27: Impact of V2X module reliability on CMFs, considering V2X-enhanced FCW and AEB compared to traditional FCW and AEB.

While the extended communication range introduced by V2X enhances situational awareness and potentially providing additional time for decision-making, it simultaneously reduces the likelihood of a vehicle encountering the high-risk conditions required to test immediate collision warning functionality. Consequently, the overall exposure to scenario crashes is diminished, limiting the ability to evaluate V2X performance in such high-risk and low-likelihood scenarios. This suggests that the primary strength of V2X lies in its potential to support preventive safety measures and enhancing broader traffic management, rather than in collision-imminent scenarios.

Expanding the scope from crash-based metrics to other surrogate safety metrics offers alternative strategies for advancing the evaluation of V2X communication systems and driver-assist technologies. Metrics such as increased time headways, decreased tailgating, harsh-braking events, and lane changes, alongside heightened driver awareness of emergency vehicles, can be effectively captured through small-scale naturalistic driving studies (*26*). However, in time-sensitive applications, understanding the causal connection between packet loss rates and the failure to trigger driver warnings remains an underexplored area. While existing studies demonstrate high reliability for message transmission under varied conditions, they often do not address the generation of actual driver warnings, and the prevalence of false positives, which can undermine system credibility and effectiveness (*60*, *61*). To advance the understanding of driver behavior and system reliability, future research should incorporate additional BSM and TIM functionalities into scenario development. Expanding the focus to include "near misses" and recovery paths is critical for identifying interactions and potential failure modes that might not result in collisions but still provide valuable insights into system performance and safety margins.

To enhance these analyses, integrating crash probability estimation methods based on speed reduction could be a valuable approach, leveraging validated simulation tools to model these scenarios. Importantly, the impact of low or delayed warnings on driver behavior—particularly those that fall outside the scope of FCW but still influence decision-making—merits further investigation. There is also a need to collect large-scale evidence of driver compliance with system recommendations and their interactions with FCW and AEB functions. Additionally, improved access to real-world crash data is crucial for both micro- and macro-level analyses. At the micro level, detailed data on the engagement status of ADAS features is essential. At the macro level, incident reporting systems should be enhanced to include specific entries for ADAS/ADS capabilities and V2X-related information, with the aim of collecting reliability and other performance indicators of these technologies in real-world applications. To address these gaps, future research should incorporate controlled experiments to systematically collect and analyze detailed vehicle dynamic data, providing a more robust foundation for understanding and improving system performance under varying operational conditions, as well as delayed and intermittent warnings.

Furthermore, it is essential to incorporate realistic deployment assumptions into V2X reliability estimations, moving beyond the current assumption that V2V and V2I communication capabilities are available within the analyzed corridor. Incorporating the impact of the proportion of vehicles equipped with V2V functionalities and the share of infrastructure equipped with V2I capacities, models can more accurately model the operational reliability of V2X systems and their scalability in diverse deployment scenarios.

Potential future research

The next phase of this project will focus on refining the risk-informed system requirements for V2X technologies and identifying key data collection needs to enhance model accuracy.

Building on the initial risk assessment framework, this phase aims to define safety-critical parameters and develop model-based system, requirements that address both vehicle-side and infrastructure-side technologies. By analyzing functional constraints and identifying single points of failure, the project aims to propose operational limits and design considerations to enhance V2X reliability and complement existing industry standards.

To improve the V2X risk assessment framework, future work will incorporate a more detailed crash data analysis and other sources to refine BBNs model that better capture the impact of weather conditions, road type, road geometry, and other scenario characteristics on scenario development. Expanding the scenarios analyzed will provide a more comprehensive understanding of how infrastructure and vehicle-side technologies interact, potentially broadening the scope to additional V2X-enabled applications.

Another key focus will be identifying critical data collection initiatives to support future model improvements. This includes gathering real-world data on V2X technology reliability, understanding operational conditions such as road and weather factors, and incorporating insights from collision and near-miss events. These efforts will help bridge current data gaps and improve the accuracy of system reliability estimations.

MoPRA implementation

The MoPRA web application is a scenario-based probabilistic risk assessment platform to analyze the safety of different mobility systems with importance measures and uncertainty quantification capabilities. This tool is designed so that users can assess the impact of different contextual elements (weather, road conditions, driver conditions), level of driving automation, and vehicle-to-everything communications on the probability of driving related incidents.

Currently, MoPRA is equipped to analyze the impact of V2X-enhanced driver warnings in collision avoidance scenarios in vehicles equipped with FCW and AEB. The user can choose from dropdown menus to select factors affecting the scenario development, such as weather, road, and driver conditions. The user can also choose to visualize the results through importance metrics and perform uncertainty analysis on different model variables.

The initial version of the user interface is shown in Figure 28 and each function is briefly described in the following sections.

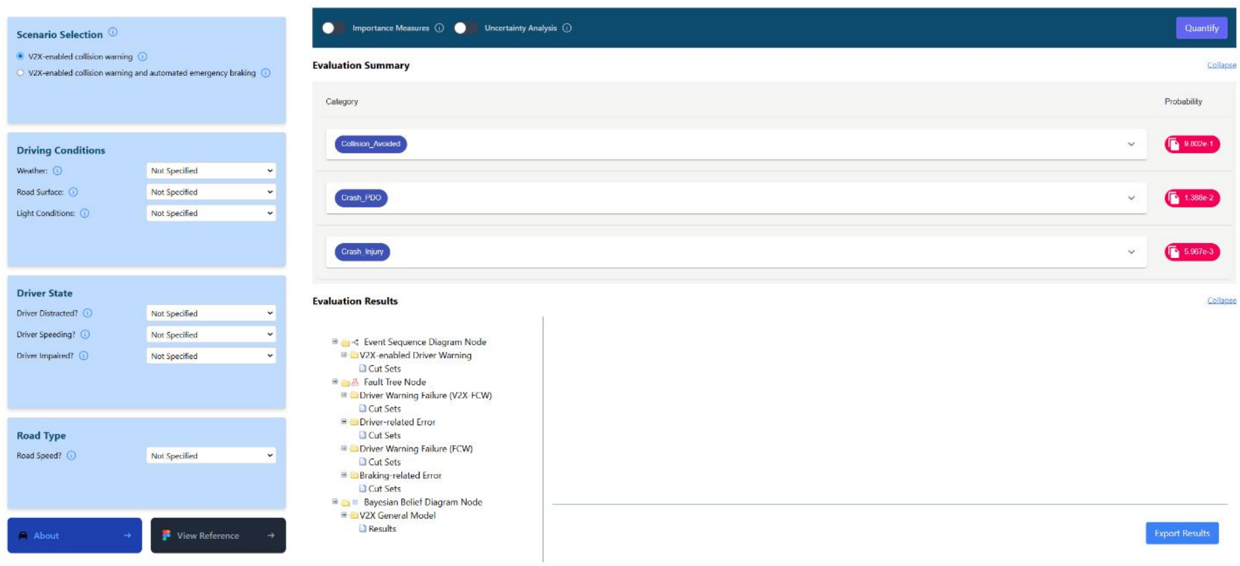


Figure 28: Sample of MoPRA user interface.

User Input

The following options are available for the user to change in MoPRA. These options do not affect the underlying HCL models but do modify event probabilities in the lower levels of the model (evidence in the BNs).

Scenario selection

The scenario considers a driver encountering a slow or stopped vehicle on a straight road (non-intersection). The driver must detect the obstacle and take the appropriate action (in this case, breaking) to avoid a collision, and is assisted by a Forward Collision Warning (FCW) system.

- **Option 1 – V2X-enabled collision warn**ing: The FCW is supported by V2X communication system providing earlier warnings to the driver.
- **Option 2** – **V2X-enabled collision warning and automated emergency braking**: In addition to the V2X-enabled FCW functionality, the vehicle is equipped with automated emergency braking (AEB) features.

Driving conditions

- **Weather**: Weather conditions in which the scenario develops. Options are “Clear”, “Adverse” (including cloudy, rain, fog, snow, and others), and “Not Specified”.
- **Road Surface**: Road surface conditions. Options are “Dry”, “Wet”, and “Not Specified”. Snow and other adverse conditions are not currently considered.
- **Light Conditions**: Light conditions affecting driver visibility. Options are “Daylight”, “Dark” (lighted, not lighted, and unknown lighting), combined ‘Dawn/Dusk” conditions, and “Not Specified”.

Driver state

- **Driver Distracted?** The driver may be distracted by non-driving related tasks, reducing their ability to detect vehicle warnings and driving conditions. Options are “Distracted”, “Attentive”, or “Not Specified”.
- **Driver Speeding?** Whether the vehicle is traveling at a speed higher than the posted limit. Options are “Speeding”, “No Speeding”, or “Not Specified”.
- **Driver Impaired?** The Driver may be impaired by alcohol or drug use, reducing their ability to detect and react to driving conditions. Options are “Yes”, “No”, or “Not Specified”.

Road type

- **Road Speed?** “The road traveled is classified by the posted speed limit as a high-speed road (>45mph) or low-speed road (<45mph). Options are “High Speed”, “Low Speed”, or “Not Specified”.

Evaluation Results

The user has the option to obtain additional information about the results. These options include:

- Uncertainty Analysis: Enabling this setting leads to sampling over uncertainty in the entire model using the given sampling method and number of samples. The current implementation has a default calculation method based on Monte Carlo sampling with $n = 100$ samples. Please review MoPRA References for more information.

- Importance Measures: Used to rank components with respect to their influence on the system reliability. The importance metrics for each cut set (i.e., combination of events leading to a system-level failure) can be shown in table or figure form. Please review MoPRA References for more information.

For more information about the methods and metrics, refer to HCL Software and Quantification Section.

Evaluation Summary

The evaluation summary portion of the interface provides the point estimate probabilities for each end-state, and the contribution of each technology to said end-state. Figure 29 presents an example for crash probabilities by crash severity (collision avoided, PDO crash, and injury crash) for Scenario #4: V2X-enabled collision warning under clear weather conditions and when the driver was speeding. When selecting a specific end-state ("Crash_Injury"), details on each of the contributing scenario branches can be found.

The evaluation summary is unchanged when the user selects using importance measures or conducting uncertainty analyses.

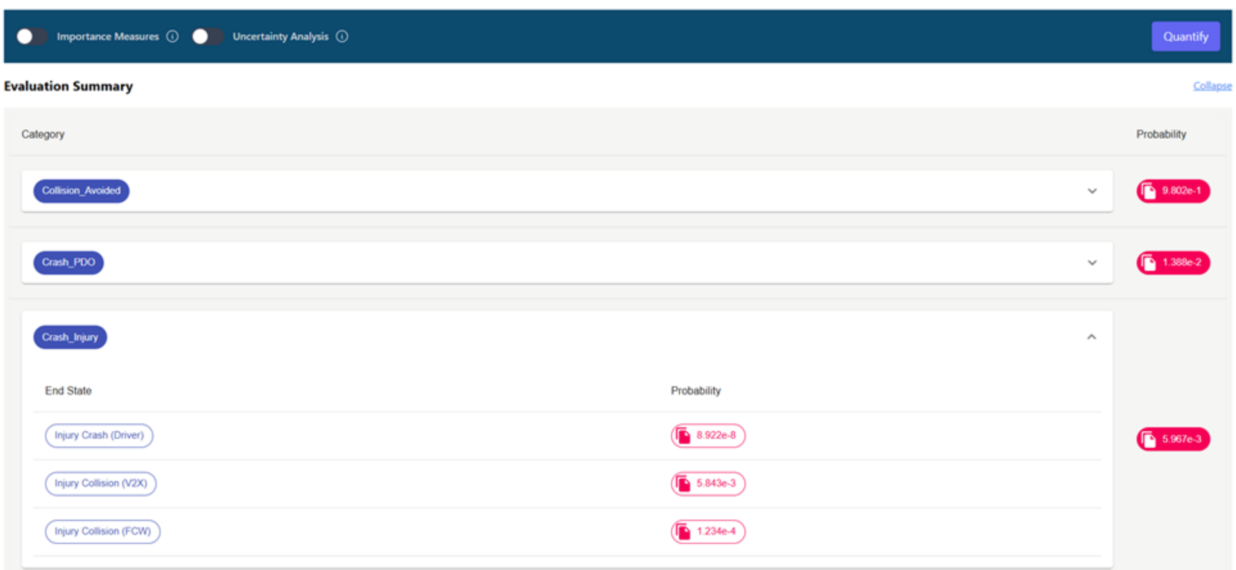


Figure 29: Sample of MoPRA user interface - Evaluation Summary.

Result Section

The evaluation results portion of the interface provides greater detail about the model's quantification. The tree structure on the left side of Figure 30 allows the user to select results at different levels of the model: ESD, FT, or BBN.

Figure 30: Sample of MoPRA user interface – Evaluation Results.

Result Tree Descriptions

Selecting each model layer, the user is presented with the following descriptions of the model:

- **Event Sequence Diagram Node – V2X-enabled Driver Warning:** A driver encounters a slow or stopped moving vehicle. The vehicle's FCW is supported by V2X communication system providing earlier warnings to the driver.

  Scenario development depends on whether the obstacle is detected by vehicle (own sensors or through V2X) and the driver alarm is triggered, (2) the driver brakes in response to detecting the obstacle, and (3) if the braking action is sufficient to avoid a collision with the obstacle.

- **Fault Tree Node – Driver Warning Failure (V2X-FCW):** Scenario development depends on whether (1) the V2X assisted driver warnings were successfully triggered and (2) the driver implemented the correct action given the driving conditions.

  A failure of the driver warning system can occur based on (1) the vehicle's sensor fail to detect the obstacle, (2) the alarm is not triggered when FCW conditions are met, (3) the human-machine interface fails to communicate the alarm (audio, visual), (4) the information received through V2X is incorrect, or (5) connectivity failures prevent V2X communication.

  This fault tree represents the contribution of the V2X-enhanced FCW failures to system-level failures.

- **Fault Tree Node – Driver Warning Failure (FCW):** Scenario development depends on whether (1) the V2X assisted driver warnings were successfully triggered and (2) the driver implemented the correct action given the driving conditions.

  A failure of the driver warning system can occur based on (1) the vehicle's sensor fail to detect the obstacle, (2) the alarm is not triggered when FCW conditions are met, (3) the human-machine interface fails to communicate the alarm (audio, visual), (4) the information received through V2X is incorrect, or (5) connectivity failures prevent V2X communication.

This fault tree represents the contribution of the host vehicle's FCW failures to system-level failures.

- **Fault Tree Node – Driver-related Error:** Scenario development depends on whether (1) the V2X assisted driver warnings were successfully triggered and (2) the driver implemented the correct action given the driving conditions.

  A driver-related error can occur if they fail to (1) react to a an obstacle on the road (i.e., the driver does not brake to avoid the collision) or (2) the action does not prevent the collision (i.e., the collision is unavoidable given the current driving conditions). These errors can occur whether the driver is (1) assisted by V2X-enabled warnings, (2) assisted by the vehicle’s own FCW, or (3) when the driver warnings have not been triggered.

  This fault tree represents the contribution of the (1) driver failing to react to an obstacle on the road (i.e., the driver does not brake to avoid the collision) to the system-level failures.

- **Fault Tree Node – Braking-related Error: S**cenario development depends on whether (1) the V2X assisted driver warnings were successfully triggered and (2) the driver implemented the correct action given the driving conditions.

  A driver-related error can occur if they fail to (1) react to an obstacle on the road (i.e., the driver does not brake to avoid the collision) or (2) the action does not prevent the collision (i.e., the collision is unavoidable given the current driving conditions). These errors can occur whether the driver is (1) assisted by V2X-enabled warnings, (2) assisted by the vehicle’s own FCW, or (3) when the driver warnings have not been triggered.

  This fault tree represents the contribution of the (1) the implemented brake action failure to prevent the collision (i.e., the collision is unavoidable given the current driving conditions) to the system-level failures.

- **Bayesian Belief Diagram Node – V2X General Model:** This network represents the effect of the driver’s state (distraction, impaired perception, speeding), driving conditions (weather, light, and road surface conditions) and road type (high/low speed) have on (1) scenario exposure rates, (2) the probability of the driver detecting and reacting to a warning or an obstacle on the road, (3) the vehicle's connectivity and sensor reliability, and (4) the complexity of the driving task.

Cut Sets and Uncertainty Analysis

When selecting the “Cut Set” node under each layer of the model, the user is presented with greater details of each path to failure, as shown on the right side of Figure 30. By selecting a specific end-state, the contributing combinations of lower-level events are shown. Figure 31 shows an example for all the events contributing to a PDO crash when the driver was successfully assisted by FCW, and their corresponding point estimate probability of occurrence.

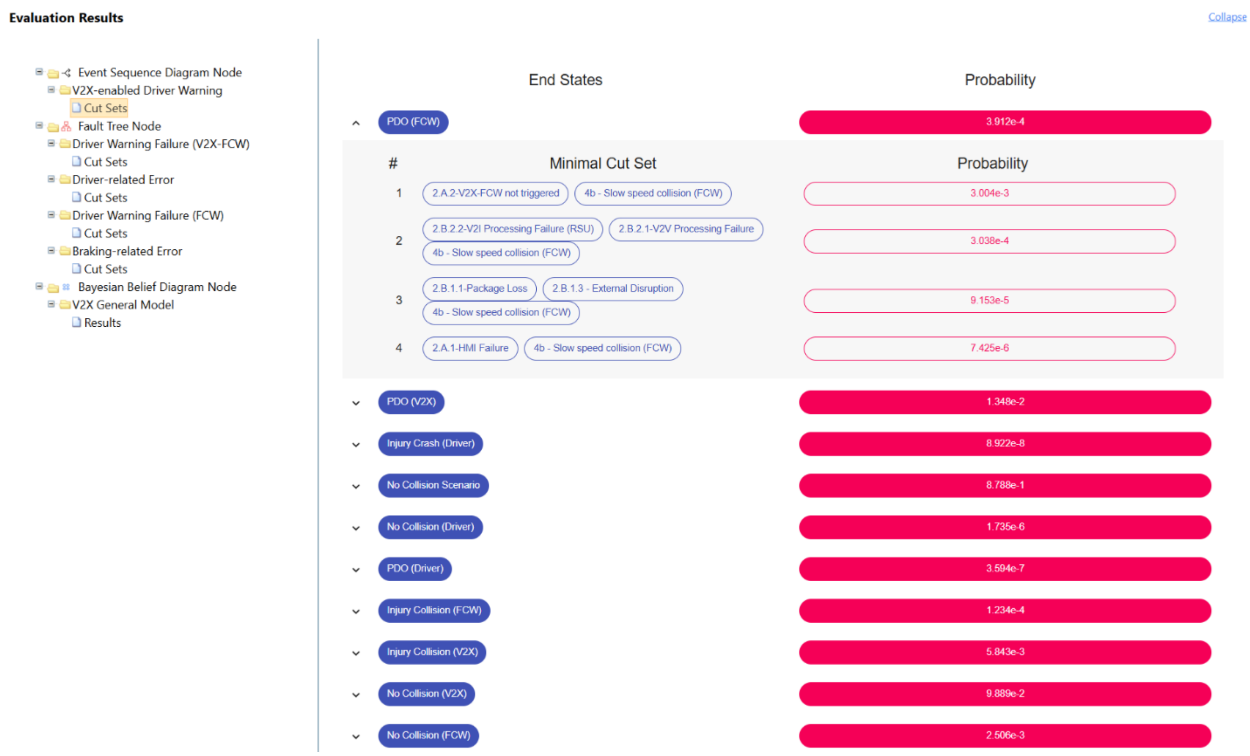


Figure 31: Sample of MoPRA user interface – Evaluation Results, Cut Sets.

While the "Cut Sets" for the ESD-level models show the results per end-state, the FT level provides information about its failed state, while the BBN shows the probabilities obtained for each node and whether evidence has been set. Figure 32 presents an example of the BBN model results.

Additionally, when selecting the option of performing uncertainty analysis, MoPRA provides the option to export the mean, median, and the 5%-95% confidence bounds of each Cut Set, as well as presenting a histogram of the sampled probabilities (Figure 33).

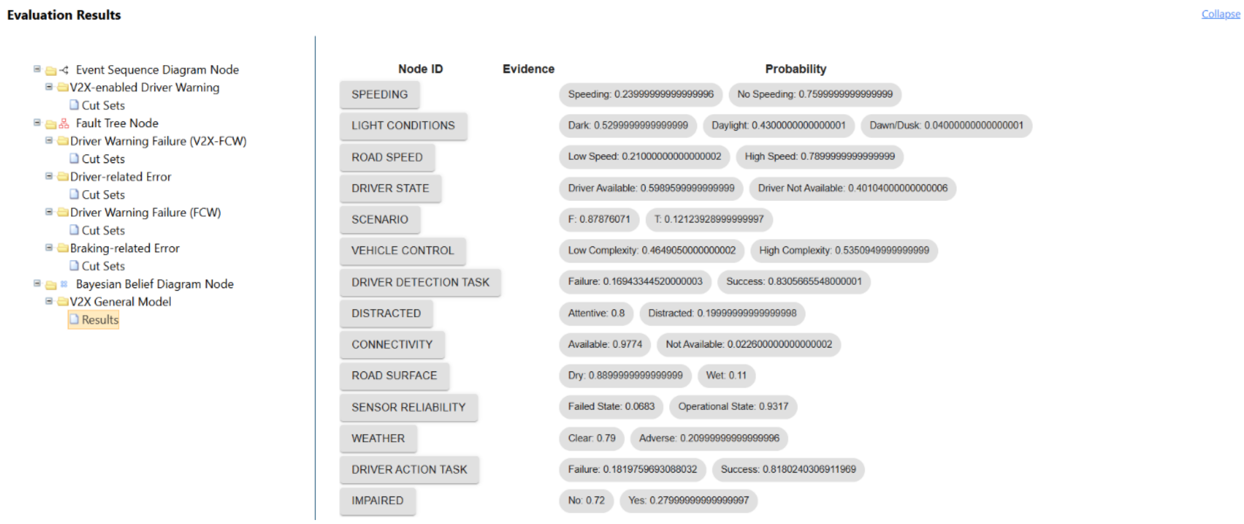
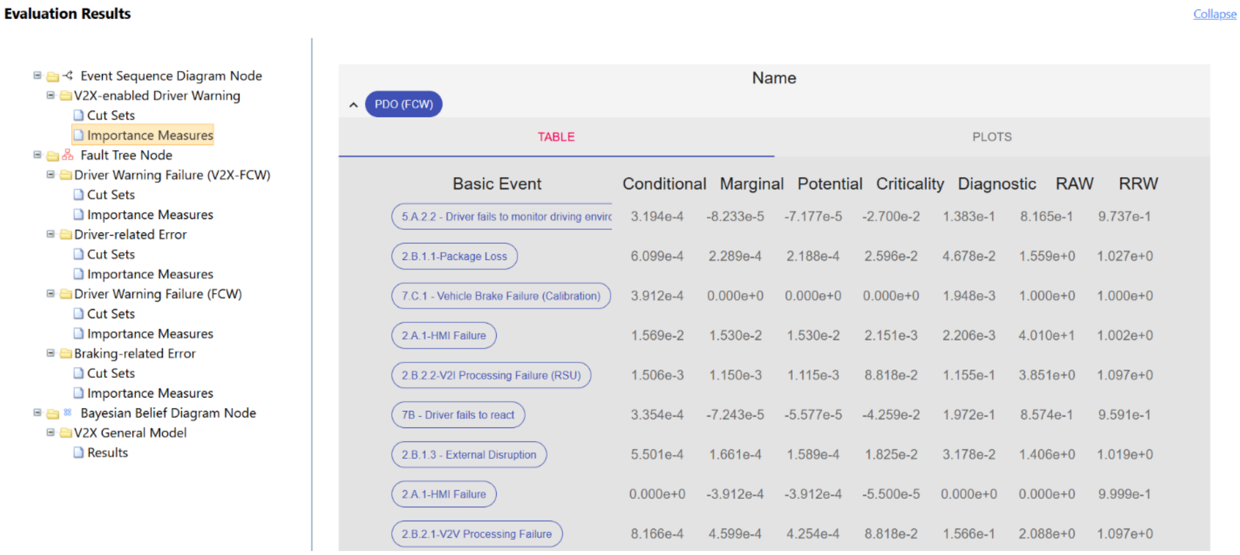


Figure 32: Sample of MoPRA user interface – Evaluation Results, Cut Sets, BBN Layer.

Figure 33: Sample of MoPRA user interface – Evaluation Results, Uncertainty Analysis.

Importance Measures

When the option for "Importance Measures" is toggled, the user may select to show the relative impact of low-level events on each failure path (Cut-Set). These results can be viewed either in table or plot form, as shown in Figure 34.



(a) Table View.

(b) Plot View

Figure 34: Sample of MoPRA user interface – Evaluation Results, Importance Measures.

Appendix

Crash Tables

The following tables (Table 46-Table 48) provide an overview of the rear-end crashes by crash severity and the percentage these represent with respect to (1) all other crashes in their severity class, (2) all rear-end crashes, (3) all crashes.

Table 46: Fatalities from rear-end crashes sampled from CRSS.

Year	Number	Percent (w.r.t. All Fatalities)	Percent (w.r.t All Rear-End Crashes)	Percent (w.r.t All Crashes)
2019	2,363	7.06%	0.11%	0.03%
2020	2,441	6.79%	0.18%	0.05%
2021	2,971	7.47%	0.18%	0.05%
Average	2,592	7.11%	0.16%	0.04%

Table 47: Injury crashes from rear-end crashes sampled from CRSS.

Year	Number	Percent (w.r.t. All Injury Crashes)	Percent (w.r.t All Rear-End Crashes)	Percent (w.r.t All Crashes)
2019	455,806	23.79%	22.18%	6.75%
2020	329,472	20.68%	24.06%	6.27%
2021	367,846	21.29%	22.13%	6.03%
Average	384,375	21.92%	22.79%	6.35%

Table 48: PDO crashes from rear-end crashes sampled from CRSS.

Year	Number	Percent (w.r.t. All PDO Crashes)	Percent (w.r.t All Rear-End Crashes)	Percent (w.r.t All Crashes)
2019	1,596,903	33.23%	77.71%	23.64%
2020	1,037,665	28.65%	75.77%	19.76%

Year	Number	Percent (w.r.t. All PDO Crashes)	Percent (w.r.t All Rear-End Crashes)	Percent (w.r.t All Crashes)
2021	1,291,605	29.79%	77.69%	21.16%
Average	1,308,724	30.56%	77.05%	21.52%

Based on the scenario criteria, the rear-end crash statistics were further refined. The following tables (Table 49-Table 50) provide an overview of the sub-sample of rear-end crashes by crash severity and the percentage these represent with respect to (1) all other crashes in their severity class, and (2) all rear-end crashes by severity class.

Table 49: Sub-sample of fatal and injury rear-end crashes.

Crash Severity	Fatal			Injury		
Year	Number	Percent (w.r.t All Fatalities)	Percent (w.r.t. Rear-End Fatalities)	Number	Percent (w.r.t. All Injuries)	Percent (w.r.t Rear-End Injuries)
2019	247	0.74%	10.45%	116,336	6.07%	25.52%
2020	259	0.72%	10.61%	86,118	5.40%	26.14%
2021	321	0.81%	10.80%	103,402	5.99%	28.11%
Average	276	0.76%	10.62%	101,952	5.82%	26.59%

Table 50: Sub-sample of PDO and total rear-end crashes.

Crash Severity	PDO			Total		
Year	Number	Percent (w.r.t All PDO Crashes)	Percent (w.r.t Rear-End PDO Crashes)	Number	Percent (w.r.t. All Rear-End Crashes)	Percent (w.r.t. All Crashes)
2019	417,141	8.68%	26.12%	533,724	25.97%	7.90%
2020	253,213	6.99%	24.40%	339,590	24.80%	6.47%
2021	324,860	7.49%	25.15%	428,583	25.78%	7.02%

Crash Severity	PDO			Total		
Average	331,738	7.72%	25.23%	433,966	25.52%	7.13%

Model Details

This section provides the summary tables containing the scenario model parameters. As the models progressively build upon the previous one, the newly introduced and adjusted parameters are highlighted in bold in Table 52 to Table 55.

Table 51: Scenario #1 model parameters.

Event	Model	Sub-Event	Model/Reference	Value/Node	State
Initiating Event	BBN General Model	--	FARS	"Scenario"	True
5a. Driver brakes	FT #1 Driver fails to brake (unassisted)	5.A.2.1 No Visibility	"Description of light-vehicle pre-crash" (2013) (*55*).	0.05	--
		5.A.2.2 Driver fails to monitor driving environment	BBN General Model	"Driver Detection Task"	False
		7.B Driver fails to react	Normal (5%, 95%)	(0.25, 0.29)	--
5b. Slow speed collision is avoided	FT #2 Braking does not avoid a collision	7.C.1 Vehicle Brake Failure	FARS	1.95E-03	--
		7.C.2 Driver fails to brake sufficiently	BBN General Model	"Driver Action Task"	False

Table 52: Scenario #2 model parameters.

Event	Model	Sub-Event	Model/Reference	Value/Node	State
Initiating Event	BBN General Model	--	FARS	"Scenario"	True
2b. Obstacle detected (FCW)	**FT #3 2.T-Driver Warning Failure (FCW)**	**2.A.1 HMI Failure**	**Uniform**	**(1e-4, 1e-5)**	**--**
		3.B.1 Sensor Failure	**Uniform**	**(0.01, 0.05)**	**--**
		3.B.2 FCW Trigger Failure	**Normal (5%, 95%)**	**(0.0073, 0.0372)**	**--**
3b. Driver brakes (FCW)	**FT #4 4B. Driver fails to brake when assisted by FCW**	**5.A.1.1 Driver fails to monitor vehicle warnings**	**BBN General Model**	**"Driver State"**	**Not Available**
		5.A.1.2 HMI Failure	**FT #3 2.T- Driver Warning Failure (FCW)**	**2.A.1 HMI Failure**	**--**
		6.B Driver fails to react	**Normal (5%, 95%)**	**(0.16, 0.20)**	**--**
4b. Slow speed collision is avoided (FCW)	**FT #5 6C. Braking does not avoid a collision (FCW)**	**6.C.1 Vehicle Brake Failure**	**FARS**	**1.95E-03**	**--**
		6.C.2 Driver fails to brake sufficiently	**Normal (5%, 95%)**	**(0.125, 0.141)**	**--**
5a. Driver brakes	**FT #1 4C. Driver fails to brake (unassisted)**	5.A.2.1 No Visibility	"Description of light-vehicle pre-crash" (2013) (*55*).	0.05	--
		5.A.2.2 Driver fails to monitor driving environment	BBN General Model	"Driver Detection Task"	False
		7.B Driver fails to react	**Normal (5%, 95%)**	**(0.22, 0.24)**	**--**

Event	Model	Sub-Event	Model/Reference	Value/Node	State
5b. Slow speed collision is avoided	FT #2 7C. Braking does not avoid a collision	7.C.1 Vehicle Brake Failure	FARS	1.95E-03	--
		7.C.2 Driver fails to brake sufficiently	BBN General Model	"Driver Action Task"	False

Table 53: Scenario #3 model parameters.

Event	Model	Sub-Event	Model/Reference	Value/Node	State
Initiating Event	BBN General Model	--	FARS	"Scenario"	True
2b. Obstacle detected (FCW)	FT #3 2.T- Driver Warning Failure (FCW)	2.A.1 HMI Failure	Uniform	(1e-4, 1e-5)	--
		3.B.1 Sensor Failure	Uniform	(0.01, 0.05)	--
		3.B.2 FCW Trigger Failure	Normal (5%, 95%)	(0.0073, 0.0372)	--
3b. Driver brakes (FCW)	FT #4 4B. Driver fails to brake when assisted by FCW	5.A.1.1 Driver fails to monitor vehicle warnings	BBN General Model	"Driver State"	Not Available
		5.A.1.2 HMI Failure	FT #3 2.T- Driver Warning Failure (FCW)	2.A.1 HMI Failure	--
		6.B Driver fails to react	Normal (5%, 95%)	(0.16, 0.20)	**--**
4b. Slow speed collision is avoided (FCW)	**FT #5 6C. Braking does not avoid a collision (FCW)**	6.C.1 Vehicle Brake Failure	FARS	1.95E-03	--
		6.C.2 Driver fails to brake sufficiently	**Normal (5%, 95%)**	**(0.145, 0.161)**	--

Event	Model	Sub-Event	Model/Reference	Value/Node	State
5a. Driver brakes	FT #1 4C. Driver fails to brake (unassisted)	5.A.2.1 No Visibility	"Description of light-vehicle pre-crash" (2013) (*55*).	0.05	--
		5.A.2.2 Driver fails to monitor driving environment	BBN General Model	"Driver Detection Task"	False
		7.B Driver fails to react	Normal (5%, 95%)	(0.22, 0.24)	--
5b. Slow speed collision is avoided	FT #2 7C. Braking does not avoid a collision	7.C.1 Vehicle Brake Failure	FARS	1.95E-03	--
		7.C.2 Driver fails to brake sufficiently	BBN General Model	"Driver Action Task"	False
6a. AEB brakes	**FT #6 AEB Failure**	**9.C AEB Trigger Failure**	**Normal (5%, 95%)**	**(0.50, 0.60)**	**--**
6b. Slow speed collision is avoided (AEB+FCW)	**FT #6 AEB Failure**	**8.C.1.1 Vehicle Brake Failure**	**FARS**	**1.95E-03**	**--**
		8.C.1.2 Driver fails to brake sufficiently	**BBN General Model**	**"Vehicle Control"**	**False**
6c. Slow speed collision is avoided (AEB+FCW)	**FT #6 AEB Failure**	**8.C.1.1 Vehicle Brake Failure**	**FARS**	**1.95E-03**	**--**
		8.C.1.2 Driver fails to brake sufficiently	**BBN General Model**	**"Vehicle Control"**	**False**

Table 54: Scenario #4 model parameters.

Event	Model	Sub-Event	Model/Reference	Value/Node	State
Initiating Event	BBN General Model	--	FARS	"Scenario"	True
2a. Obstacle detected (V2X)	**FT #7 1.T-Driver Warning Failure (V2X)**	**2.A.1 HMI Failure**	**Uniform**	**(1e-4, 1e-5)**	**--**
		2.B.1.1 Package Loss	**Normal (5%, 95%)**	**(0.025, 0.035)**	**--**
		2.B.1.2 External Network Disruption	**BBN General Model**	**"Connectivity"**	**Not Available**
		2.B.2.1 V2V Processing Failure	**Normal (5%, 95%)**	**(0.05, 0.10)**	**--**
		2.B.2.2 V2I Processing Failure (RSU)	**Normal (5%, 95%)**	**(0.01, 0.05)**	**--**
3a. Driver brakes (V2X)	**FT #8 4A. Driver fails to brake when assisted by V2X-FCW**	5.A.1.1 Driver fails to monitor vehicle warnings	BBN General Model	"Driver State"	Not Available
		5.A.1.2 HMI Failure	FT #3 2.T- Driver Warning Failure (FCW)	2.A.1 HMI Failure	--
		5.B Driver fails to react	**Normal (5%, 95%)**	**(0.10, 0.15)**	**--**
4a. Slow speed collision is avoided (V2X)	**FT #9 5C. Braking does not avoid a collision (V2X)**	**5.C.1 Vehicle Brake Failure**	**FARS**	**1.95E-03**	**--**
		5.C.2 Driver fails to brake sufficiently	**Normal (5%, 95%)**	**(0.105, 0.131)**	**--**
2b. Obstacle	FT #3 2.T-Driver	2.A.1 HMI Failure	Uniform	(1e-4, 1e-5)	--

Event	Model	Sub-Event	Model/Reference	Value/Node	State
detected (FCW)	Warning Failure (FCW)	3.B.1 Sensor Failure	Uniform	(0.01, 0.05)	--
		3.B.2 FCW Trigger Failure	Normal (5%, 95%)	(0.0073, 0.0372)	--
3b. Driver brakes (FCW)	FT #4 4B. Driver fails to brake when assisted by FCW	5.A.1.1 Driver fails to monitor vehicle warnings	BBN General Model	"Driver State"	Not Available
		5.A.1.2 HMI Failure	FT #3 2.T- Driver Warning Failure (FCW)	2.A.1 HMI Failure	--
		6.B Driver fails to react	Normal (5%, 95%)	(0.16, 0.20)	--
4b. Slow speed collision is avoided (FCW)	FT #5 6C. Braking does not avoid a collision (FCW)	6.C.1 Vehicle Brake Failure	FARS	1.95E-03	--
		6.C.2 Driver fails to brake sufficiently	Normal (5%, 95%)	(0.125, 0.141)	--
5a. Driver brakes	FT #1 4C. Driver fails to brake (unassisted)	5.A.2.1 No Visibility	"Description of light-vehicle pre-crash" (2013) (*55*).	0.05	--
		5.A.2.2 Driver fails to monitor driving environment	BBN General Model	"Driver Detection Task"	False
		7.B Driver fails to react	Normal (5%, 95%)	(0.22, 0.24)	--
5b. Slow speed collision is avoided	FT #2 7C. Braking does not avoid a collision	7.C.1 Vehicle Brake Failure	FARS	1.95E-03	--
		7.C.2 Driver fails to brake sufficiently	BBN General Model	"Driver Action Task"	False

Table 55: Scenario #5 model parameters.

Event	Model	Sub-Event	Model/Reference	Value/Node	State
Initiating Event	BBN General Model	--	FARS	"Scenario"	True
2a. Obstacle detected (V2X)	**FT #7 1.T-Driver Warning Failure (V2X)**	**2.A.1 HMI Failure**	**Uniform**	**(1e-4, 1e-5)**	**--**
		2.B.1.1 Package Loss	**Normal (5%, 95%)**	**(0.025, 0.035)**	**--**
		2.B.1.2 External Network Disruption	**BBN General Model**	**"Connectivity"**	**Not Available**
		2.B.2.1 V2V Processing Failure	**Normal (5%, 95%)**	**(0.05, 0.10)**	**--**
		2.B.2.2 V2I Processing Failure (RSU)	**Normal (5%, 95%)**	**(0.01, 0.05)**	**--**
3a. Driver brakes (V2X)	**FT #8 4A. Driver fails to brake when assisted by V2X-FCW**	5.A.1.1 Driver fails to monitor vehicle warnings	BBN General Model	"Driver State"	Not Available
		5.A.1.2 HMI Failure	FT #3 2.T- Driver Warning Failure (FCW)	2.A.1 HMI Failure	--
		5.B Driver fails to react	**Normal (5%, 95%)**	**(0.10, 0.15)**	**--**
4a. Slow speed collision is avoided (V2X)	**FT #9 5C. Braking does not avoid a collision (V2X)**	**5.C.1 Vehicle Brake Failure**	**FARS**	**1.95E-03**	**--**
		5.C.2 Driver fails to brake sufficiently	**Normal (5%, 95%)**	**(0.105, 0.131)**	**--**
2b. Obstacle	FT #3 2.T-Driver	2.A.1 HMI Failure	Uniform	(1e-4, 1e-5)	--

Event	Model	Sub-Event	Model/Reference	Value/Node	State
detected (FCW)	Warning Failure (FCW)	3.B.1 Sensor Failure	Uniform	(0.01, 0.05)	--
		3.B.2 FCW Trigger Failure	Normal (5%, 95%)	(0.0073, 0.0372)	--
3b. Driver brakes (FCW)	FT #4 4B. Driver fails to brake when assisted by FCW	5.A.1.1 Driver fails to monitor vehicle warnings	BBN General Model	"Driver State"	Not Available
		5.A.1.2 HMI Failure	FT #3 2.T- Driver Warning Failure (FCW)	2.A.1 HMI Failure	--
		6.B Driver fails to react	Normal (5%, 95%)	(0.16, 0.20)	--
4b. Slow speed collision is avoided (FCW)	FT #5 6C. Braking does not avoid a collision (FCW)	6.C.1 Vehicle Brake Failure	FARS	1.95E-03	--
		6.C.2 Driver fails to brake sufficiently	Normal (5%, 95%)	(0.125, 0.141)	--
5a. Driver brakes	FT #1 4C. Driver fails to brake (unassisted)	5.A.2.1 No Visibility	"Description of light-vehicle pre-crash" (2013) (*55*).	0.05	--
		5.A.2.2 Driver fails to monitor driving environment	BBN General Model	"Driver Detection Task"	False
		7.B Driver fails to react	Normal (5%, 95%)	(0.22, 0.24)	**--**
5b. Slow speed collision is avoided	FT #2 7C. Braking does not avoid a collision	7.C.1 Vehicle Brake Failure	FARS	1.95E-03	--
		7.C.2 Driver fails to brake sufficiently	BBN General Model	"Driver Action Task"	False

Event	Model	Sub-Event	Model/Reference	Value/Node	State
6a. AEB brakes	FT #6 AEB Failure	9.C AEB Trigger Failure	Normal (5%, 95%)	(0.50, 0.60)	--
6b. Slow speed collision is avoided (AEB+FCW)	FT #6 AEB Failure	8.C.1.1 Vehicle Brake Failure	FARS	1.95E-03	--
		8.C.1.2 Driver fails to brake sufficiently	BBN General Model	“Vehicle Control”	False
6c. Slow speed collision is avoided (AEB+FCW)	FT #6 AEB Failure	8.C.1.1 Vehicle Brake Failure	FARS	1.95E-03	--
		8.C.1.2 Driver fails to brake sufficiently	BBN General Model	“Vehicle Control”	False

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