REDUCING FATALITIES IN ROAD CRASHES IN JAPAN, GERMANY, AND USA WITH V2X-ENHANCED-ADAS

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Paper Number 23-0082

ABSTRACT

Objective

While Advanced Driver Assistance Systems (ADAS) improve safety, on-board sensors such as cameras, radar and lidar have limitations in preventing crashes: a) early recognition of non-line-of-sight (NLOS) vehicles and vulnerable road users (VRU: pedestrians, bicyclists, and motorcyclists) and b) early recognition of the intention of other road users. V2X technology can overcome this challenge.

Basic V2X use direct short-range communication between vehicles and provides only a gradual solution toward improving ADAS. First, the slow introduction rate of V2X results in a low likelihood of both vehicles being equipped with V2X and therefore in preventing a crash. Second, there are impediments to VRU participation in V2X communication, resulting in a lack of VRU protection in NLOS scenarios.

Collective Perception V2X using sensor data sharing can help to protect vehicles without V2X technology. Collective Perception V2X can also help to protect VRU by sharing information on road users that is collected by sensors in other vehicles or on intelligent infrastructure.

The first objective of this paper is to quantify how Basic V2X can address fatal crashes in conjunction with ADAS by improving situational awareness in non-line-of-sight scenarios, and by providing information on the intention of traffic participants in critical situations.

The second objective of this paper is to quantify how Collective Perception V2X can further boost the effective equipment rate in vehicles and protect VRU that are not otherwise protected by Basic V2X and ADAS.

Method

Using crash statistics from Japan, Germany, and the US, we analyzed the share of fatal crashes between vehicles and VRU. Crash scenarios due to limitations of on-board sensors were identified to quantify the target population for V2X. Starting with the V2X introduction rates presumed by the US DOT NPRM [1], we modeled the effective V2X communication rates for vehicles and VRU over time, assuming that all vehicles were equipped with ADAS.

We analyzed the benefit of Basic V2X, in addition to conventional ADAS, in addressing vehicle-vs-vehicle and vehicle-vs-VRU crashes. We investigated whether Collective Perception V2X could increase the effective communication rate between vehicles. Additionally, we examined how Collective Perception V2X could help to detect VRU that are insufficiently addressed in NLOS circumstances. The analysis included intersections with potential intelligent infrastructure and roadways without infrastructure.

Results

The following three fields-of-action of Basic V2X and Collective Perception V2X were identified, and the potential in addressing vehicle-vs-vehicle and vehicle-vs-VRU crashes, were quantified:

- Basic V2X raises the awareness of other equipped vehicles,
- Collective Perception V2X boosts the effective vehicle equipment rate,
- Collective Perception V2X protects VRU that are otherwise unprotected.

Outlook

The results indicate that the combination of Basic V2X, Collective Perception V2X, and ADAS can be highly beneficial for road safety. It is therefore important to ensure sufficient and protected frequency spectrum in the 5.9 GHz band for basic and advanced V2X messages like BSM/CAM and SDSM/CPM. Subsequent research should focus on analyzing the potential of V2X for automatic emergency braking, including safety level considerations when utilizing over-the-air V2X data.

1. INTRODUCTION

Modern cars are equipped with Advanced Driver Assistance Systems (ADAS) that use on-board line-of-sight (LoS) sensors such as cameras, radar and lidar. They prevent or mitigate traffic crashes by controlling actuators for braking, accelerating, or steering. While ADAS are key for improving safety, they have limitations due to the nature of the LoS sensors to provide sufficiently early notifications. Other traffic participants may be obstructed or outside the coverage of the on-board sensor and therefore may not be detected. Also, the movement of other vehicles cannot easily be anticipated at the time of pedal or steering wheel actuation but perhaps only after such actuation has resulted in vehicle acceleration in any direction. In both cases, critical situations may not be detected in time to prevent an accident.

V2X technology aims at closing this gap and provides additional information about other vehicles, their movement and intent, as well as VRU. Thus, ADAS benefit from this additional information and further by earlier detection of non-light-of-sight vehicles and VRU, and by indications of the intention of other road users. Namely Basic V2X and Collective Perception V2X contribute relevant information to an V2X-enhanced ADAS.

Figure 1 shows how vehicle-vs-vehicle and vehicle-vs-VRU crashes are addressed by V2X-enhanced ADAS. V2X communication can extend the field of action in which a safety system can become active.

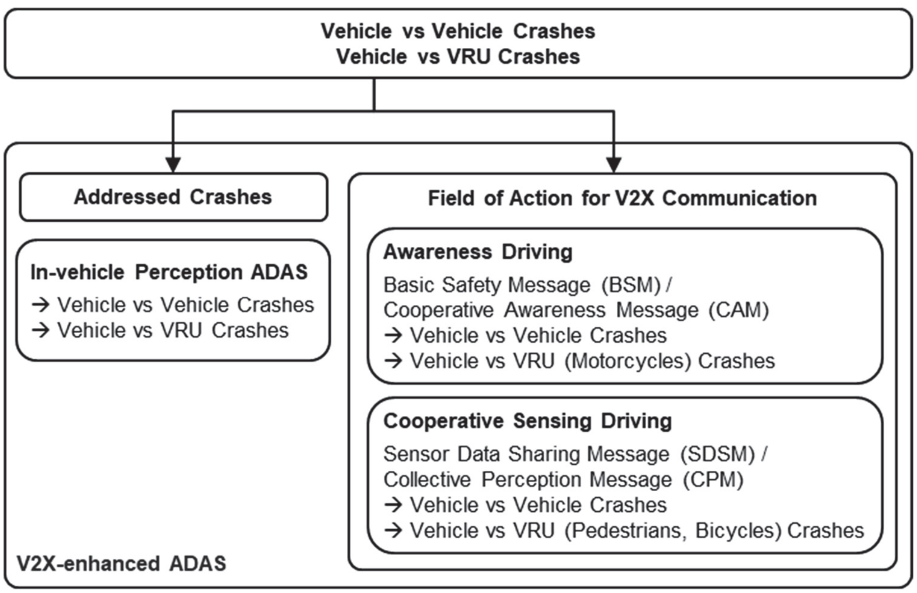

Figure 1: V2X-enhanced ADAS addressing vehicle-vs-vehicle crashes and vehicle-vs-VRU crashes.

This paper aims to answer the following research questions:

- To what extent does V2X-enhanced ADAS, that utilizes Basic V2X and Collective Perception V2X, address vehicle-vs-vehicle crashes?
- To what extent does V2X-enhanced ADAS, that utilizes Basic V2X and Collective Perception V2X, improve VRU safety?

These research questions will be discussed using accident data inflicting fatal injuries from Japan in 2021 [2], Germany in 2020 [3], [4] and the US in 2020 [5].

2. BASIC V2X AND COLLECTIVE PERCEPTION V2X

V2X communication utilizes different message types to exchange information between vehicles and with roadside units, including the position and movement of vehicles and VRU. Basic Safety Messages (BSM) are directly exchanged between vehicles that are equipped with V2X technology. Each vehicle transmits regular BSM providing its own status. As BSM are used in the US, the corresponding Cooperative Awareness Messages (CAM) with similar data contents are used in Europe.

Sensor Data Sharing Messages (SDSM) can provide information about vehicles that are not fitted with V2X technology or about VRU that do not participate in V2X communication. The equivalent Collective Perception Messages (CPM) are specified for Europe.

The goal of BSM/CAM and SDSM/CPM is to inform receiving vehicles on impeding dangerous situations due to position, movement, or status of other vehicles and VRU.

Table 1 describes the relevant message types used in this analysis. The usage of message types is independent of the specific V2X radio communication technology (IEEE 802.11p / LTE-V2X / 5G NR-V2X / IEEE 802.11bd).

Table 1: Definition of important V2X message types enabling different V2X applications.

V2X level	Message types	Classes of cooperation	Description and related technical standards
Basic V2X	BSM/ CAM	Awareness Driving (Status Sharing)	Basic Safety Messages (BSM) or Cooperative Awareness Messages (CAM) increase the awareness horizon by sharing the vehicle status (position, movement vector, vehicle class, wiper, and brake pedal status) and alert on impending dangerous situations. SAE J2735, SAE J2945/1, ETSI EN 302 637-2.
Collective Perception V2X	SDSM/ CPM	Cooperative Sensing Driving (Sensor Data Sharing)	Sensor Data Sharing Messages (SDSM) or Collective Perception Messages (CPM) provide information on detected objects (traffic participants, road objects) in the surroundings of a vehicle or road infrastructure by sharing the vehicle or VRU status (position, movement vector, object type). SAE J3224, ETSI TS 103 324, ETSI TR 103 562.

Figure 2 shows the functionality of Collective Perception V2X in addressing vehicle-vs-vehicle crashes and vehicle-vs-VRU crashes. If a vehicle is not equipped with V2X, it cannot communicate to other vehicles itself. However, third-party V2X-equipped vehicles can detect the non-equipped vehicle using their on-board sensors and transmit this detection to other V2X-capable traffic participants. VRU who do not participate in V2X communication themselves, can be detected by V2X-equipped vehicles and by roadside units, who in return can provide this information to other V2X participants. Thus, Collective Perception V2X can be thought of as "seeing through the eyes of others" to improve awareness of non-equipped vehicles and VRU.

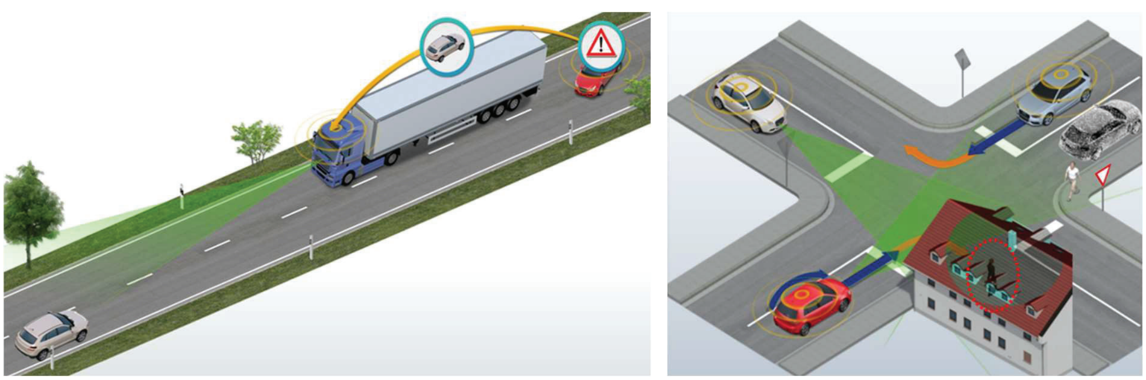

Figure 2: Left: Truck sends information to red vehicle regarding non-V2X-equipped white vehicle. Right: White vehicle sends information to red vehicle regarding NLOS VRU [6].

Note that in the following analysis we model the Basic V2X communication rate over time using the example of BSM and the Collective Perception V2X communication rate over time using the example of SDSM. However identical results will be achieved using the corresponding message types CAM and CPM, respectively.

3. FATAL ROAD CRASHES

Traffic crashes in Japan, Germany, and the US are analyzed to quantify the field-of-action, in which V2X-enhanced ADAS can become effective. To allow for an overview of the total accident situation in each country, the fatal crashes are grouped into single-vehicle crashes and crashes that are caused in conflict situations between two participants. While the former are often due to loss of control, the latter are mostly caused by negligence or driver inattentiveness.

Figure 3 gives an overview of fatal crashes in Japan, Germany, and the US. The distribution significantly varies between the countries. Conflict crashes involving two cars are dominant in Germany and the US, being responsible for 16% and 25% of fatalities, respectively. Car crashes with pedestrians are of high relevance, especially in Japan where these account for 27% of traffic fatalities. In Germany and the US, they cause 9% and 13% of fatalities, respectively. In Japan 54 of traffic fatalities are caused in vehicle-vs-VRU crashes.

In the following, two different target populations are defined to show the potential of V2X-enhanced ADAS in addressing fatal crashes and particularly the additional benefit of Basic V2X and Collective Perception V2X: Vehicle-vs-vehicle crashes and vehicle-vs-VRU crashes.

Please note that no consideration has been given to the change of road traffic participation and thus to the distribution of accident participants and accident conflicts, due to Covid-related travel patterns and social circumstances.

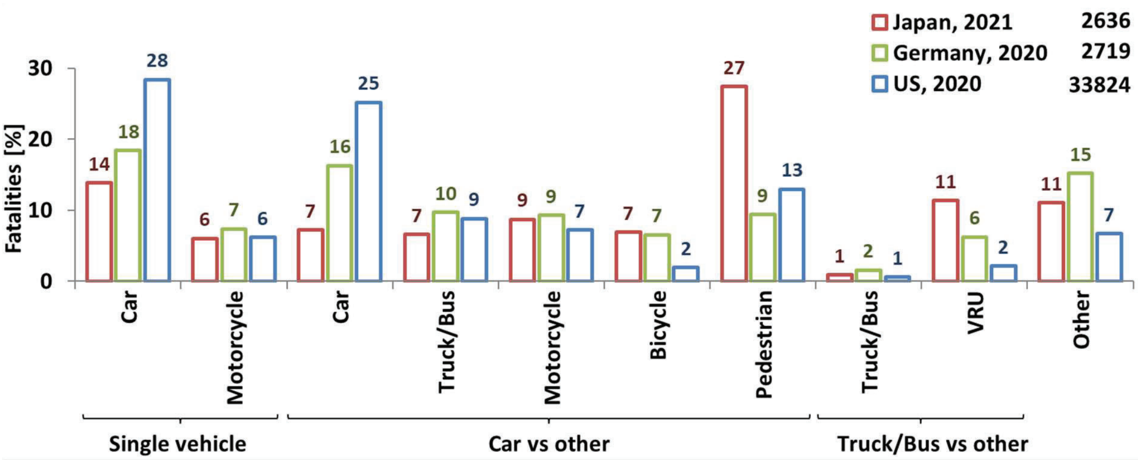

Figure 3: Traffic fatalities in Japan, Germany and the US.

The group of vehicle-vs-vehicle crashes split up into three combinations of conflicts between cars and trucks. The largest share are crashes between two cars, accounting for 186 fatalities in Japan, 442 in Germany and 9,773 in the US, in the respective years. The second largest group are crashes between cars and trucks, followed by crashes involving two trucks. It should be noted that busses are treated together with trucks in this analysis.

In all vehicle-vs-vehicle crashes, crossing/turning scenarios (39% in Germany) and oncoming scenarios (40% in Japan) are most relevant in causing fatalities. See Figure 4 for an overview of all fatal vehicle-vs-vehicles in the different countries.

Pedestrians are most vulnerable and make up the largest share of all fatalities in vehicle-vs-VRU crashes. In crashes with cars, 708 pedestrians were killed in Japan, 255 in Germany and 5,027 in the US, in the analyzed data years. Note that motorcycles are counted as VRU in this analysis. They represent the second most endangered group of VRU with 2,794 motorcyclists killed in the US alone in 2020. Bicycles are the third relevant group of endangered VRU in crashes with cars. The large number of 178 bicyclist fatalities in crashes with cars in Germany in 2020 correlates with the high bicycle usage in this country. Finally, trucks play a crucial role in fatal crashes with VRU.

The majority of vehicle-vs-VRU crashes occur in crossing and turning scenarios. These are scenarios with an ego vehicle going straight or turning at an intersection and the respective VRU crossing the path of the ego vehicle. Crossing/turning account for the highest share of fatal vehicle-vs-pedestrian crashes: 74% in Japan, 74% in Germany and 63% in the US. Crossing/turning crashes are equally relevant in car-vs-motorcycle crashes: 66% in Japan, 49% in Germany and 55% in the US. Within the group of car-vs-bicycle crashes, crossing/turning scenarios in are significant in Japan and Germany with 69% and 80% of fatal crashes. A detailed analysis of car-vs-bicycle crashes including the relevant scenarios and pre-crash characteristics are described in [7]. Figure 5 shows the different shares of fatal vehicle-vs-VRU crashes.

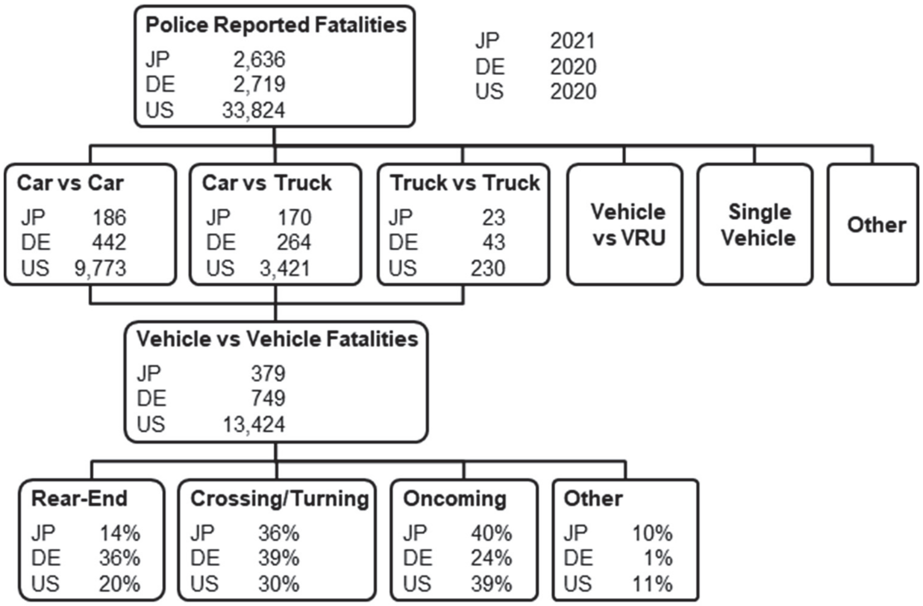

Figure 4: Fatalities in vehicle-vs-vehicle crashes in Japan, Germany and the US.

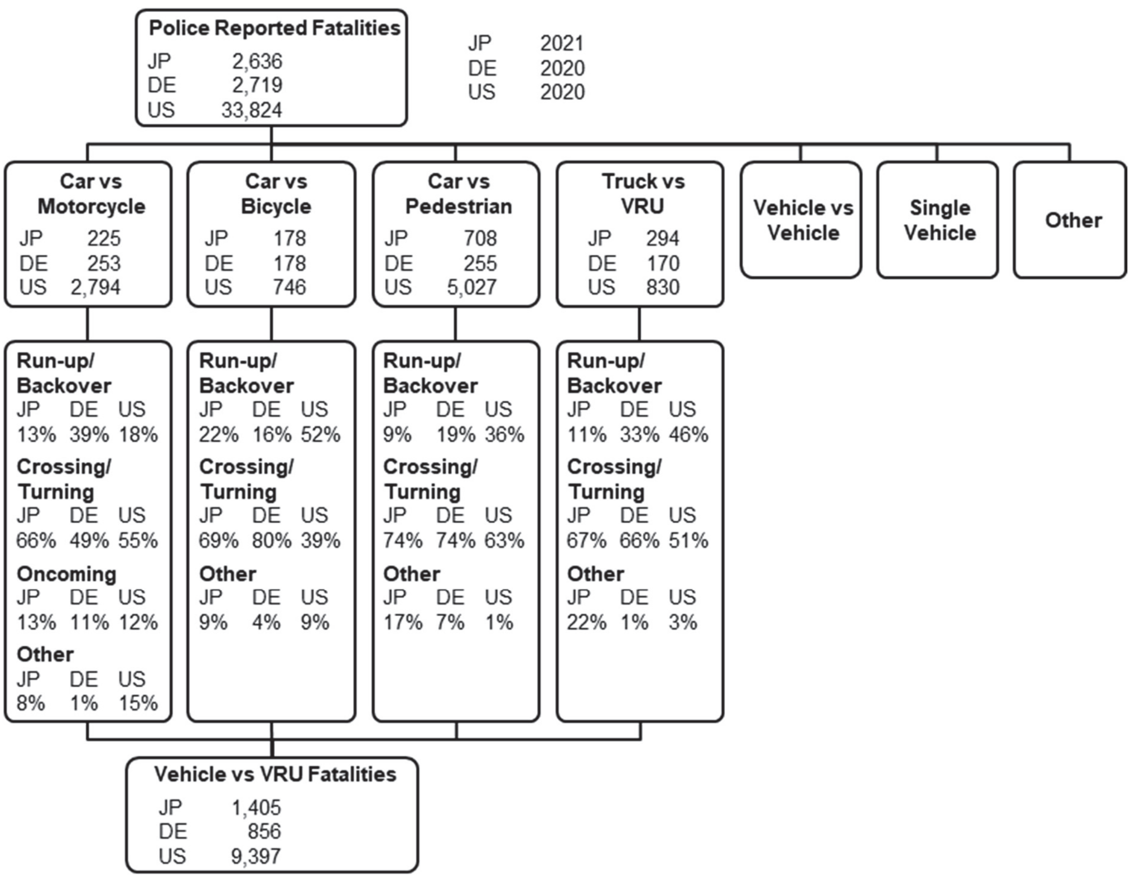

Figure 5: Fatalities in vehicle-vs-VRU crashes in Japan, Germany and the US.

Obstructed traffic participants that are in non-line-of-sight cannot be detected by ADAS onboard sensors. Other vehicles and VRU might be obstructed, due to stationary objects such as parked vehicles, or due to roadside structures such as buildings or trees.

The GIDAS pre-crash data PCM was analyzed to quantify view obstructions in vehicle-vs-vehicle and vehicle-vs-VRU crashes [8]. At time-to-collision TTC=2s, 32% of crossing cars, 30% of crossing motorcycles, 25% of crossing bicycles, and 34% of crossing pedestrians are obstructed. At that time, typical Euro NCAP tests require the detection of crash targets [9].Since GIDAS considers only stationary obstructions at the scene of the accidents, the real share of crashes with obstructions will be even higher. V2X technology can support by providing information about the obstructed vehicles or VRU. Figure 6 shows the share of stationary obstructed vehicles and VRU in crossing crashes from left and right.

The Euro NCAP project SECUR identified relevant participants, specific crash scenarios, and important environment conditions where V2X communication can support to improve vehicle safety [10].

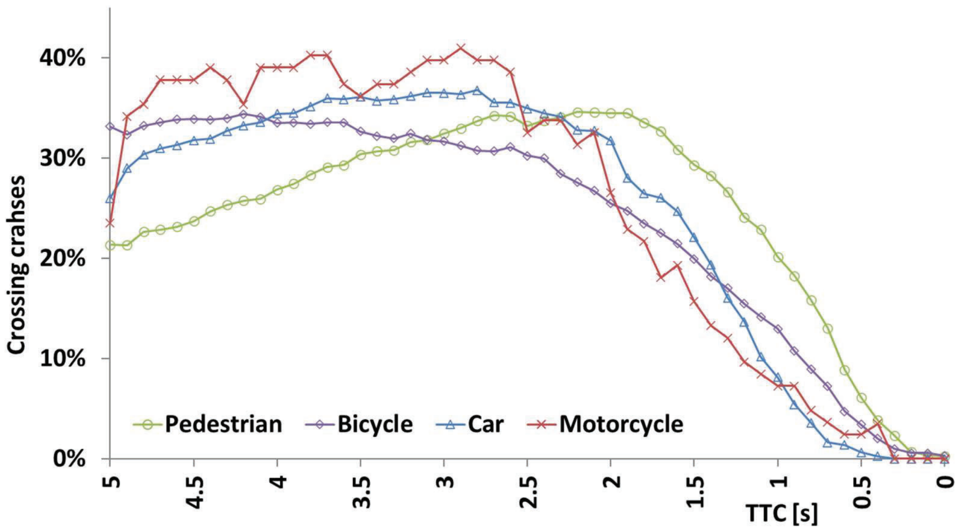

Figure 6: Share of stationary obstructions in crossing crashes (from left or right) with different objects.

ADAS predict the velocities of other objects to determine the likelihood that a crash is unavoidable and to activate automatic braking or steering. Depending on the viewpoint of the ego vehicle, crossing crashes can be considered as two individual scenarios, with crossing vehicles from different directions, left or right, [11]. Therefore, ADAS need to include the causer and the non-causer perspective of the crash, in case the other vehicles might not be equipped with a safety system.

If the ego vehicle is not causer of the crash, it typically moves at speeds of around 50 km/h, whereas the causing object vehicles travels at lower speeds. In 40% of crossing vehicle-vs-vehicles crashes, in which the opponent vehicle is causer, the object speeds are smaller than 20 km/h. However, slow crossing vehicles are difficult to judge by using on-board sensors and might be excluded from the ADAS coverage to avoid false-positive activations. Currently, also Euro NCAP covers crossing Global Vehicles Targets (GVT) at test speeds of 20 km/h and above only, [12]. V2X technology can support the detection of slow-moving crossing vehicles by providing the driver intention based on pedal actuation, and the actual vehicle dynamics measured by wheel sensors. Figure 7 shows the pre-crash speeds of ego vehicles and crossing vehicles, in case the crossing vehicle is crash causer.

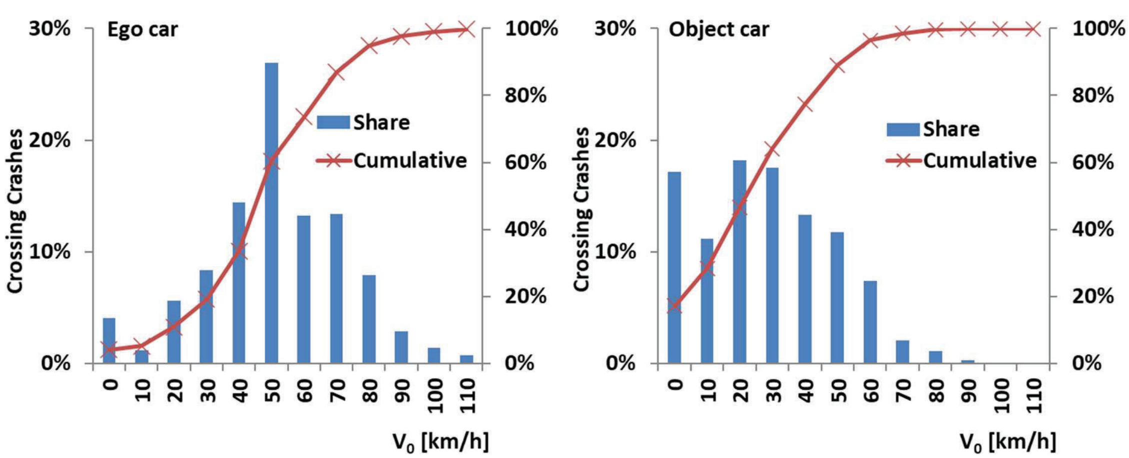

Figure 7: Pre-crash speeds in car-vs-car crossing crashes (from left or right) - if ego is non-causer.

4. V2X TECHNOLOGY ADRESSING VEHICLE-VS-VEHICLE CRASHES

Effective V2X communication between two vehicles depends on overall vehicle equipment rates and increases over time beginning with the introduction of V2X technology. Basic V2X applying BSM, and Collective Perception V2X applying SDSM, can detect opponent vehicles in critical situations. Three communication paths between vehicles are possible:

- Basic V2X - using BSM V2V: The communication rate between two vehicles exchanging CAM, dependent on the average V2X equipment rate in vehicles.
- Collective Perception V2X - using SDSM V2I: Vehicles that are not equipped with V2X can be detected by roadside units in smart intersections using cameras or radar sensors. The roadside units then broadcast information regarding the vehicles via SDSM.
- Collective Perception V2X - using SDSM V2V: Vehicles can be detected by third-party vehicles which use their own on-board sensors, and those third-party vehicles then can broadcast this information via SDSM. The effective communication rate depends on the existence of a third-party vehicle and whether it detects the target vehicle.

Table 2 explains how the different individual communication rates for vehicle-to-vehicle communication are calculated. See also in [13] for more details.

Table 2: V2X communication rates relevant for vehicle-vs-vehicle communication.

Individual communication rates		Description
BSM V2V	$C_{BSM\ V2V} = ER_{Veh} * ER_{Veh}$	Two vehicles communicating via BSM. Assume vehicle equipment rate ER_{Veh} as in mass V2X introduction according to NHTSA NPRM [1].
SDSM V2I	$C_{SDSM\ V2I} = ER_{Veh} * ER_{Int} * G$	Vehicle and smart intersection communicating via SDSM and sharing information about a non-equipped vehicle. Assume that intersection equipment rate ER_{Int} is increasing along with ER_{Veh}.to max 60% each in 30 years. Assume that intersections with the highest traffic throughput will be equipped more quickly than other intersections: G = 3.5 in year 6 and 1 in year 15.
SDSM V2V	$C_{SDSM\ V2V} = ER_{Veh} * ER_{Veh} * 0.6$	Two vehicles communicating via SDSM and sharing information about a non-equipped vehicle. Assume the likelihood of a second vehicle being present and detecting the non-equipped vehicle is 0.6. Note: The non-equipped vehicle is not a factor for calculating the communication rate, because the detection and communication rates for this calculation applies equally for detecting V2X-equipped vehicles and non-V2X-equipped vehicles.

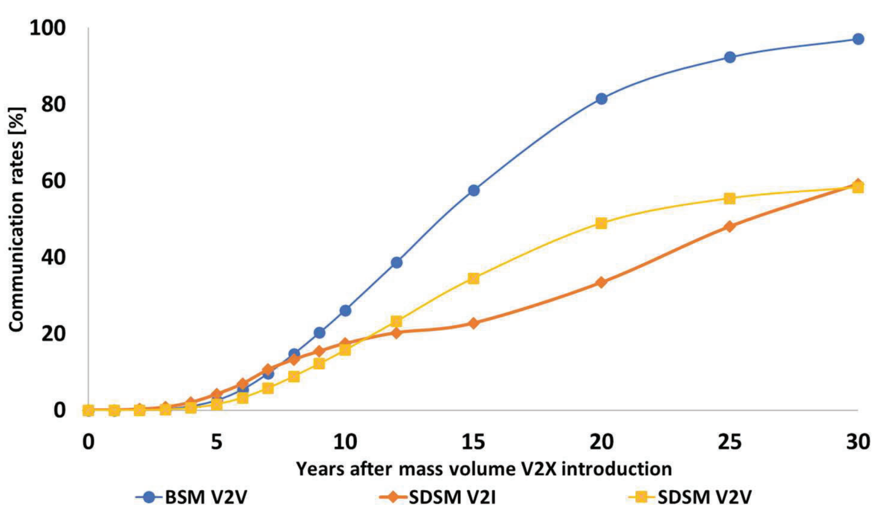

Figure 8: Communication rates for vehicle awareness, using BSM and SDSM.

Figure 8 shows the three individual vehicle-to-vehicle communication rates over time, as calculated according to the formulas in Table 2. Each can increase the awareness of other vehicles in critical situations and thus address the same target population of vehicle-vs-vehicle crashes. The SDSM V2I communication rate grows more quickly in the early years due to the assumed higher installation rate of smart intersections. SDSM V2I has a larger effect than SDSM V2V up to year 10. Note that this does not equate to the actual number of crashes prevented which depends on how effectively a safety system would act on this information.

The different V2X communication paths are not mutually exclusive and sometimes provide vehicle awareness in the very same critical situation. The individual communication rates are therefore applied sequentially when calculating the individual effective shares in the V2X communication. Table 3 explains the formulas for calculating the effective SDSM communication rates, that apply on top of BSM communication, for vehicle-vs-vehicle communication, inside and outside of smart intersections. Here the following order introducing V2X technology is assumed: BSM, SDSM inside intersections, SDSM outside intersections.

Table 3: Effective SDSM communication rates for vehicle-vs-vehicle communication.

<table>
<tr><th colspan="2">Effective communication rates</th><th>Description</th></tr>
<tr><td rowspan="2">Inside intersections</td><td>$C_{SDSM\,V2I\,eff} = C_{BSM\,V2V} \cup C_{SDSM\,V2I} - C_{BSM\,V2V}$</td><td>Vehicle and smart intersection communicating via SDSM and sharing information about a non-equipped vehicle.
Additional effect on top of BSM communication.
Applies to share of intersection crashes.</td></tr>
<tr><td>$C_{CPM\,V2V\,eff} = C_{BSM\,V2V} \cup C_{SDSM\,V2I} \cup C_{SDSM\,V2V} - C_{BSM\,V2V} \cup C_{SDSM\,V2I}$</td><td>Two vehicles communicating via SDSM and sharing information about a non-equipped vehicle.
Additional effect on top of only BSM communication and on top of only SDSM vehicle and smart intersection communication.
Applies to share of intersection crashes.</td></tr>
<tr><td>Outside intersections</td><td>$C_{SDMS\,V2V\,eff} = C_{BSM\,V2V} \cup C_{SDMS\,V2V} - C_{SDMS\,V2V}$</td><td>Two vehicles communicating via SDSM and sharing information on non-equipped vehicle.
Additional effect on top of BSM communication.
Applies to share of non-intersection crashes.</td></tr>
</table>

The total effective SDSM communication rate is calculated by summing up $C_{SDMS\,V2I\,eff}$ and $C_{SDMS\,V2V\,eff}$, for inside and outside intersections. The calculation assumes a 35% share of vehicle-vs-vehicle crashes at intersections as analyzed for the US. The total effective SDSM communication rate peaks at around year 12 after market introduction. The additional benefit of SDSM communication on top of BSM communication is shown in Figure 9. It should be noted that the delta additional benefit of SDSM is non-zero across all 30 years under study, and is expected to provide positive, crash-reducing benefit. SDSM can therefore boost the effective V2X vehicle equipment rate, and thus accelerate the introduction of V2X technology.

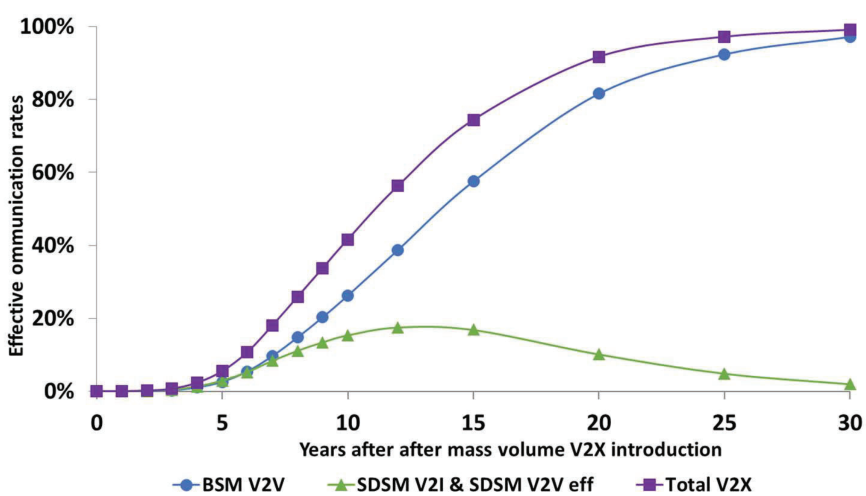

Figure 9: Effective vehicle-vs-vehicle communication: SDSM in addition to BSM.

5. V2X-ENHANCED ADAS ADRESSING VEHICLE-VS-VEHICLE CRASHES

The effectiveness of ADAS using on-board sensors, in addressing vehicle-vs-vehicle crashes, is limited in non-line-of-sight situations or where the intention of the other vehicle is unclear. State-of-the art ADAS, particularly by using emergency braking (AEBS), can prevent around 50% of vehicle-vs-vehicle crashes, [14], [15], [16]. This assumes 100% ADAS market penetration. It should be noted that although 100% ADAS market penetration was assumed for these calculations, it should be understood that not every vehicle on the road is equipped with ADAS today. Rather, as of 2021, more than half of all new vehicles sold in the US, Japan, and Europe were equipped with some type of ADAS, and by 2030, it has been forecast that about 50% of all cars on the road globally (as of 2020, there were more than 1 billion cars on the road) will be equipped with ADAS [17]. BSM and SDSM can help to address these crashes by raising awareness of other vehicles and their intention. The conventional ADAS and the discussed V2X communication paths need to be considered as complementary to calculate the total number of crashes addressed, [10], [18].

Figure 10: shows the method of calculating the total number of vehicle-vs-vehicle crashes addressed by ADAS and by the different V2X communication paths. The addressed shares of the different technologies are deducted subsequently from the total number of crashes, in the order: ADAS, BSM, SDSM inside intersections, SDSM outside intersections. This order is according to the expected maturity and deployment of the different systems. The remaining number of crashes cannot be addressed by the discussed technologies. The given example shows the numbers in year 15 after V2X mass introduction.

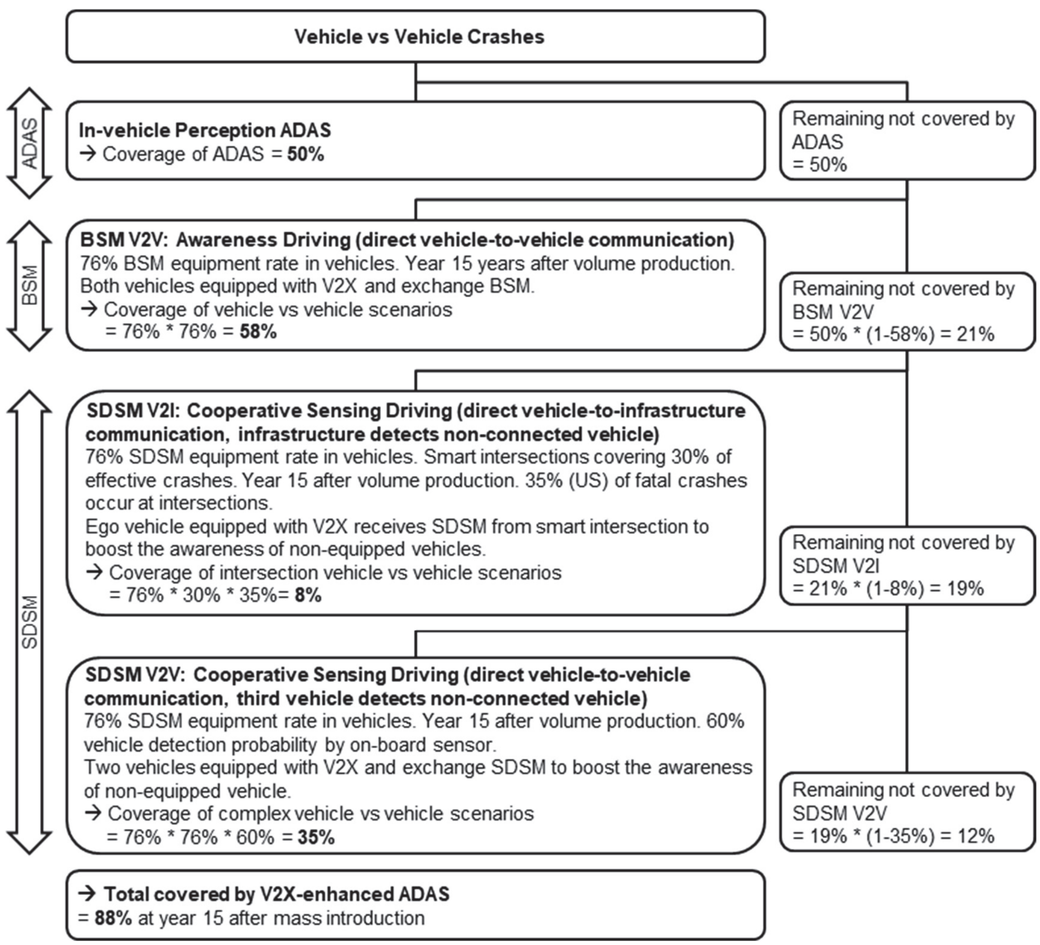

Figure 10: Complementary pairing of ADAS and V2X in addressing vehicle-vs-vehicle in year 15.

Figure 11 provides a different visualization of the overlapping fields-of-action addressed by the different technologies. Note that this assumes that the share of crashes addressed by ADAS is constant over time due to continuing use of line-of-sight sensors. In year 15 after V2X mass introduction a total of 88% of vehicle-vs-vehicle crashes are addressed by V2X-enhanced ADAS. At year 30 this number increases to 98%. As the share of BSM is growing over time, they cover almost the complete number of vehicle-vs-vehicle crashes at year 30. The relevance of SDSM in addressing vehicle-vs-vehicle crashes is mainly in early years to accelerate the safety benefits of V2X. Note that this describes the set of crashes addressed by the system and not how effectively such crashes can be prevented or mitigated.

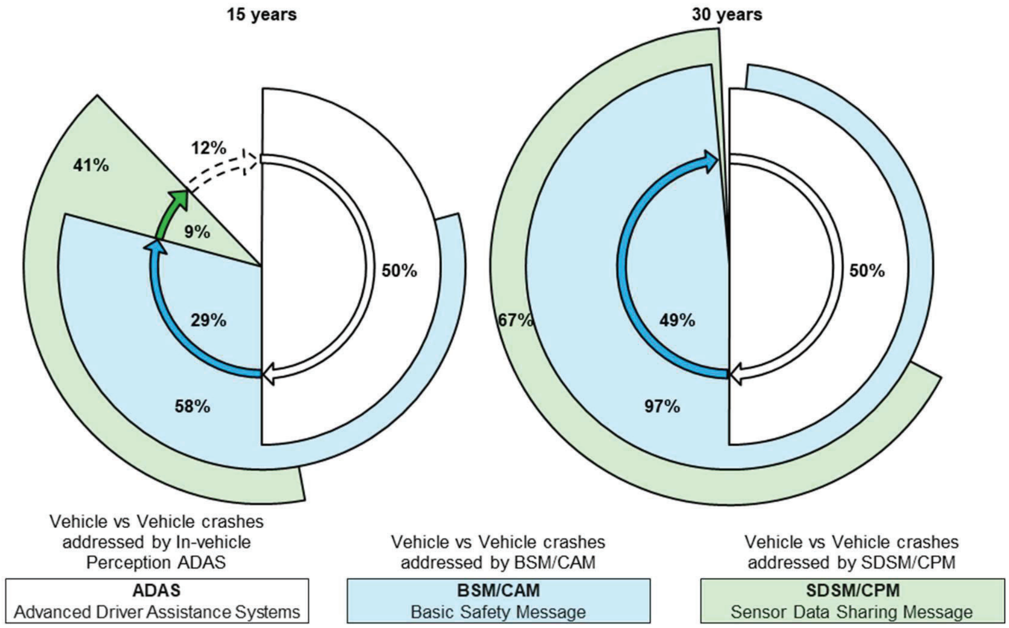

Figure 11: Fields-of-action of V2X-enhanced ADAS addressing vehicle vs vehicle crashes. At year 15 and year 30 of introduction.

The following benefits of adding Basic V2X and Collective Perception V2X to create V2X-enhanced ADAS, for addressing vehicle-vs-vehicle crashes, have been shown:

- Basic V2X, in addition to ADAS, can address relevant vehicle-vs-vehicle crashes by raising the awareness of other traffic participants in non-line-of-sight situations, and by providing information on the intention of traffic participants in critical situations.
- Collective Perception V2X, when combined with ADAS and Basic V2X, can accelerate the safety benefits of V2X technology by addressing an increased number of vehicle-vs-vehicle crashes, essentially by boosting the effective communication rate between vehicles over time.

The total numbers of vehicle-vs-vehicle fatalities addressed by the different technologies, in year 6, year 15 and year 30 in the different countries, are shown in Table 4. Additionally, it shows cumulative benefits up to the respective years.

Table 4: Vehicle-vs-vehicle fatalities addressed by V2X-enhanced ADAS.

		ADAS	**Basic V2X on top of ADAS (not already covered by ADAS)**		**Collective Perception V2X on top of ADAS and Basic V2X (not already covered by ADAS or Basic V2X)**	
		per year	**per year**	**cumulative**	**per year**	**cumulative**
JP	Year 6	190	10	20	10	15
	Year 15	190	100	330	30	160
	Year 30	190	180	850	5	200
DE	Year 6	370	20	35	20	35
	Year 15	370	200	660	60	330
	Year 30	370	350	1 600	10	400
US	Year 6	6 700	350	600	350	670
	Year 15	6 700	3 800	11 800	1 100	6 200
	Year 30	6 700	6 500	30 000	120	7 300

6. V2X TECHNOLOGY ADRESSING VEHICLE-VS-VRU CRASHES

In the foreseeable future, VRU are highly unlikely to communicate via BSM due to a combination of factors including voluntary app installation and usage rates, no means to mandate that a smart device be carried by every VRU at all times, positioning accuracy, power consumption, and other factors. Therefore, VRU can best be addressed by Collective Perception V2X using infrastructure- and vehicle-oriented communication. An exception are motorcycles that can readily be fitted with V2X technology. The majority of VRU could therefore only be detected indirectly using vehicle and infrastructure sensors with SDSM communication. The communication paths for detecting VRU are as follows:

- Basic V2X - using BSM V2V: Direct vehicle-vs-VRU communication. Applies for motorcycles only. Other VRU cannot directly participate in V2X communication.
- Collective Perception V2X - using SDSM V2I: VRU can be detected by roadside units in smart intersections using cameras or radar sensors. The roadside units could then broadcast the relevant information about the VRU via SDSM.
- Collective Perception V2X - using SDSM V2V: VRU can be detected by third-party vehicles, using the third-party vehicles' own on-board sensors, which could transmit this information using SDSM. The communication rate depends on the existence of a third-party vehicle and whether it detects the VRU.

Table 5 shows the different individual communication rates for VRU awareness detection. The formulas correspond to those in vehicle-vs-vehicle communication because the sensor-based mechanisms of SDSM in increasing the awareness of non-V2X-equipped vehicles and of VRU are identical. See also in [13].

Table 5: V2X communication rates relevant for vehicle-vs-VRU communication.

Individual communication rates		**Description**
BSM V2V	$C_{BSM\ V2V} = ER_{Veh} * ER_{Veh}$	For detecting motorcycles only. Note: VRU (except for motorcycles) cannot participate in SDSM communication.
SDSM V2I	$C_{SDSM\ V2I} = ER_{Veh} * ER_{Int} * G$	Vehicle and smart intersection communicating via SDSM and sharing information on VRU. Assume that intersection equipment rate ER_{Int} is increasing over time along with ER_{Veh}.to max 60%. Assume that intersections with highest traffic throughput will be equipped more quickly than other intersections: G = 3.5 in year 6 and 1 in year 15.
SDSM V2V	$C_{SDSM\ V2V} = ER_{Veh} * ER_{Veh} * 0.6$	Two vehicles communicating via SDSM and sharing information on VRU. Assume the likelihood of a second vehicle being present and detecting a non-equipped vehicle is 0.6.

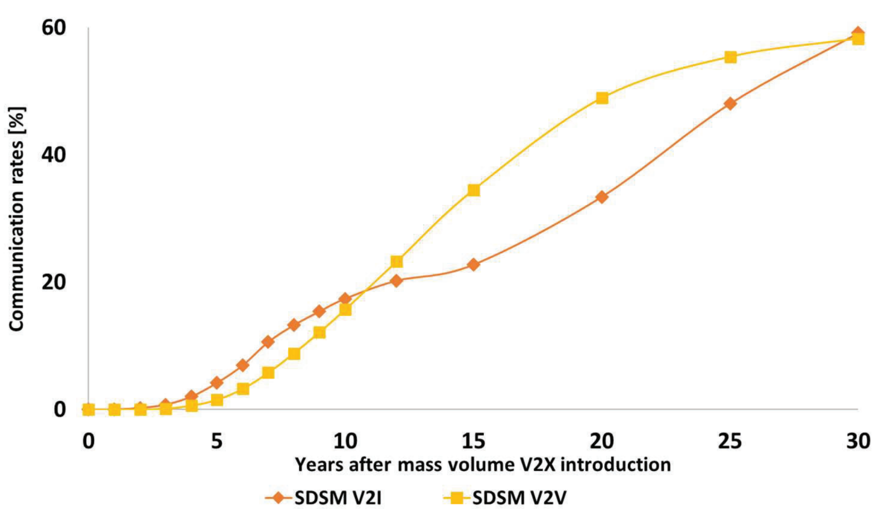

Figure 12: Communication rates for VRU awareness, using SDSM.

Figure 12 depicts the run-up curves for VRU awareness using SDSM communication as calculated according to Table 5, not including BSM communication that can address motorcycles. Both communication paths address the same target population of vehicle-vs-VRU crashes. The SDSM V2I communication rate grows more quickly in the early years due to the assumed higher installation rate of smart intersections. SDSM V2I has a larger effect than SDSM V2V up to year 10. Note that this only shows the share of addressed crashes, not the actual prevented crashes, as those depend on the effectiveness of the applied safety function.

The SDSM communication paths for detecting VRU are not mutually exclusive, because they address the same target population of vehicle-vs-VRU crashes. Therefore, the effective communication rates are calculated by deducting the area where another communication path has already been effective. The following order of calculating the effective communication rates is assumed, according to the expected introduction of SDSM: SDSM inside intersections, SDSM outside intersections. Table 6 describes the formulas to calculate the effective SDSM communication rates for vehicle-vs-VRU communication.

Table 6: Effective SDSM communication rates for vehicle-vs-VRU communication.

Effective communication rates		Description
Inside intersections	$C_{SDSM\ V2I\ eff} = C_{SDSM\ V2I}$	Vehicle and smart intersection communicating via SDSM and sharing information about VRU. Applies to share of intersection crashes.
	$C_{SDSM\ V2V\ eff} = C_{SDSM\ V2I} \cup C_{SDSM\ V2V} - C_{SDSM\ V2I}$	Two vehicles communicating via SDSM and sharing information about VRU. Additional effect on top of BSM communication and on top of SDSM smart intersection communication. Applies to share of intersection crashes.
Outside intersections	$C_{SDSM\ V2V\ eff} = C_{BSM\ V2V}$	Two vehicles communicating via SDSM and sharing information on VRU. Applies to share of non-intersection crashes.

The total effective V2X communication rate, not including BSM communication that can address motorcycles, is calculated by adding $C_{SDSM\ V2I\ eff}$ and $C_{SDSM\ V2V\ eff}$, for inside and outside intersections. The calculation assumes that 36% of vehicle-vs-VRU crashes occur inside intersections as analyzed for the US. The total V2X communication rate increases over time to cover 66% of VRU in year 30 after market introduction. SDSM V2I communication is effective inside intersections whereas SDSM V2V communication is effective inside and outside intersections. SDSM V2I between vehicles and smart intersection plays and important role in addressing vehicle-vs-VRU crashes and provides 6% effective communication rate at year 10 growing to 21% in year 30. Figure 13 shows the SDSM V2I and SDSM V2V communication rates and the total V2X communication rate for vehicle-vs-VRU communication.

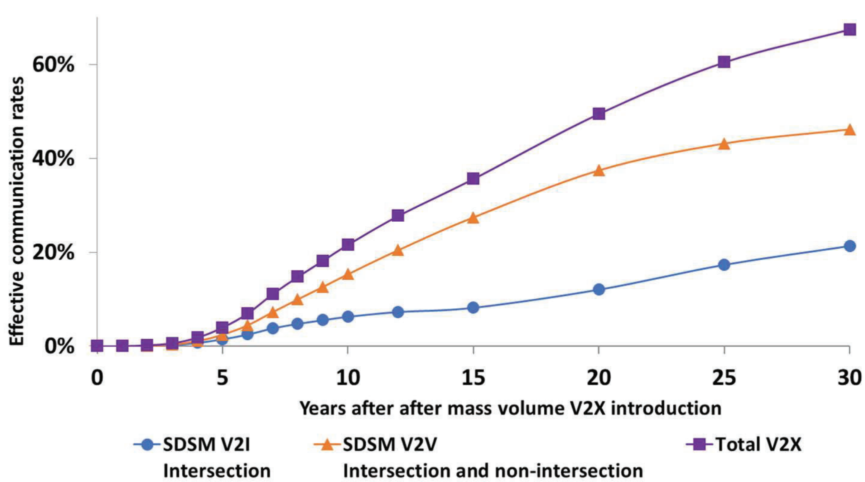

Figure 13: Effective vehicle-vs-VRU communication: SDSM V2V in addition to SDSM V2I.

7. V2X-ENHANCED ADAS ADRESSING VEHICLE-VS-VRU CRASHES

ADAS using on-board sensors often have limits in detecting VRU that are obstructed by vehicles or roadside structures and are therefore non-line-of-sight. ADAS including emergency braking (VRU-AEBS) functions can prevent around 55% of vehicle-vs-VRU crashes, [19], [20], [15]. Detailed accident scenarios with pedestrians and bicycles, in which conventional ADAS might not activate or might only mitigate, are also identified in [10], [18]. SDSM communication can, however, provide an additional input to the V2X-enhanced ADAS and help to raise awareness of VRU that are otherwise unprotected. Both ADAS using on-board sensors and V2X with SDSM communication complement one another to increase the total number of addressed vehicle-vs-VRU crashes.

In Figure 14, a method is described to derive the total number of addressed vehicle-vs-VRU crashes. Note that motorcycles are considered as VRU in this analysis, and thus are shown as participating in BSM communication. The benefit of BSM communication in addressing vehicle-vs-VRU crashes, however, only applies to the share of motorcycles within all VRU crashes. The following order is used to calculate the total number of addressed crashes: ADAS, BSM (for motorcycles only), SDSM inside intersections, SDSM outside intersections. All numbers are based on year 15 after V2X mass introduction.

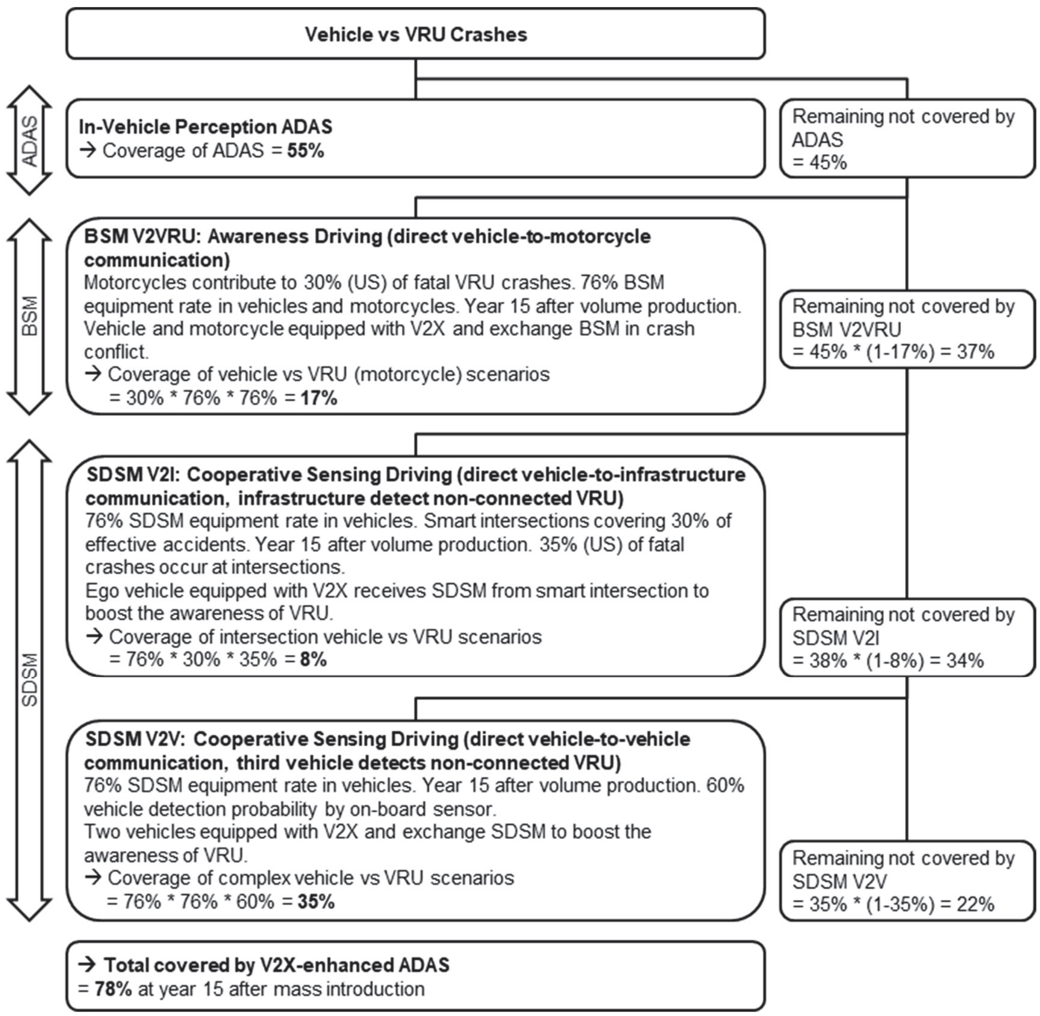

Figure 14: Complementary pairing of ADAS and V2X in addressing vehicle-vs-VRU crashes in year 15.

A visualization of the overlapping fields-of-action that are addressed by V2X-enhanced ADAS is shown in Figure 15. In year 15 after V2X mass introduction, 78% of vehicle-vs-VRU crashes are addressed, increasing to 89% in year 30. Direct communication via BSM plays a relatively small role in addressing vehicle-vs-VRU crashes, as V2X technology can only be added to motorcycles and not easily to pedestrians or bicycles. It should be emphasized that SDSM communication can play a crucial role in addressing vehicle-vs-VRU crashes. Roadside units in smart intersections can detect VRU and broadcast SDSM to raise awareness of VRU in critical situations in which the VRU might be obstructed. Outside of intersections, SDSM can be sent by vehicles that detect VRU using their on-board sensors to inform other vehicles. SDSM can help close the gap in VRU protection in difficult non-line-of-sight situations that cannot be addressed by conventional ADAS. Note that the areas shown describe the share of vehicle-vs-VRU crashes that can be addressed by V2X-enhanced ADAS, without determining whether such crashes are prevented or mitigated which would be a factor of the action taken upon receipt of the information.

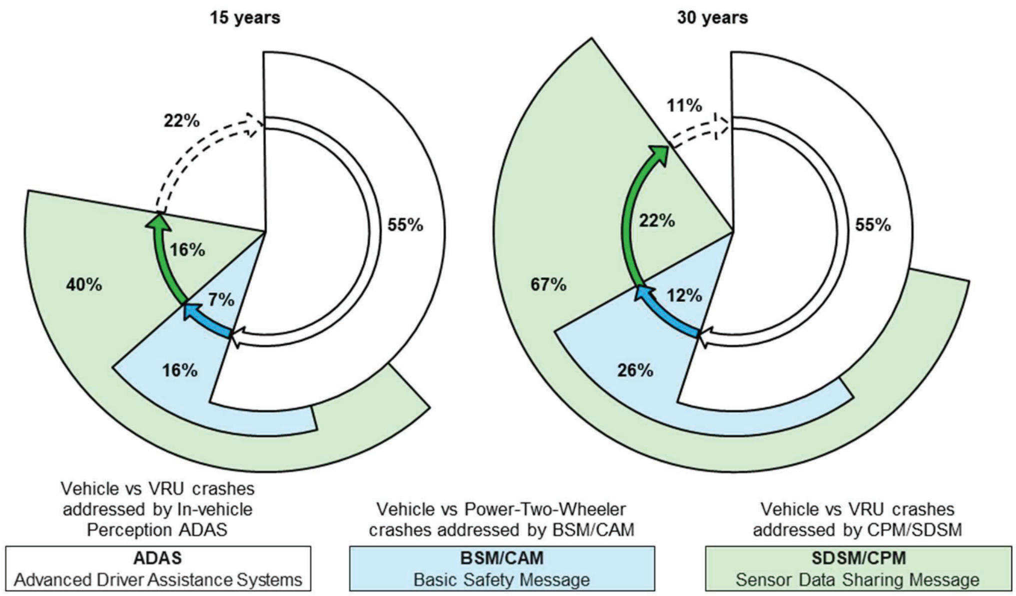

Figure 15: Fields-of-action of V2X-enhanced ADAS addressing vehicle vs VRU crashes. At year 15 and year 30 after introduction.

The following benefits of adding Basic V2X and Collective Perception V2X to create V2X-enhanced ADAS, for addressing vehicle-vs-VRU crashes, have been shown:

- Basic V2X, in addition to ADAS, can address vehicle-vs-motorcycle crashes by improving awareness in critical situations where the motorcycle is in non-line-of-sight.
- Collective Perception V2X, in addition to ADAS, can protect VRU in non-line-of-sight situations by improving awareness of NLOS VRU in critical situations.

Table 7 shows the number of vehicle-vs-VRU fatalities addressed by the different technologies, in year 6, year 15 and year 30 in the different countries and the cumulative benefits up to the respective years.

Table 7: Vehicle-vs-VRU fatalities addressed V2X-enhanced ADAS.

		ADAS	Basic V2X on top of ADAS (not already covered by ADAS) (Motorcycles only)		Collective Perception V2X on top of ADAS (not already covered by ADAS) (all VRU)	
		per year	per year	cumulative	per year	cumulative
JP	Year 6	770	5	10	40	70
	Year 15	770	50	180	230	870
	Year 30	770	100	450	360	1 900
DE	Year 6	470	5	10	20	40
	Year 15	470	65	200	120	500
	Year 30	470	110	500	180	1 000
US	Year 6	5 100	60	110	230	440
	Year 15	5 100	700	2 200	1 400	5 300
	Year 30	5 100	1 200	5 600	2 000	11 000

8. CONCLUSION

The effective V2X communication rates for vehicles and VRU were modelled, when utilizing different V2X technologies, Figure 9 and Figure 13:

- Basic V2X - using BSM/CAM: Status sharing by direct short-range communication between vehicles.
- Collective Perception V2X - using SDSM/CPM: Sensor data sharing by short-range communication to detect vehicles without V2X technology and to detect VRU.

The benefit of Basic V2X and Collective Perception V2X in conjunction with ADAS, was shown. Three fields-of-action to address vehicle-vs-vehicle and vehicle-vs-VRU crashes were identified, Figure 11 and Figure 15:

- Basic V2X raises the awareness of other equipped vehicles,
- Collective Perception V2X boosts the effective vehicle equipment rate,
- Collective Perception V2X protects VRU that are otherwise unprotected.

The total crash reduction potential of V2X-enhanced ADAS, as a combination of Basic V2X, Collective Perception V2X and ADAS, was quantified, Figure 11 and Figure 15:

- Vehicle-vs-vehicle crashes addressed: 88% in year 15 and 98% in year 30 after V2X introduction.
- Vehicle-vs-VRU crashes addressed: 78% in year 15 and 89% in year 30 after V2X introduction.

The crash reduction potential of Collective Perception V2X in addition to Basic V2X was identified. Over the first six years after V2X introduction the cumulative additional field-of-action was quantified, Table 8:

- Collective Perception V2X doubles the vehicle-vs-vehicle crashes addressed by V2X technology
  US example: 600 fatalities by Basic V2X + 670 fatalities by Collective Perception V2X,
- Collective Perception V2X quintuples the vehicle-vs-VRU crashes addressed by V2X technology
  US example: 110 fatalities by Basic V2X + 440 fatalities by Collective Perception V2X.

The advantage of smart intersections for Collective Perception V2X to address vehicle-vs-VRU crashes was shown, Figure 13:

- Collective Perception V2I (vehicle-to-infrastructure) covers 6% of VRU in year 10 after V2X introduction,
- Collective Perception V2I (vehicle-to-infrastructure) covers 21% of VRU in year 30 after V2X introduction.

Since V2X enhanced-ADAS, namely Basic V2X, Collective Perception V2X in conjunction with ADAS, are shown to be highly beneficial for road safety of all traffic participants, it is important to ensure sufficient and protected frequency spectrum in the 5.9 GHz band for direct short-range V2X communication.

Table 8 shows the number of crash fatalities, cumulatively addressed by Basic V2X and Collective Perception V2X in the different countries, for year 6, year 15 and year 30 after start of V2X mass deployment.

Table 8: Crash fatalities addressed by V2X in addition to ADAS.

		Vehicle-vs-vehicle		Vehicle-vs-VRU		Total crashes addressed by V2X
		Basic V2X on top of ADAS	Collective Perception V2X on top of ADAS and Basic V2X	Basic V2X on top of ADAS (Motorcycle only)	Collective Perception V2X on top of ADAS (all VRU)	
		cumulative until respective year				
JP	Year 6	20	15	10	70	115
	Year 15	330	160	180	870	1 540
	Year 30	850	200	450	1 900	3 400
DE	Year 6	35	35	10	40	120
	Year 15	660	330	200	500	1 690
	Year 30	1 600	400	500	1 000	3 500
US	Year 6	600	670	110	440	1 820
	Year 15	11 800	6 200	2 200	5300	25 500
	Year 30	30 000	7 300	5 600	11 000	53 900

This paper quantifies crash fatalities addressed by V2X-enhanced ADAS. However, the number of injured persons in road crashes is much higher: 100 times in Japan, 120 times in Germany and 60 times in the US.

Note that the actual number of prevented or mitigated crashes depends on how effectively safety systems will react on the V2X information by driver warning or automatic intervention.

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AUTOMATIC EMERGENCY BRAKING – HOW CAN WE SET THE BAR TO MAXIMIZE SAFETY?

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Paper Number: 23-0103

ABSTRACT

It is estimated that Automatic Emergency Braking (AEB) systems could potentially help mitigate 80% of rear end and pedestrian/cyclist crashes assuming they can stop the vehicle under all circumstances. In practice, however, technical limitations of systems (sensors, control unit, and actuators), vehicle dynamics, and environmental conditions (e.g., lighting, road conditions) reduce the overall crash avoidance performance of AEB systems.

In an effort to better understand these limitations, Transport Canada initiated a study aiming at establishing the general AEB performance of the Canadian vehicle fleet. Three collision scenarios from recognized test protocols were considered: 1) stopped lead vehicle, 2) slower moving lead vehicle, and 3) crossing pedestrian. A total of 43 light duty vehicles (passenger cars, SUVs, and pickup trucks) from 26 different manufacturers were tested for car-to-car scenarios, and 30 vehicles were tested for car-to-pedestrian scenarios. Vehicles' model years ranged from 2013 to 2022. The large sample size of this study covers a significant proportion of the most popular vehicles sold in Canada. To ensure test repeatability, vehicles were equipped with precision positioning systems, audio alert detectors and driving robots. The optimal AEB operating speed range needed to address most real-world collisions was determined from recent crash data. Overall, the performance of vehicles tested was found to improve over the years when compared to the thresholds defined in the U.S. DOT/NHTSA Commitments, but a large proportion struggled to meet the requirements defined in UN regulation No. 152. Interestingly, the results obtained with the best performing systems suggest that it is now possible to achieve even better speed reduction outcomes than the criteria defined in the selected references

The results of this study demonstrate that, with the continuous improvements of AEB systems, it is now possible to exceed performance levels defined in existing requirements. Technological advancements and added capabilities, including pedestrian detection, continue to increase the crash avoidance potential of these systems and, thus, enhance road safety. The methods and criteria evaluated in this study can help to inform future international policy and regulatory requirements.

INTRODUCTION

Automatic Emergency Braking (AEB) systems are designed to detect potential collisions with obstacles and automatically apply vehicle brakes to avoid or mitigate impacts [1]. A recent study estimated that front-to-rear crashes were reduced by about 50% if the striking vehicles were equipped with AEB compared to those not equipped with the technology [2]. In Canada, this would have corresponded to a reduction of at least 19,600 injuries and 70 fatalities in 2019 alone [3]. Canada has embraced the systems-based approach of Vision Zero [4] with the aim of reducing road fatalities and serious injuries to zero. AEB can be a part of the solution to achieve this goal and the research presented here will help support the development of best practices and the setting of the highest standards, for the cars of tomorrow.

To assess the potential safety benefits of AEB and to better understand technology limitations, Transport Canada and PMG Technologies have been performing Car-to-Car (C2C) and Car-to-Pedestrian (C2P) evaluations on various types of vehicles available to Canadians [5]. Since 2014, over 11,500 AEB tests have been conducted using performance-based evaluation protocols to assess systems' capabilities in preventing or mitigating collisions.

This study used the data collected over time to establish the overall AEB performance of the Canadian vehicle fleet and the results were compared to the reference criteria defined in the U.S. DOT/NHTSA Commitments [6] and UN regulation No. 152 [7]–[9]. The requirements defined in these documents encourage manufacturers to offer AEB on vehicles with a minimum safety performance. Canada has no AEB regulations or consumer assessment program at this point, so the present study benchmarked AEB performance against test procedures available in similar markets (United States and European Union).

The U.S. DOT/NHTSA Commitments (further referenced as "US AEB") is a voluntary agreement between the U.S. government and industry, where the latter committed to include AEB as standard equipment on 95% of their light-duty vehicles and trucks by 2022 (GVWR≤8,500 lbs) and 2025 (8,500 lbs<GVWR<10,500 lbs), depending on Gross Vehicle Weight Rating (GVWR). The US AEB defines a minimum performance criteria for these systems when tested to the protocol developed by the Insurance Institute for Highway Safety in 2013 [10]. UN Regulation No.152 "Uniform Provisions Concerning the Approval of Motor Vehicles with Regard to the Advanced Emergency Braking System (AEBS) for M1 and N1 Vehicles" (further referenced as "UN R152") specifies test methods and performance requirements for AEB car-to-car and car-to-pedestrian evaluations under the type-approval regulatory regime. Comparison of test results with these well-defined criteria provides information on the overall performance of the Canadian vehicle fleet and a benchmarking of the current state of AEB technology.

It is also essential to consider statistics on the type of crashes that this technology is designed to prevent. Recent data from the Canadian National Collision Database, where a collision speed was reported, suggest that 90% of rear-end fatal collisions occur below 120 km/h, and 90% of fatal pedestrian collisions occur below 100 km/h (Figure 1 and Figure 2). A speed was reported for 10 of the fatalities and 3,189 of the injuries that occurred in rear-end collisions (out of a total of 72 and 22,156 respectively). For casualties in single vehicle collisions involving pedestrians, 86 out of the 214 pedestrian fatalities and 1,883 of the 5,572 pedestrian injuries had a reported speed associated with the corresponding collision. While it is not possible to collect impact speed for all collisions, the trends observed in these figures are assumed to represent the overall speed distributions for the respective crash configurations.

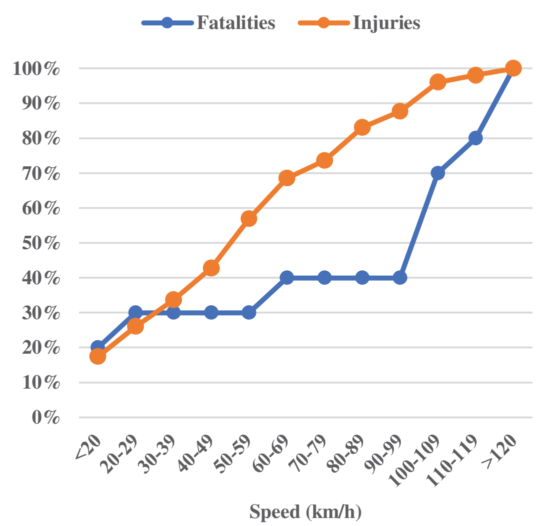


Figure 1. Cumulative Distribution of Casualties in Rear End Collisions (2020)

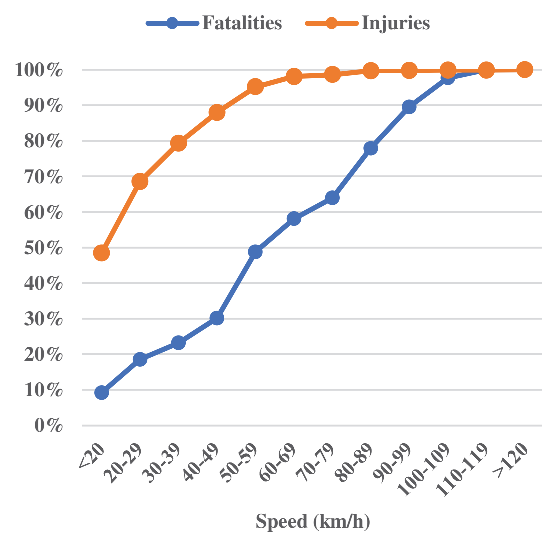


Figure 2. Cumulative Distribution of Pedestrian Casualties in Single Vehicle Collisions (2020)

In summary, the aims of this research were to:

1. assess the potential safety benefits of AEB and better understand technology limitations;
2. compare the performance of AEB car-to-car and car-to-pedestrian systems over the years and across vehicles; and
3. identify potential gaps between AEB performance during controlled testing and real-world collisions.

METHODOLOGY

AEB Test Protocols and Performance Criteria

This study uses data from tests performed on 54 light duty vehicles (passenger cars, sport utility vehicles, and pickup trucks) from 26 different manufacturers with model years varying from 2013 to 2022. The large sample size covers a significant proportion of the most popular vehicles sold in Canada. The vehicles were evaluated using a subset of scenarios from the following test protocols:

- NHTSA CIB: National Highway Traffic Safety Administration's Crash Imminent Brake System Performance Evaluation for the New Car Assessment Program [11]
- IIHS AEB: Insurance Institute for Highway Safety's Autonomous Emergency Braking Test Protocol [10]
- UN R152: UN Regulation No 152 - Advanced Emergency Braking System for M1 and N1 vehicles [7]–[9]
- Euro NCAP VRU: Euro NCAP AEB VRU Systems Test Protocol valid at the time of testing [12]

The aim of a typical test series was to determine the maximum avoidance speed of a given vehicle by increasing the test speed successively until an impact occurred. An alternative method used for certain test series consisted of performing evaluations at discrete speeds as specified in the relevant test protocols (e.g., UN R152 and C2C B1). The maximum avoidance speed was determined to be the highest speed up to 50 km/h for which a minimum of five avoidances occurred over seven tests, or the equivalent ratio if a different number of tests were performed. For certain scenarios (UN R152), the maximum avoidance speed was found to be the speed at which two tests out of three avoided an impact, or the equivalent ratio. For certain vehicles that performed well at 50 km/h, the speed was increased to further challenge the system under test.

To ensure test repeatability and data accuracy, vehicles were equipped with centimeter-level positioning systems, audio alert detectors and, in most cases, driving robots [5]. Data were verified after each test run to confirm that the tolerances of the test protocols were respected. Figure 3 presents the standardized targets that were used to perform the different test scenarios.

Euro NCAP Vehicle Target (EVT) | Strikeable Surrogate Vehicle (SSV) | Global Vehicle Target (GVT) | Euro NCAP Pedestrian Targets – adult & 7-year-old child (EPTa & EPTc)

Figure 3. Test Targets

The data were analyzed to assess how system performances evolved over the years. Three common test scenarios were considered: 1) stopped lead vehicle [C2C A1], 2) slower moving lead vehicle [C2C B1] and 3) crossing pedestrian [C2P], as described in Table 1 and
Table 2.

Table 1. AEB Car-to-Car Test Protocols and Scenarios

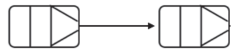
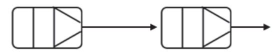
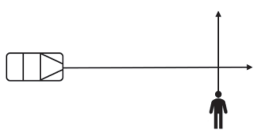
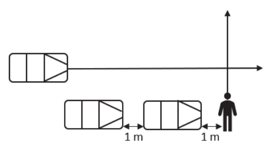
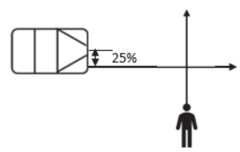
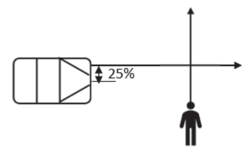
Test Protocol	**NHTSA CIB / IIHS AEB (A1 only) / R152**	
Scenario	A1	B1
	Stopped Lead Vehicle 	Slower Moving Lead Vehicle 
Impact Point	50%	50%
Target	EVT, SSV and/or GVT	EVT, SSV and/or GVT

Table 2. AEB Car-to-Pedestrian Test Protocols and Scenarios

Test Protocol	**R152**	**Euro NCAP VRU**		
Scenario	Par.6.6	CPNC-50	CPNA-25	CPNA-75
	Child pedestrian crossing from nearside	Child pedestrian crossing from nearside with obstruction	Adult pedestrian crossing from nearside	Adult pedestrian crossing from nearside
				
Impact Point	50%	50%	25%	75%
Target	EPTc	EPTc	EPTa	EPTa

To evaluate the performance of the systems against a common reference, the results for each scenario were compared to the requirements defined in the US AEB and UN R152. Table 3 specifies which criteria was used for the different scenarios and the corresponding pass/fail requirements. Some scenarios were evaluated using both criteria to compare requirements. When necessary, the criteria were adapted for speeds outside of the original requirements, as noted in the table below, and for a reduced number of test runs (i.e., some criteria require five repeated tests at a same speed while for the purposes of this analysis, a smaller number of tests may have been used).

Table 3. AEB Summary of Requirements

<table>
<tr><th>Test Scenario</th><th>Performance Criteria</th><th>Requirement</th></tr>
<tr><td rowspan="2">C2C (A1)</td><td>US AEB*</td><td>Option A: “Average speed reduction across 5 repeated tests that is greater than 10 miles per hour (mph) in either the 12 or 24 mph tests involving a stationary lead vehicle
OR
Option B: Average speed reduction across 5 repeated tests that is greater than 5 mph in both the 12 and 24 mph tests involving a stationary lead vehicle.”</td></tr>
<tr><td>UN R152</td><td>Maximum relative impact speed (km/h)
<table>
<tr><th>Relative speed (km/h)</th><th>Maximum mass</th><th>Mass in running order</th></tr>
<tr><td>10</td><td>0</td><td>0</td></tr>
<tr><td>15</td><td>0</td><td>0</td></tr>
<tr><td>20</td><td>0</td><td>0</td></tr>
<tr><td>25</td><td>0</td><td>0</td></tr>
<tr><td>30</td><td>0</td><td>0</td></tr>
<tr><td>35</td><td>0</td><td>0</td></tr>
</table></td></tr>
</table>

<table>
<tr><th>Test Scenario</th><th>Performance Criteria</th><th>Requirement</th></tr>
<tr><td></td><td></td><td>
<table>
<tr><td>40</td><td>0</td><td>0</td></tr>
<tr><td>42</td><td>10</td><td>0</td></tr>
<tr><td>45</td><td>15</td><td>15</td></tr>
<tr><td>50</td><td>25</td><td>25</td></tr>
<tr><td>55</td><td>30</td><td>30</td></tr>
<tr><td>60</td><td>35</td><td>35</td></tr>
</table>
For relative speeds between the listed values (e.g. 53 km/h), the maximum relative impact speed (i.e. 35/30 km/h) assigned to the next higher relative speed (i.e. 55 km/h) shall apply.
</td></tr>
<tr><td>C2C (B1)</td><td>UN R152</td><td>Maximum relative impact speed: 0 km/h</td></tr>
<tr><td>C2P (all)</td><td>UN R152</td><td>
Maximum relative impact speed (km/h)
<table>
<tr><td>Relative speed (km/h)</td><td>Maximum mass</td><td>Mass in running order</td></tr>
<tr><td>10</td><td>0</td><td>0</td></tr>
<tr><td>15</td><td>0</td><td>0</td></tr>
<tr><td>20</td><td>0</td><td>0</td></tr>
<tr><td>25</td><td>0</td><td>0</td></tr>
<tr><td>30</td><td>0</td><td>0</td></tr>
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<tr><td>40</td><td>0</td><td>0</td></tr>
<tr><td>42</td><td>10</td><td>0</td></tr>
<tr><td>45</td><td>15</td><td>15</td></tr>
<tr><td>50</td><td>25</td><td>25</td></tr>
<tr><td>55</td><td>30</td><td>30</td></tr>
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</table>
For relative speeds between the listed values (e.g. 53 km/h), the maximum relative impact speed (i.e. 35/30 km/h) assigned to the next higher relative speed (i.e. 55 km/h) shall apply.
</td></tr>
</table>

*The same speed reduction requirement was used as a performance criterion for all tested speeds (i.e., speeds below or above 12 and 24 mph)

Experimental Data Selection and Analysis

Although specific test protocols are referenced for each performance criteria (i.e., the US AEB references the IIHS AEB test protocol while UN R152 references the R152 test protocol), similar tests performed with a different protocol were selected to increase the sample size. The following assumptions were made during data selection:

- AEB performance is independent from the vehicle target. All test results were grouped together under the same scenario regardless of the vehicle target used (EVT, SSV, or GVT). Evidence from testing has shown that the differences between the vehicles' system responses to different targets are negligible. A comparative study by NHTSA showed that there is negligible effect on the vehicle's response time between the SSV and GVT targets [13]. A similar study conducted earlier between the EVT and SSV targets also concluded that these targets have negligible effect on the response of the vehicles tested [14].
- Scenarios performed as per the Euro NCAP AEB VRU protocol were included in the study to complement the small sample size of UN R152 C2P tests. The same performance criteria were used for all configurations, even if there were several differences between the scenarios (no obstruction vs. obstruction, child vs. adult pedestrian target, 50% impact point vs. 25% and 75%).
- The UN R152 test protocol requires tests to be performed with the vehicle at different masses (mass in running order and maximum mass). Only results from tests performed with the mass in running order were retained for the analysis since it corresponds to the configuration used in the other test protocols evaluated.

Table 4 contains the total number of tests performed per scenario type and model year.

Table 4. Number of Tests per Vehicle

Model Year	Make	Model	Number of tests

			C2C	C2P
2013	Subaru	Legacy	139	
	Volvo	S60	111	
2014	Chevrolet	Impala	58	
	Infiniti	Q50	142	
	Jeep	Grand Cherokee	51	
	Mazda	6	75	
	Mitsubishi	Outlander	25	
	Subaru	Outback	95	
	Toyota	Prius	54	
2015	Audi	A3	60	
	BMW	i3	174	
	Chrysler	200C	81	
	Honda	CRV	71	
	Hyundai	Genesis	127	
	Mercedes-Benz	C400	52	28
	Subaru	Impreza	39	26
2016	Lincoln	MKX	76	30
2017	Ford	Fusion	57	30
	GMC	Acadia	44	33
	Honda	Civic	59	
	Hyundai	Elantra	99	28
	Kia	Sportage	64	27
	Land Rover	Discovery	82	
	Mazda	CX-5	56	
	Mercedes-Benz	E300	55	41
	Nissan	Rogue	32	32
	Tesla	Model S	143	
	Toyota	Corolla	41	29
	Volkswagen	Golf	75	
	Volvo	XC 90	40	32
2018	Cadillac	CT6	56	
	Subaru	Crosstrek	66	26
	Toyota	Prius		23
2019	Audi	e-tron	22	9
	Hyundai	Santa Fe	65	42
	Nissan	Leaf		43
	Tesla	Model 3		26
2020	BMW	330i	118	90
	Buick	Enclave		26
	Ford	Explorer		33
	Honda	Accord		29
	Mazda	3	127	71
	Mercedes-Benz	A220	87	54
2021	Alfa Romeo	Stelvio	14	
	Chevrolet	Silverado		45
	Genesis	GV80		52
	Subaru	Ascent		51
	Toyota	Camry	20	16
	Volkswagen	Jetta	19	
	Volvo	XC 60		49
2022	Jeep	Grand Cherokee	20	10
	Mitsubishi	Outlander	9	

Model Year	Make	Model	Number of tests	
			C2C	C2P
	Volkswagen	Taos	8	40

For each vehicle, test runs were grouped by scenario and by the relative speed between the vehicle and the target (0 km/h was used in the case of A1 and C2P scenarios). The average relative impact speed was calculated and evaluated per the relevant performance criteria to determine if any result fell outside the requirements. This process was repeated for each scenario and performance criterion. The maximum avoidance speed reached for each scenario was also determined for all vehicles. It should be noted however that many of the tested vehicles may not have been designed to meet the specific test requirements.

RESULTS

Table 5 presents the results for all vehicles by performance criteria and scenario tested. For a cell highlighted in red, the number indicates the minimum speed at which the result was lower than the evaluated criterion. The green cells indicate that all tests performed by the vehicle met the performance criterion and the maximum speed reached is noted. The table also presents the percentage of vehicles for which all runs met the performance criterion versus the percentage of vehicles for which at least one run did not meet the criterion.

For C2C static target tests (A1), most vehicles met the US AEB criterion, with a larger percentage of vehicles meeting Option A (93%) than Option B (88%). On the other hand, almost two-thirds of the vehicles evaluated had at least one test that fell outside of the UN R152 criterion. In the case of the dynamic target tests (B1), about half of the vehicles met the UN R152 criterion.

When comparing both scenarios performed with the child pedestrian, a larger percentage of vehicles did not meet the UN R152 performance criterion in the occluded scenario (96% for CPNC-50 compared to 43% for Par. 6.6 of UN R152). The 75% impact point scenario with the adult pedestrian (CPNA-75) resulted in a larger percentage of vehicles meeting the requirement (56%) than the scenario with a 25% impact point (37%).

Table 5. Test Vehicle Performance

Model Year	Make	Model	Car-to-Car				Car-to-Pedestrian			
			US AEB		UN R152		UN R152			
			Option A	Option B	A1	B1	Par. 6.6	CPNC-50	CPNA-25	CPNA-75
2013	Subaru	Legacy	55	55	55	40				
2013	Volvo	S60	40	40	34	30				
2014	Mazda	6	20	30	20	10				
2014	Mitsubishi	Outlander	20	35	20					
2014	Toyota	Prius Plug-In	20	40	20	24				
2014	Subaru	Outback	70	70	70	40				
2014	Jeep	Grand Cherokee	15	15	15	24				
2014	Chevrolet	Impala	40	40	30	40				
2014	Infiniti	Q50	50	50	15	24				
2015	Mercedes-Benz	C400	50	50	40	24		15	15	50
2015	BMW	i3	10	40	10	24				
2015	Honda	CRV	50	50	30	40				
2015	Audi	A3	30	30	10	24				
2015	Hyundai	Genesis	55	55	20	40				
2015	Subaru	Impreza	50	50	50	40		25	20	50
2015	Chrysler	200 C	40	40	25	40				
2016	Lincoln	MKX	50	50	35	40		15	15	15
2017	Tesla	Model S	60	60	60	24				
2017	Volvo	XC 90	50	50	50	40		40	50	50
2017	Hyundai	Elantra	50	50	20	24		15	15	15

Model Year	Make	Model	Car-to-Car				Car-to-Pedestrian			
			US AEB		UN R152		UN R152			
			Option A	Option B	A1	B1	Par. 6.6	CPNC-50	CPNA-25	CPNA-75
2017	Mercedes-Benz	E300	50	50	50	40		40	60	60
2017	Ford	Fusion	50	50	15	40		10	10	20
2017	GMC	Acadia	25	30	25	24		25	20	35
2017	Toyota	Corolla	50	50	50	40		10	10	30
2017	Nissan	Rogue	40	40	35	24		20	10	25
2017	Kia	Sportage	50	50	35	40		30	30	40
2017	Volkswagen	Golf	45	50	35	24				
2017	Land Rover	Discovery	50	50	30	24				
2017	Honda	Civic	55	55	20	40				
2017	Mazda	CX-5	50	50	50	40				
2018	Toyota	Prius						20	20	50
2018	Subaru	Crosstrek	50	50	50	40		20	50	50
2018	Cadillac	CT6	55	55	55	40				
2019	Hyundai	Santa Fe	60	60	60	40		30	40	50
2019	Nissan	Leaf						40	60	60
2019	Tesla	Model 3							50	60
2019	Audi	e-tron	70	70	70	40	60			
2020	Ford	Explorer						30	45	50
2020	Honda	Accord							30	25
2020	Buick	Enclave						20	10	45
2020	Mercedes-Benz	A220	42	42	20	40				
2020	BMW	330i	42	42	20	40	20	30	60	60
2020	Mazda	3	60	60	60	40	60	35	30	60
2020	Mercedes-Benz	A220						35	60	60
2021	Volvo	XC 60						40	50	60
2021	Genesis	GV80					55	40	50	60
2021	Subaru	Ascent						35	60	60
2021	Volkswagen	Jetta	50	50	50	40				
2021	Alfa Romeo	Stelvio	50	50	50	40				
2021	Chevrolet	Silverado						45	20	45
2021	Toyota	Camry	70	60	60	40	45			
2022	Volkswagen	Taos	30	30	25	40	40	20	30	40
2022	Mitsubishi	Outlander	40	40	35					
2022	Jeep	Grand Cherokee	60	60	60	40	45			
		% Pass	93%	88%	37%	51%	57%	4%	37%	56%
		% Fail	7%	12%	64%	49%	43%	96%	63%	44%

Next, the maximum avoidance speed reached by each vehicle grouped and averaged by model year and manufacturer was plotted. In order to compare vehicles, the maximum speeds were evaluated up to 50 km/h (indicated by the red line in the graphs below), except for the B1 scenario where the relative speed never exceeded 40 km/h. For the few vehicles evaluated at speeds above 50 k/h, the maximum avoidance speed is indicated on the graph.

The speed reduction in all tests was also calculated for each vehicle and was normalized to the vehicle's test speed. The results were also grouped by model year and by manufacturer. In the case of the C2C B1 scenario (Figure ***4***b and Figure ***6***b), the speed reduction was capped at the maximum relative speed between the vehicle and target to get a maximum of 1 as a normalized speed reduction. However, certain vehicles braked to speeds lower than the target speed, with some coming to a full stop.

In the following graphs, each bar corresponds to the average value with the minimum and maximum represented by the error bars. The sample size is presented at the bottom of each bar.

The C2C results by model year, as presented in Figure 4, show an evolution in the performance of the vehicles. Apart from 2013, the vehicles progressively reached higher maximum avoidance speeds up to 2019 in the A1 scenario (Figure ***4***a). Similarly, the vehicles' normalized speed reduction saw a spike from 2014 to 2016, after which the performance remained above 80% for all subsequent years (Figure ***4***c). The maximum avoidance speeds reached in the B1 scenario also increased over the years up to 2018 (Figure ***4***b). After 2018, all the vehicles performed full avoidances at all tested speeds, which went up to relative speeds of 40 km/h. The normalized speed reduction also showed that the vehicles were able to reduce the full speed in all tests as of 2018 (Figure ***4***d).

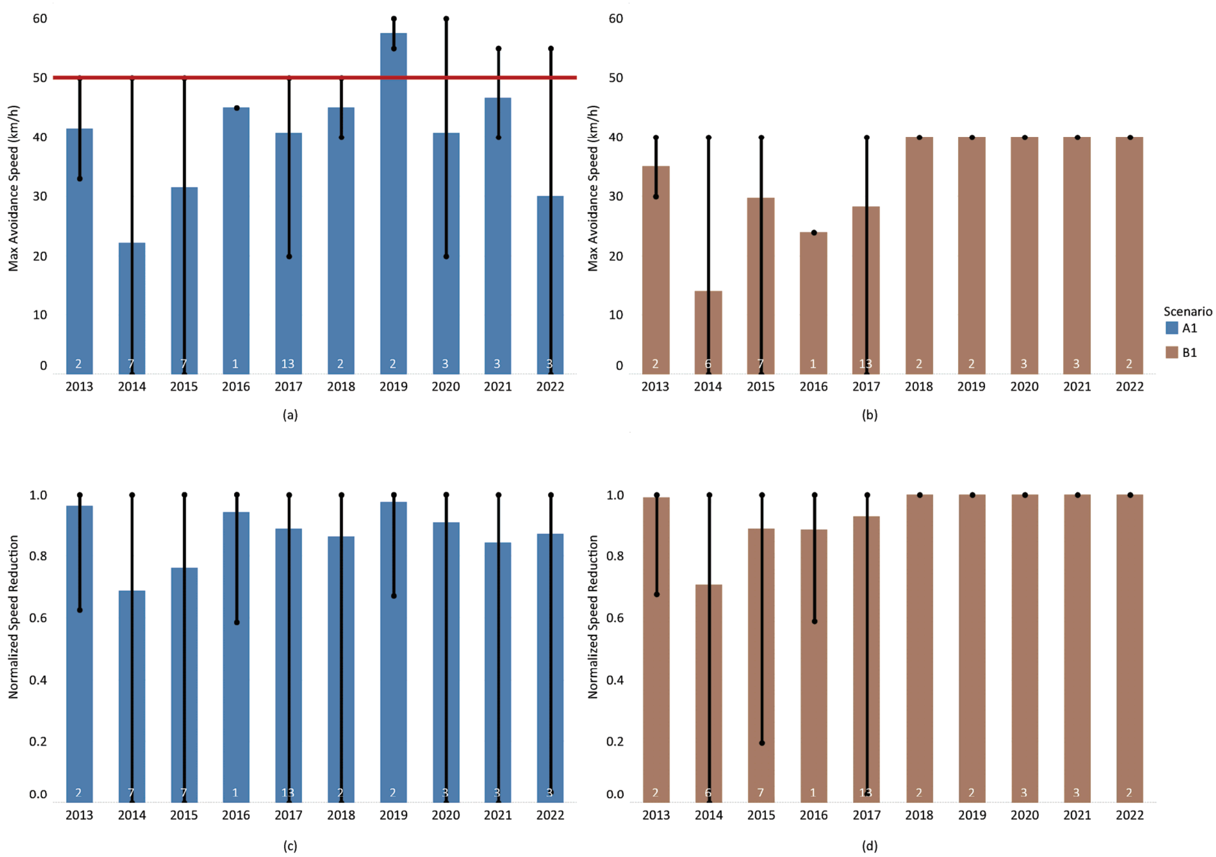

Figure 4. Normalized Speed Reduction and Maximum Avoidance Speed per Model Year for C2C Scenarios

As was the case for the C2C scenarios, the C2P adult and child pedestrian scenarios also saw a rise in maximum avoidance speeds up to 2019 (Figure ***5***a and Figure ***5***b respectively). After which, the results varied by type of scenario. The R152 Par. 6.6 scenario had a large decrease in performance from 2019 to 2020, but then increased again in 2021, while the CPNC remained within 10 km/h from 2020 to 2022. In terms of normalized speed reduction, there was an increase to over 95% for the adult and over 85% for the child in 2019 (Figure ***5***c and Figure ***5***d respectively). After which, the normalized speed reduction remained high (between 85% to 90% for the adult and 75% to 90% for the child).

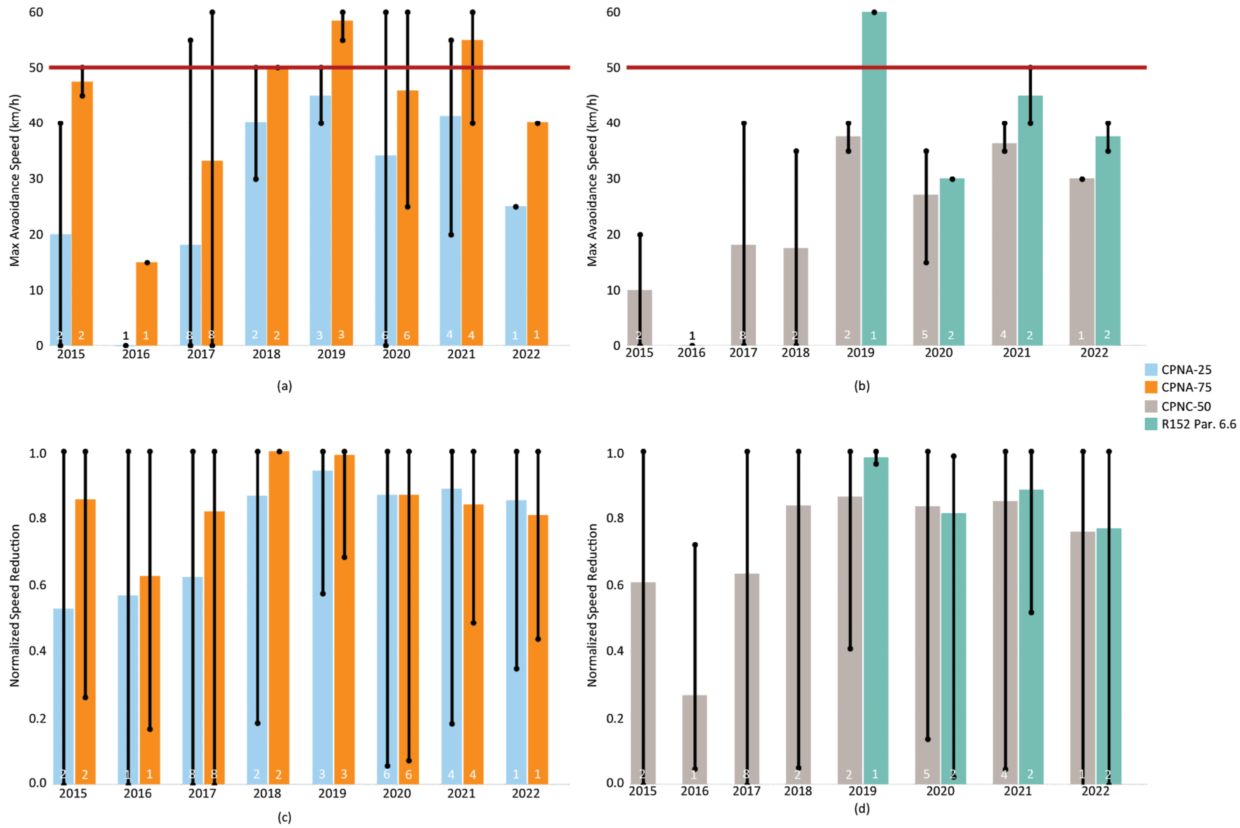

Figure 5. Normalized Speed Reduction and Maximum Avoidance Speed per Model Year for C2P Scenarios

Subaru, Kia, Honda and Hyundai were in the top performers for the C2C A1 scenario, all reaching average maximum avoidance speeds over 45 km/h (Figure ***6***a). In the C2C B1 scenario, 9 out of 23 reached the full maximum avoidance speed tested (40 km/h) (Figure ***6***b). The four top performers in the A1 scenario were also part of the nine manufacturers that achieved maximum avoidance speed in the B1 scenario. The normalized speed reduction results (Figure ***6***c and Figure ***6***d) show that most manufacturers achieved a speed reduction of more than 80% (63% for A1 and 52% for B1).

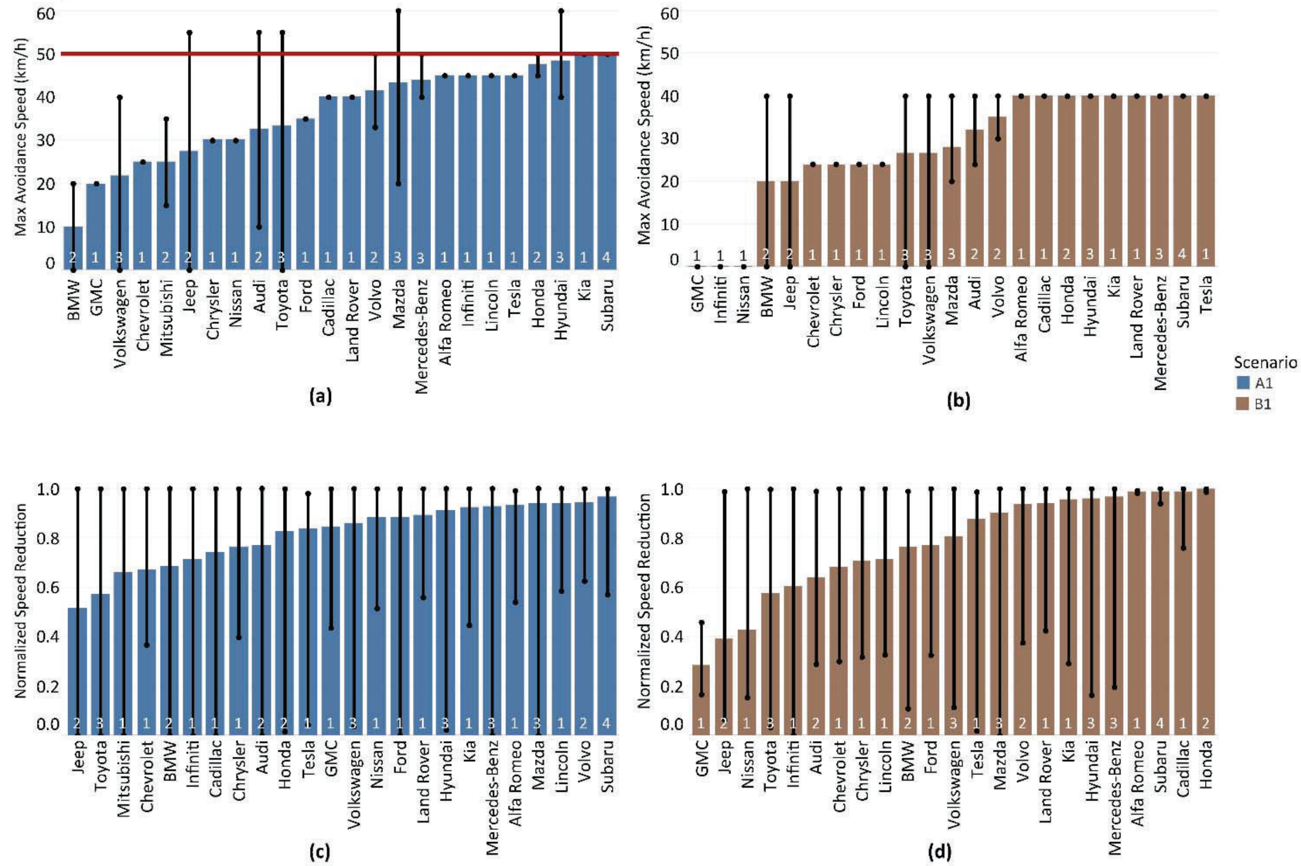

Figure 6. Normalized Speed Reduction and Maximum Avoidance Speed per Manufacturer for C2C Scenarios

Seven manufacturers (BMW, Genesis, Mazda, Mercedes-Benz, Subaru, Tesla and Volvo) reached the maximum avoidance speed tested (50 km/h) for the CPNA-75 scenario, with six of them even reaching higher speeds, while only two manufacturers (BMW and Tesla) reached the maximum avoidance speed of 50 km/h for the CPNA-25 scenario (Figure *7*a). With the child pedestrian (Figure *7*b), Chevrolet, Volvo and Genesis reached the highest avoidance speeds (40 km/h, 35 km/h and 35 km/h respectively) for the CPNC-50 scenario, while Audi and Genesis reached the highest speed for the UN R152 scenario (60 and 50 km/h respectively). In the scenarios with the adult target (Figure *7*c), 72% of manufacturers had a normalized speed reduction above 80% in the CPNA-75 scenario while 55% reached this level of reduction in the CPNA-25 scenario. On the other hand, in the scenarios involving the child target (Figure *7*d) only 38% of manufacturers achieved at least 80% speed reduction when the target was occluded (CPNC-50) and 57% when unobstructed (UNECE R152 Par 6.6).

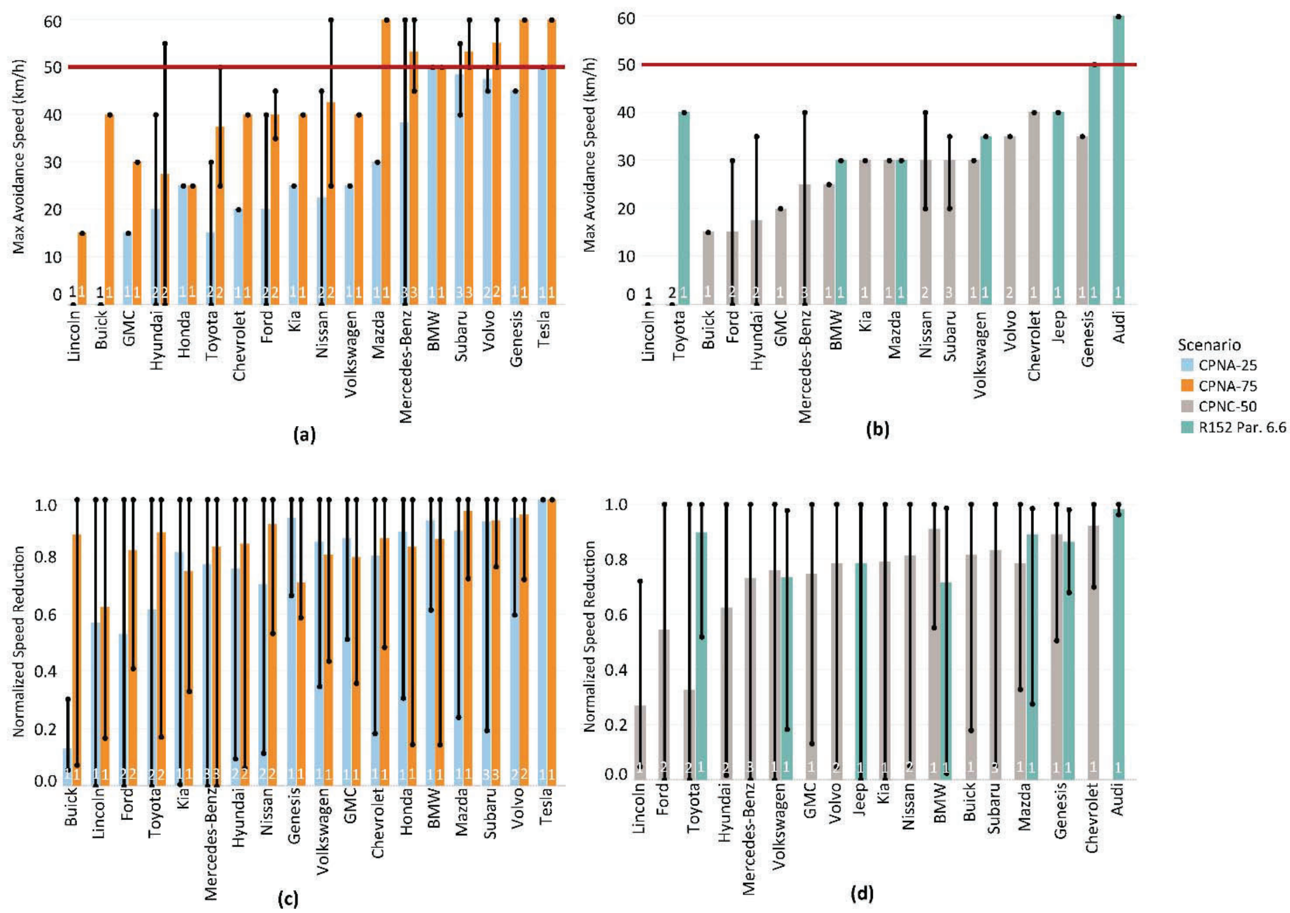

Figure 7. Normalized Speed Reduction and Maximum Avoidance Speed per Manufacturer for C2P Scenarios

DISCUSSION

The goal of this study was to evaluate the performance of AEB car-to-car and car-to-pedestrian systems available in vehicles and their evolution over time. The study evaluated the systems based on currently published performance criteria (UN R152 and US AEB) and looked at how they performed relative to one another. Finally, relevant Canadian road injuries and fatalities and corresponding vehicle speeds were examined to determine if the performance of current AEB systems has the potential to reduce those numbers or if a gap remains to be addressed.

Performance criteria differ between the UN and US requirements. The UN Regulation, which includes requirements for both C2C and C2P AEB, was published after the US AEB and thus considers newer AEB technology available in Europe. As well, the differences in scope of the requirements translate to a higher success rate when comparing the A1 scenario results of the tested vehicles evaluated against the US AEB Option A versus the UN R152. However, it should be noted that while test performance thresholds are relevant to safety, they may not directly translate into a reduction of the risk of collisions in the real world if these thresholds are set too low. On the other hand, if these performance thresholds are set too high, they may be unattainable by many systems or the costs of reaching such thresholds may exceed the benefits.

Also, the number of test repetitions required by the test protocol can be a factor in determining vehicle performance. The US AEB approach, which takes the average of 5 repeated tests, can dilute the robustness of the system by averaging results as compared to the single test requirement of the UN R152 protocol. Since AEB is an emergency device, the robustness and reliability of a system should be considered in the design of a test to reflect the spontaneity of AEB activation in the real world.

For both C2C and C2P tests, vehicle performance appears to improve over the years, as manufacturers began offering systems able to perform above the minimum requirements of the US AEB and that perform well per UN R152. In fact, before 2019, the best performing systems would only be tested up to speeds of 50 km/h as the impacts with the target were more frequent and to reduce potential damage to equipment. As time progressed, confidence in testing at speeds higher than 50 km/h also increased.

The availability of systems in North America has also been on the rise, with previously-rare systems such as AEB with pedestrian detection (P-AEB) becoming more readily available. Given that pedestrians accounted for 15.2% of road fatalities in Canada in 2020 [3], the introduction of such systems can help in reducing pedestrian fatality risk. Due to the rarity of P-AEB in earlier years, evaluations were limited for C2P scenarios. Furthermore, the P-AEB systems would only slightly reduce vehicle speed before an impact and only luxury vehicles performed well (e.g., Mercedes, Volvo).

When evaluating the system responses to the different C2P scenarios, the Euro NCAP CPNC-50 was found to be the most challenging due to the limited direct visibility (the pedestrian is obstructed by two parked vehicles up until the last instant). This scenario is also believed to represent the most realistic urban scenario, in which pedestrians are at greater risk. The performance has evolved, with avoidance speeds going from below 20 km/h to above 25 km/h in the later years (2019 and later). If the trends continue, vehicles that offer P-AEB are expected to improve even further over the next few years.

The increased performance trend in C2C scenarios is an indicator of the technological advances that have occurred since the start of this test program. As such, the percentage of vehicle models that meet the requirements is expected to increase as AEB technology matures, thus paving the way for more stringent performance criteria. In fact, the slower moving lead vehicle scenario (B1) shows that the technology of all tested systems has surpassed the requirements since 2016.

Although not presented in the figures, some systems performed full stops in the slower moving lead vehicle scenario (B1), which exceeded the deceleration needed to avoid an impact. If a following vehicle is not equipped with a similar system or has an inattentive driver, this AEB overreaction could increase the risk of rear-end collisions. A safer response would likely be to reduce speeds to match the lead vehicle’s speed. More research is needed to investigate this issue of excessive AEB braking responses.

Some model years, such as 2013, 2019 and 2022 stand out from the overall observed trend as they show significantly higher (2013 and 2019) or lower (2022) performance. The small sample size for these years amplifies the effect of the difference in technology performance observed between different manufacturers. In 2013 and 2019 the tested vehicles were made by manufacturers that are consistently at the higher end of the performance spectrum. In 2022, one vehicle which had significantly lower performances, contributed to reduce the average level for that model year.

As vehicle performance is likely to increase due to the evolution of sensor technologies and detection algorithms, considerations for a wider prescribed requirement would be beneficial to help reduce the risks at higher speeds. Based on the results, some of the latest models can avoid collisions at speeds up to 60 km/h for C2C as well as some C2P configurations. Setting the bar to a higher speed of operation would address a larger portion of the on-road risk. In fact, when looking at the collision data, speeds up to 69 km/h capture 70 % of injuries and 40 % of fatalities of rear-end collisions (Figure 1), and over 95 % of injuries and 60 % of fatalities of pedestrian collisions (Figure 2). Therefore, setting minimum requirements to 60 km/h for both C2C and C2P could have the potential of addressing the majority of injuries occurring on the roads and seems attainable by most vehicle manufacturers at this time. As AEB technology continues to progress, performance requirements could be set to even higher speeds in the future.

Testing at several speeds in a given range, as currently done in UN R152, enables an assessment at lower city speeds (as low as 10 km/h) and higher speeds (up to 60 km/h) for the C2C scenarios. This also ensure that systems work at all speeds and not just at higher speeds. As for the C2P, a similar approach should be taken for scenarios in which the systems have a better view of the target, leaving adequate time for the vehicle to react. Gradually pushing the upper limit of performance appears to be a logical path when comparing results to the current procedures available for the evaluation of AEB.

It is important to note that the test samples were not random. Vehicles were selected based on the models' sales volume (popular models), new technology offered, availability, cost, and to represent different manufacturers. Although the large sample size of this study means the results are more representative of the Canadian vehicle fleet, the distribution over the years and by manufacturer limit the analyses possible. In other words, if a model year contained more vehicles from the top performing manufacturers, the results would be skewed for that specific year. Similarly, the number of tests performed was not equally distributed between the years and by manufacturer. Certain averages contained a small number of vehicles whereas others contained a larger number.

Finally, the statistics presented in Figure 1 and Figure 2 represent collisions occurring on Canadian roads in diverse weather, road conditions and crash configurations. Only a small subset of conditions is represented by the test methods used in this study, which focused on ideal conditions. Also, the data do not include the severity of injuries, which would be valuable information when determining priorities in scenarios and prescribing test speeds. Nevertheless, the collision data presented gives an indication of the current landscape and can help setting targets to improve road safety for all.

Transport Canada will continue to evaluate the safety performance of the latest crash avoidance systems to identify risks and opportunities to improve safety. Specifically, AEB systems will be tested at higher speeds, with different vehicles targets, under different configurations (e.g., nighttime, intersection, rain, snow) and using real-world driving behaviour (e.g., allowing more steering and accelerator inputs compared to the small tolerances of test standards).

CONCLUSIONS

Most vehicles tested since 2013 were able to mitigate rear-end crashes according to the criteria defined in the US AEB protocol while less than a third met the UN R152 requirement for the stopped lead vehicle condition and half for slower moving lead vehicle scenario. The car-to-pedestrian configurations were found more challenging overall with better mitigation for the adult pedestrian crossing from nearside to a predicted impact point at 75% of the vehicle width. The worst AEB performance were observed for the occluded child scenario. Overall, the AEB performance, characterized by the speed reduction and the maximum avoidance speed, progressed over the years with more systems now capable of exceeding the requirements defined in the selected protocols.

The best performing AEB systems could avoid a collision at speeds (0-60 km/h) where a considerable number of casualties occur (49% pedestrian fatalities, 30% rear-end crash fatalities). This represents significant progress for systems that should help improve road safety. As AEB systems continue to advance, it is expected that not only the maximum avoidance speed will increase but the range of scenarios and crash configurations will expand (e.g., nighttime, intersection, rain, snow) to address a wider range of real-world risks.

Transport Canada's assessment capabilities have evolved since the early days of AEB performance testing. By using state-of-the-art equipment, novel methodologies and innovative test scenarios, emerging technologies available to Canadians will continue to be evaluated to determine the implications they have for safety and their potential contribution to help reaching zero road casualties.

ACKNOWLEDGEMENTS

This work was funded by Transport Canada, through its Innovation Centre and the Multimodal and Road Safety Programs and supports research to address the future needs of Canadians. The authors would like to thank the rest of the members of the PMG testing team for their support during testing and data analysis. The authors are also thankful to Brenton Heyburgh of the National Collision Database for providing essential crash statistics to support the rational of this project.

DISCLAIMER

The authors report that there is no competing interest to declare, testing facility and equipment is property of Transport Canada and vehicles were purchased by Transport Canada for the sole purpose of research activities. The brands and models selected were part of a research fleet available to the department and were purchased through a competitive process without the manufacturer's knowledge. The observations made in this report are the sole expression of the authors and do not necessarily reflect Transport Canada's policies and regulations.

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PEER REVIEW PAPER

This paper has been peer-reviewed and published in a special edition of Traffic Injury Prevention 24(S1), by Taylor & Francis Group. The complete paper will be available on the Traffic Injury Prevention website soon. To access ESV Peer-reviewed papers click the link below
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THE ESTIMATED POTENTIAL EFFECTIVENESS OF AEB AND LKA SYSTEMS FOR HEAD-ON CRASHES

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ABSTRACT

Research Question/Objective
In 2019, there were over 3,600 fatal head-on crashes in the US. This represents 10.9% of all fatal crashes despite accounting for 2.7% of all police-reported crashes. Lane departure warning (LDW) and lane keeping assist (LKA) systems could help address cross-centerline crashes. We consider LDW systems to be those that alert the driver prior to the lane crossing event while LKA systems might perform automated steering that may help prevent the vehicle from departing the lane. Automatic emergency braking (AEB) has been effective in preventing or mitigating front-to-rear crashes by providing significant crash-imminent braking. The purpose of this study was to estimate the effectiveness of a simulated LDW or LKA system with a hypothetical AEB system that could activate in cross-centerline head-on crashes.

Methods
The National Automotive Sampling System Crashworthiness Data System (NASS/CDS) is a representative sample of tow-away passenger vehicle crashes in the U.S. containing in-depth crash data. Trajectory data was extracted from scaled scene diagrams for 232 cross-centerline NASS/CDS cases with available event data recorder (EDR) information. There were 111 cross-centerline crashes reconstructed based on the trajectory and EDR recorded crash pulse. This effort to predict the benefits of LDW and LKA systems for cross-centerline crashes, involved modeling the crash, including the road geometry and vehicle dynamics. The encroaching vehicle that crossed the centerline was simulated with hypothetical LDW and LKA systems and the impacted vehicle was simulated with and without an AEB system. The outcomes of the simulations were combined to estimate the potential crash reduction of a hypothetical LDW and LKA combined with AEB. For simulations that resulted in a crash, a frontal injury model was used to predict the probability of the occupants sustaining a moderate to fatal injury (MAIS2+F).

Results
The hypothetical LDW system had an estimated crash benefit between 7.5% and 10.8% and the hypothetical LKA system had a higher estimated benefit of 32%. With the AEB system in the impacted vehicle, the estimated benefit for LDW increased to 13% to 15%, but the estimated benefit for LKA remained the same. The AEB system with the LDW system resulted in an estimated 50.8% to 54.3% reduction of MAIS2+F injured occupants and an estimated 68.4% reduction with the LKA system.

Discussion and Limitations
The simulations indicated that AEB has only a small effect on preventing head-on crashes. However, AEB can mitigate the crash by rapidly reducing the speed of the impacted vehicle prior to the collision. While the hypothetical

AEB system does not prevent many additional simulated head-on crashes, it can assist in reducing the likelihood of passengers sustaining a moderate to fatal injury.

Conclusion and Relevance to Session Submitted

Previous studies have investigated the benefit of LDW and LKA systems for road departure and head-on crashes. This is the first study to investigate the combined benefit of a hypothetical AEB and lane keeping systems for head-on crashes. This paper is relevant to the session because it evaluates the estimated safety benefits of these systems using EDR pre-crash and crash data.

INTRODUCTION

Every year, approximately 34,000 individuals are fatally injured in crashes on roads in the US [1]. These fatalities occur across many types of crash scenarios, each of which has its own set of causation factors. One way to prioritize research on a preventive technology for a specific crash scenario is to look at number of occupant fatalities relative to the total number of occupants involved in this crash scenario. According to Kusano, four crash modes are overrepresented among fatalities: single vehicle road departure crashes, control loss crashes, cross-centerline head-on crashes, and pedestrian/cyclist crashes [2]. Interestingly, two of these crash scenarios require the subject vehicle to depart from the initial lane of travel before the crash occurs. Another method of prioritizing research is to determine factors common among the fatal crashes. Head-on crashes comprise of only 4% of non-intersection crashes but account for 49% of fatalities in non-intersection crashes [3]. Cross-centerline head-on crashes consist of a vehicle crossing the centerline and colliding with a vehicle traveling the opposite direction. Head-on crashes can be dangerous due to the large deceleration experienced upon impact since the vehicles were moving in opposite directions.

The potentially high severity head-on crashes and road departure crashes has been a motivation for the development of active safety systems, such as lane departure warning (LDW) systems. LDW systems are designed to alert the driver, through audible, visual or haptic signals, that the vehicle has inadvertently left the lane of travel [4]. Ideally, the driver reacts to the warning and returns to the lane, preventing an impact (Figure 1). However, the effectiveness of an operational warning system is limited by the reaction time of the driver and the ability of the driver to return to the road without impacting any roadside objects [4]. The reaction time of a driver to a haptic or audible LDW system can vary from as low as 0.38s to 1.36s [5]. Additionally, LDW effectiveness is dependent on the evasive action taken by the driver. Lane departure prevention (LDP) systems may not need the driver to react by automatically steering the vehicle back toward the original lane. Some LDP systems can provide steering input before departing the lane and may also be referred to as lane keeping assist (LKA) systems.

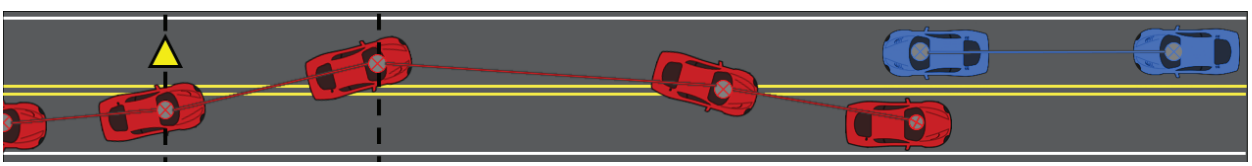

Figure 1. Visual representation of a hypothetical LDW and LKA system. LDW systems may alert the driver that the vehicle has departed its lane of travel. LKA operate similar to the LDW systems, except the LKA system might provide an automated steering response.

Assuming there were no system limitations present, from 2011 to 2015, almost 50% of the moderate to fatal injury crashes that could theoretically benefit from LDW/LKA systems [6]. Over 65% of these LDW/LKA applicable scenarios were drift-out-of-lane (DROOL) road departure crashes. Riexinger found from crash data that roughly 80% of drivers in DROOL road departure crashes responded with a steering maneuver [6]. Several studies have estimated the effectiveness of LDW in road departures, however due to the higher relative speed that the subject vehicles approach each other during a head-on collision, the estimated effectiveness of LDW and LKA systems may be different for head-on than in road departures (Table 1). Cicchino estimated the number of lane departure crashes, including head-on crashes, that were prevented by LDW/LKA systems using insurance claim information. The estimated benefit is lower than other simulated studies since drivers can disable the LDW system and it combines the effect of many system types. The purpose of this study is to estimate the benefit of LDW/LKA systems in head-on crashes.

Table 1. Summary of LDW/LKA effectiveness estimates in the literature.

Source	System Type	Estimated Effectiveness
Cicchino 2018 [7]	Single vehicle road departure, head-on, sideswipe crashes in US	11% (LDW/LKA)
Sternlund 2017 [108]	Single vehicle road departure, head-on crashes on high-speed roads in Sweden	53% (LDW/LKA)
Riexinger 2018 [4]	Single Vehicle Road Departure crashes in US	16.7%-21.5% (LDW) 24.3% (LKA) (Assuming that the system is activated)

APPROACH

Datasets

NASS/CDS and CISS The National Automotive Sampling System (NASS) Crashworthiness Data System (CDS) data set is a nationally representative sample of all crashes in which at least one passenger vehicle was towed away [9]. Every case in NASS/CDS is assigned a weight to represent the total number of similar crashes that occurred in the US during that case year. NASS/CDS provides detailed information on each case including vehicle deformation, crash causation factors, a scaled scene diagram of the crash, and occupant injury information records. Each case in the data set includes a scaled scene diagram with the vehicle trajectory and impact locations. If possible, the vehicle delta-v is calculated from an energy reconstruction based on the crush profile of the vehicle using Win-Smash [10-12].

EDR Database The Virginia Tech Event Data Recorder (EDR) Database is a collection of the information retrieved from EDRs in vehicles involved in real-world crashes that were investigated in NASS/CDS. The EDR database is continuing to expand to also include cases from the Crash Investigation Sampling System (CISS). Most recently manufactured vehicles have an EDR installed, which records basic vehicle information in the event of a crash. The EDR database is a unique source of direct measurements of vehicle speed before and during a crash. The EDR records data, such as delta-v, during the crash to capture the crash pulse. Additionally, five seconds of pre-crash information, such as vehicle speed, throttle position, brake activation and engine RPM, are also recorded. Some advanced EDRs record information such as the steering-wheel position, the activation of electronic stability control (ESC) and the activation of the antilock brakes system (ABS). EDRs have been shown to accurately measure the crash delta-v within 14% [11] and are frequently used to understand driver precrash behavior [13, 14].

Cross-Centerline Crash Database The cross-centerline crash database contains additional data elements extracted from NASS/CDS scene diagrams and scene photographs by the authors. This dataset follows the same methodology used to extract information on roadside crashes as a part of the National Cooperative Highway Research Program Project 17-43 database [15]. The crashes in the cross-centerline crash database were selected from NASS/CDS case years 2011 to 2015. This dataset contains the trajectory positions and headings of every vehicle involved in the 232 NASS/CDS cross-centerline crashes where at least one passenger vehicle had EDR information available. The road geometry for each road segment was also recorded in this dataset.

Data Selection

NASS/CDS cross-centerline head-on crashes from 2011 to 2015 were selected for estimating the effectiveness of LDW/LKA systems. This is the most recent five years available in NASS/CDS. The cross-centerline crash database was used to provide the coded trajectory of the vehicle before the crash. The EDR pre-crash velocity data was used to determine the vehicle's speed at each point along the trajectory. To be included in the study, the first event for the encroaching vehicle had to be the head-on crash in NASS/CDS (ACCTYPE = 50, 51). Additionally, the EDR needed to record either an airbag deployment or a delta-v greater than 8kph (5mph) for the encroaching vehicle [13]. The bag deployment locks the EDR data preventing subsequent events from overwriting EDR data. In cases where the airbag did not deploy, the 8 kph delta-v requirement increases the likelihood that the event stored in the EDR corresponds to the NASS/CDS case rather than a minor impact. A crash of at least 8 kph will produce significant damage and would be unlikely to be overwritten by a post-crash event, e.g., hitting a pothole while being towed from the scene. Finally, the EDR must have recorded values for the pre-crash velocity to be used in this study.

In the dataset, there were three cases in which the encroaching vehicle departed the road at least once before the head-on crash. In each of these cases, the encroaching vehicle departed the road to the right, overcorrected, crossed the centerline, and impacted a vehicle travelling in the opposite direction. The first intervention opportunity for this particular scenario involves activating the LDW or LKA system during the road departure rather than when the vehicle crosses the centerline. Therefore, the three cases where a road departure occurred before the cross-centerline crash were removed from the dataset. Although these cases were excluded from this study, it is still possible that implementing avoidance countermeasures may have mitigated or prevented the impact. Overall, there were 111 encroaching vehicles in the simulation dataset. After applying NASS/CDS sampling weights, this represents 35,677 real-world crashes used in this study (Table 2).

Table 2. Case selection criteria.

	Number of Cases	Weighted Cases
Vehicles with EDR information and in the cross-centerline database	183	58,298
Air bag deployment or delta-v > 8 kph	165	48,728
Valid pre-crash data	164	48,641
First event	164	48,641
Single departure cases	161	47,885
Remove large trucks	148	46,509
Valid crash delta-v	134	44,991
Valid pre-crash velocity	111	33,677

Crash Reconstruction

Often the EDR was only available in one of the vehicles involved in the cross-centerline head-on collision. To accurately model both vehicles in the crash, the speed of the vehicle without the EDR was reconstructed. Using the delta-v of one vehicle from the EDR, the mass of both vehicles, and the impact angle of both vehicles, the delta-v of the other vehicle was computed based on the conservation of momentum. The delta-v of the other vehicle was computed in both the x and y directions. This assumes that all of the vehicle motion was planar and there was no rotation of the vehicles from the impact. The mass of each vehicle was the sum of the curb weight and cargo weight reported in NASS/CDS. The reconstructed delta-v for the vehicle without an EDR was compared with the WinSmash reconstructed delta-v [10]. Our reconstructed delta-v overestimated the WinSmash delta-v by about 17 percent on average (Figure 2) because it does not account for the rebound velocity of the vehicle and because it does not consider rotation of either vehicle. These assumptions were particularly highlighted by case 717020839, which had a reconstructed delta-v of 122 kph but a WinSmash delta-v of 55 kph. Our estimate was higher than the WinSmash because the small sedan experienced extreme deformation to the occupant compartment. However, WinSmash underestimates the true crash delta-v by roughly 10%, which may indicate that our delta-v estimates are close to the true delta-v [11].

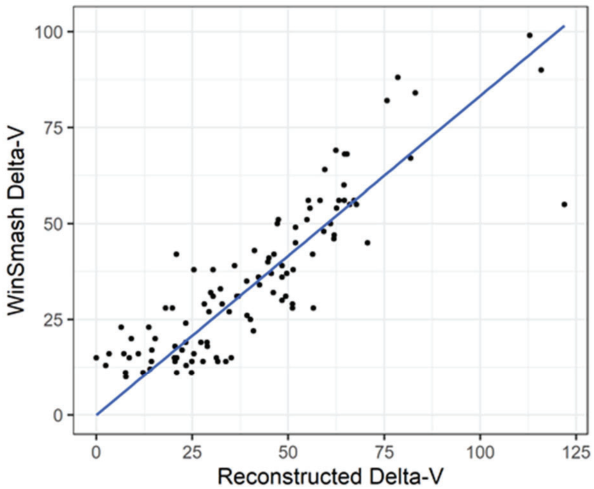

Figure 2. Validation of the delta-v reconstruction.

The velocity of the vehicle after impact was approximated based on the linear distance (D) to the final rest position from the point of impact. The energy absorbed during that distance was estimated from a 0.2g deceleration along the distance to the final rest position. This value was chosen to maximize the agreement between the predicted and actual impact velocities. From the delta-v and the velocity immediately following the impact, the impact velocity was computed. Depending on which vehicle, encroaching, or impacted, contained the EDR information, the initial travel speed changed. For cases in which the impacted vehicle contained an EDR, the first recorded speed was assumed to be its travel speed. For cases in which the encroaching vehicle contained an EDR, the velocity measurements were mapped onto the vehicle trajectory assuming a linear acceleration between measurements [4, 16]. The travel speed was the speed of the vehicle when its center of mass crossed the centerline. The impact velocity reconstructed from the delta-v was compared with the last recorded pre-crash velocity of the vehicle (Figure 3). A linear regression between the reconstructed and last pre-crash velocity determined that the predicted impact speed was on average 9.6% below the last pre-crash velocity with an r^2 value of 0.85. Because many EDRs do not record the exact impact velocity, the last recorded pre-crash velocity does not capture any decrease in speed due to braking before impact.

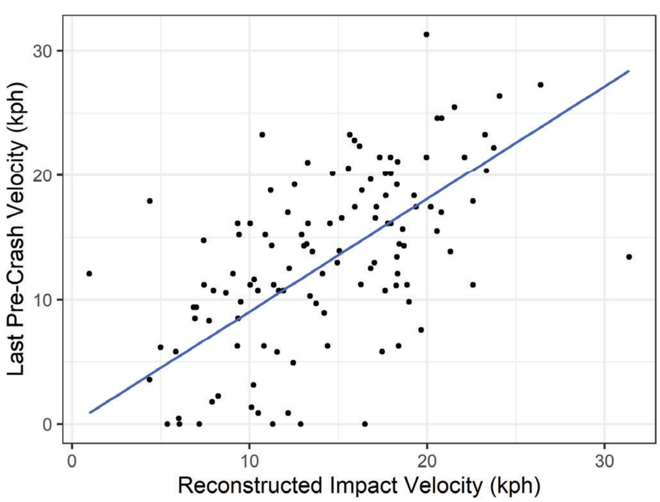

Figure 3. Validation of the delta-v reconstruction.

Vehicle Model

The vehicles in the crash were represented by a rectangle with a length and width equivalent to the overall length and width from NASS/CDS of each vehicle. The vehicle dynamics were modeled as a point with a time step of 0.01s. The total force exerted by the tires was limited to the force available from friction. Therefore, any combination of steering and acceleration could not exceed 1g. If the 1g limit was exceeded, then the braking force was maintained, and the steering was scaled down such that the magnitude was equal to 1g.

Driver Model
The encroaching vehicle follows its original crash trajectory, but the impacted vehicle was simulated to follow the road by remaining centered in its lane. The vehicle steering was controlled by a theoretical proportional-integral-derivative (PID) controller with the following assumed parameters: K_p = 743.5, K_i = 0.1, K_d = 0. The PID controller was minimizing the distance between the predicted vehicle center in half a second to the intended path of the vehicle. The 0.5s look-ahead was used to more closely resemble how humans drive; drivers do not steer based on their current position but where they will be [19]. Additional length equal to 0.5s of travel was added to the end of the trajectory because the steering model looked ahead 0.5s.

Encroaching Vehicle The encroaching vehicle follows its original crash trajectory. When the LDW system activates, there is an estimated reaction period during which the vehicle continues travelling as before until the driver is estimated to react. Our model considered three different reaction times: 0.0s, 0.38s, and 1.36s [5]. This represents the fastest possible response, a fast response and a slow response to haptic or audible warnings based on simulator studies. We also used two different theoretical braking magnitudes (0.0g and 0.41g) and three different maximum turning rates (0 deg/s, 11.4 deg/s, and 34.1 deg/s) based on EDR data [18]. The steering maneuver was governed by the PID controller, which tried to steer back into the original lane of travel. Thus, there were six different possible maneuvers (Table 3).

Table 3. Probability of simulated encroaching vehicle evasive actions.

	No Braking	Braking
No Steering	16.5%	5.1%
Light Steering	11.4%	27.8%
Heavy Steering	11.4%	27.8%

Impacted Vehicle The impacted vehicle begins the simulation traveling at the reconstructed initial velocity. The impacted vehicle had a constant deceleration such that it would be traveling at the reconstructed impact velocity at the point of impact. The model assumed that the driver of the impacted vehicle was paying attention to the road and anticipated the encroachment of the other vehicle. While this assumption is not valid for all real-world cases, an analysis of EDRs in cross-centerline crashes showed that every impacted vehicle in the sample performed an evasive action prior to impact [20]. Therefore, as soon as the encroaching vehicle touched the lane line, the driver of the impacted vehicle was simulated to perform a braking maneuver with a magnitude of either 0.0g or 0.27g [18]. The driver was assumed to follow their intended path by remaining centered in their lane. There were two possible options for the impacted vehicle and the frequency of the braking responses were based on EDR data [18] (Table 4).

Table 4. Probability of simulated impacted vehicle evasive action.

	No Braking	Braking
Lane Centering	6.4%	93.6%

Hypothetical Active Safety Operation Criterions
Our model investigated hypothetical LDW and LKA systems with an activation speed of 50 kph [21]. The time to lane crossing (TTLC) activation threshold of the systems ranged from 0 to 1.2 s. AEB systems are typically for car following scenarios. Although not the typical use case, our hypothetical AEB system could be used to identify vehicles that have crossed the centerline. Due to the vehicle approaching from the side, the AEB parameters were chosen to be similar to other studies of Intersection advanced driver assist systems (I-ADAS) [7, 19-20].

LDW/LKA Estimated Effectiveness
The LDW's estimated effectiveness was determined by calculating the total possible permutations of LDW activation speeds, time to lane crossing (TTLC) of warning activation, reaction times, steering types, and braking types for both vehicles which resulted in a total of 16,539 simulations of cross-centerline collisions These simulations were performed on multiple CPU cores by a custom python script. Each simulation was weighted based on the frequency of each driver evasive action if the system was of the LDW model or weighted based on the case weight if the system was of the LKA model. A crash was predicted to be prevented with an LDW/LKA system if the vehicle continued driving without striking the opposing vehicle or came to a stop. A crash was predicted to not be prevented if both vehicles impacted each other or the vehicle took no evasive action and departed the road.

Residual Injury Computation

The probability of front occupant injury for cross-centerline crashes was estimated using the injury model developed in by Bareiss in 2019 [20]. The logistic injury model has seven inputs: delta-v, belt use, sex, age, crash compatibility, BMI, and striking location (Table 5). Delta-v and BMI were continuous covariates and all other injury model parameters were binary. The injury model was constructed based on the injury data of front seat occupants that were at least 12 years old and involved in a frontal crash with another vehicle. For cross-centerline crashes, the rear of a vehicle is not struck and therefore the striking location was zero for all cases. Of the 111 simulated cases, 101 cases involving 182 occupants contained all the information necessary to utilize the injury model and estimate the injury benefit. If the vehicle stopped or returned to the lane, the probability of an occupant sustaining a MAIS2+F injury was assumed to be zero. For crashed and parted simulation outcomes, the last velocity was assumed to be the impact velocity.

Table 5. Frontal impact injury model

Variable	Parameter	Estimate	Standard Error	p-value
Intercept	--	-6.516	0.863	<0.001
Total Delta-V	Delta-V (kph)	0.090	0.019	<0.001
Belt Use	Belted	-0.769	0.396	0.054
Sex	Male	-0.891	0.333	0.008
Age	≥65	1.070	0.492	0.031
Crash Compatibility	Car Struck LTV	1.222	0.368	0.001
BMI	BMI (kg/m^2)	0.084	0.021	<0.001
Striking Location	Rear	-1.455	0.501	0.004

The delta-v was estimated based on the computed final velocity (Equation 2-3). The final velocity was computed based on the mass of each vehicle (m_1, m_2), and the impact velocity of each vehicle (V_{1i}, V_{2i}). The coefficient of restitution (C_R) was assumed to be 1 which follows an assumption used in WinSmash [4]. Often, the two vehicles in cross-centerline crashes are not perfectly aligned and much of the energy is transferred into rotational energy. In order to match the actual crash injury outcomes with the predicted injury outcomes for the baseline configuration and account for any rotation after impact, we assumed that 29.5% of the total delta-v was longitudinal.

$$V_{1f} = \frac{m_1 V_{1i} + m_2 V_{2i} + m_2 C_R (V_{2i} - V_{1i})}{m_1 + m_2} \#(2)$$

$$V_{2f} = \frac{m_1 V_{1i} + m_2 V_{2i} + m_1 C_R (V_{1i} - V_{2i})}{m_1 + m_2} \#(3)$$

For each simulated system configuration, the estimated number of injuries was computed using Equation 4 below. The standard errors from the logistic model was used in the calculation to compute 95th percentile confidence intervals of all estimates. The estimated injury reduction for each system configuration was computed relative to the predicted number of injured occupants in the baseline configuration.

$$Predicted\ Injuries = \sum_{i=1}^{111} Probability\ of\ Injury * Case\ Weight\ \#(4)$$

RESULTS

Crash Benefit

The overall system benefit was defined to be the percentage of cases in which the system successfully avoided a crash, compared to the percentage of cases in which the crash still occurred. The baseline model was defined as a vehicle without an LDW or LKA system in which the encroaching vehicle followed the original crash trajectory. The benefit of different system type is shown in Figure 4. The crash avoidance benefit of the LDW system increased for systems that delivered an earlier warning. LKA systems that automatically steered produced a greater estimated crash reduction than LDW systems. The speed models that worked at a lower speed showed a higher estimated benefit than the same model with a higher activation speed.

With AEB, the LDW systems had a 5.2% increase in benefit and the LKA system received no increase in benefit. An interesting trend was that the additional benefit due to an AEB system in the impacted vehicle diminished as the system activated earlier. This is because the AEB system allowed the impacted vehicle to brake harder, which granted the driver of the encroaching vehicle more time to respond to the situation. A quicker response time from the driver showed higher estimated benefit for the vehicles with the basic LDW model because the warning was delivered as soon as the vehicle crosses the lane line. The LDW with lower activation speed and earlier TTLC had almost the same increase in benefit because they depend on the driver input. No additional estimated benefit was seen for the LKA system. The benefit due to the LKA system is independent of the driver's reaction time because the LKA system produces an immediate automated evasive maneuver. The extra time available due to the AEB system in the impacted vehicle produced no additional estimated benefit.

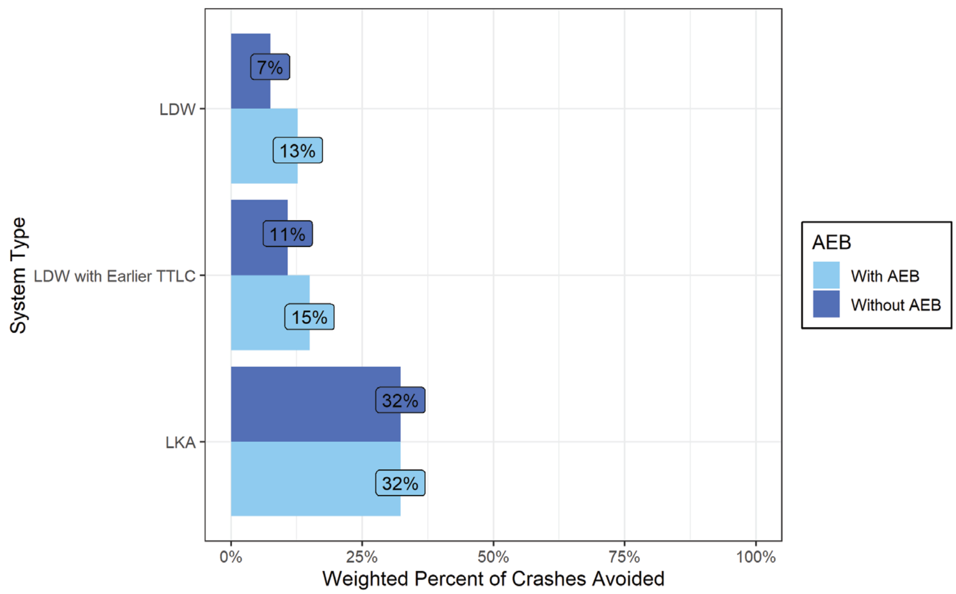

Figure 4. Weighted percent of crashes avoided for each system model and activation speed.

Injury Benefit

The predicted injury benefit for each LDW/LKA system was higher than the crash benefit (Table 6). As expected, systems with an estimated larger crash reduction benefit also had a larger injury benefit. Therefore, each expanded activation speed system performed better than its basic counterpart and systems with an earlier activation also performed better. All LDW/LKA systems showed a higher estimated injury benefit when the impacted vehicle was equipped with an AEB system. The AEB system, if activated, might be able to slow the impacted vehicle down which can lower the delta-v for all crash occupants. However, the increase in injury benefit from the AEB system diminished as a higher proportion of crashes were estimated to be avoided. The LKA system with a lower activation speed is estimated to have the highest crash avoidance and injury mitigation.

Table 6. Estimated injury reduction for each LDW/LKA system

System Design	No AEB in the Impacted Vehicle		AEB in the Impacted Vehicle	
	Number of Injured Occupants	Percent Injury Benefit	Number of Injured Occupants	Percent Benefit
Baseline	6,320 ± 680	0.0%	-	-
LDW	4,970 ± 200	21.4% ± 9.0%	3,110 ± 150	50.8% ± 5.8%
LDW with Early TTLC	4,560 ± 200	27.8% ± 8.3%	2,890 ± 150	54.3% ± 5.4%
LKA	3,070 ± 500	47.3% ± 9.7%	2,000 ± 380	68.4% ± 6.9%

DISCUSSION

The basic LDW model provided the smallest benefit since it activated much later than the other systems, a TTLC of 0.0s. For the base LDW system, the predicted crash benefit was 7% and more advanced LKA systems had predicted crash benefit up to 51%. The range of these benefits encompass estimates by Cicchino and Sternlund that combined the analysis LDW and LKA systems in road departure, sideswipe, and head-on crashes [7, 8] (Table 7).

Table 7. Summary of previous LDW studies with head-on crashes.

Study	Case Selection	LDW/LKA Injury Benefit
Cicchino 2018 [7]	Single vehicle road departure, head-on, sideswipe crashes in US	Reduction of minor injurious crashes 21% (LDW/LKA)
Sternlund 2017 [8]	Single vehicle road departure, head-on crashes on high-speed roads in Sweden	Reduction of minor injurious crashes 30% (LDW/LKA)
Present Study	Cross-centerline head-on crashes in the US	7%-17% (LDW) 32%-51% (LKA)
		13%-25% (LDW+AEB) 32%-51% (LKA+AEB)

The basic LDW model provided the smallest benefit since it activated much later than the other systems. For the base LDW system, the predicted crash benefit was 13%. No warning was delivered to the driver in 62% of LDW cases because the encroaching vehicle was travelling below the activation speed when crossing the lane line. After accounting for the NASS/CDS case weights, it was determined that the maximum additional benefit to the lower activation speed is 20.0%. The LDW system with earlier TTLC activation predicted a benefit of 15%. This is a 2% increase in benefit compared to the base LDW model. Previous studies have shown that the highest benefits are to be expected when driver reaction times are the fastest [4, 16]. For the LKA system, the vehicle responds immediately and automatically provides steering input without any driver input. Therefore, the LKA system had the greatest crash benefit.

Due to the nature of cross-centerline crashes, many road departure crashes were not avoided in the simulations because there was very little time for the driver to respond. The fastest driver reaction time (0.38s) and even an early warning of 0.5s TTLC often left very little time for the driver to steer or brake to avoid the object. The time available for the driver of the encroaching vehicle to respond is related to the distance from the departure to the impact location and the speed of the vehicle. Slower moving vehicles with larger distances to travel before impact will have more time to respond than fast moving vehicles with smaller distances to travel before impact. Figure 5 shows the simulation outcome based on the encroaching vehicle's speed and distance between the impact location and point of departure for the two different reaction times for the LDW system and the LDW system with early TTLC activation. For the cases without the expanded activation speed, there was a clear boundary at 50 kph, below which the vehicle crashed in the simulation.

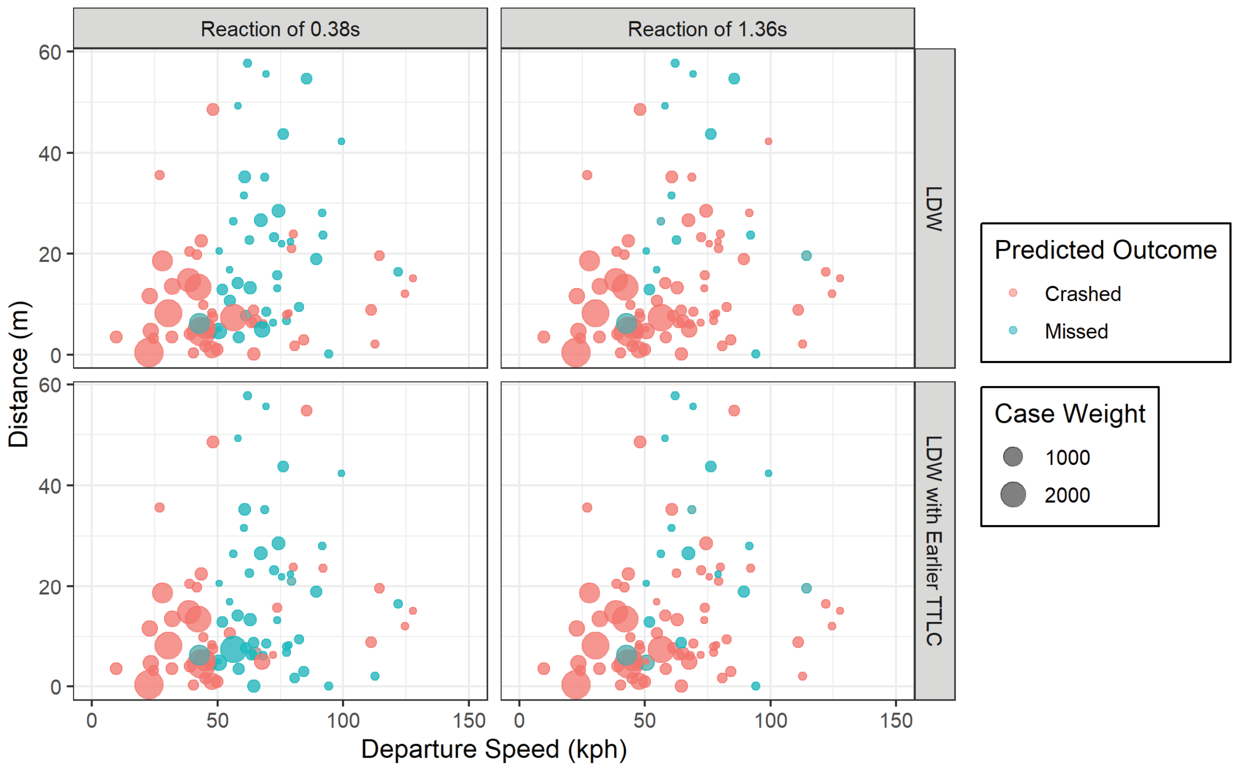

Figure 5. Crash outcome based on the departure speed and the straight-line distance to the impact point from the point of departure. The crash outcome is shown for each reaction time for Advanced LDW and Advanced LDW with Expanded Speed simulations with AEB. The encroaching driver model involved heavy steering (34.1 deg/s) and no braking (0.0 g), and the impacted driver model involved following the intended path and braking (0.27 g)

Limitations

This study used the road geometries and vehicle speeds from real-world head-on crashes to estimate the effectiveness of LDW/LKA and a hypothetical AEB system. The vehicles were simulated in an idealized environment with simplified driver behavior models and simple active safety activation criteria. While the limitations detailed below influence the effectiveness of these systems in the real-world, the trends found from the simulations can provide insight into the potential benefits of these systems.

In many cases, an EDR was present for one of the involved vehicles. While the delta-v was recorded for one vehicle, the delta-v of the other vehicle was reconstructed. This reconstruction assumed that all the vehicle motion was planar and there was no rotation of the vehicles from the impact, which may not always be the case for an oblique frontal crash. Additionally, this study assumed that there were no other vehicles or objects to be avoided, which may increase the effectiveness estimates. Another limitation to the study was that the friction coefficient is assumed to be constant for every case regardless of the weather and road conditions. This would affect a select few cases where road conditions, such as rain and snow, decrease the turning/braking effects. This study did not account for the grade of the road which could alter the deceleration of the simulated vehicles. However, this effect is likely overcome by any braking performed by the driver. The vehicle model limited the acceleration to 1 g. This represents the upper limit of the tire force available for a maneuver. Due to tire tread, the driving surface, and the shape of the vehicle, the actual tire force is likely much lower.

Additionally, this model assumed that the driver of the impacted vehicle was fully attentive and anticipated the encroachment of the other vehicle because drivers in the impacted vehicle always performed an evasive action [36]. However, this may not be true if the driver of the impacted vehicle was also distracted, the road was curved, or the view was obstructed such that the encroaching vehicle approached from a blind turn. The driver of the impacted vehicle did not perform an evasive steering maneuver. Instead, the driver of the impacted vehicle braked and followed their intended path by remaining centered in their lane. These simulated behaviors are derived from analysis of EDR data on pre-crash behavior in cross-centerline crashes [18]. This study did not account for driver actions throughout the lane crossing event that could disable the LDW/LKA system. Our study did not consider cases with multiple departures and assumed that the drivers may not overcorrect after the initial lane departure event.

CONCLUSIONS

The purpose of this study was to estimate the safety benefits of LDW/LKA systems and hypothetical AEB systems for cross-centerline crashes. AEB improved the crash benefit for LDW systems, but the effect diminished as LDW/LKA system activated earlier. The AEB system reduced the delta-v in the residual crashes which significantly increased the injury benefit for all LDW/LKA systems. Future iterations of this study should analyze if there is a significant change in crash prevention benefits if the trajectory of the impacted vehicle deviates from the center of their lane or if the impacted vehicle performs a steering evasive maneuver.

ACKNOWLEDGEMENTS

The authors would like to thank the Toyota Collaborative Safety Research Center for funding this study. We would also like to recognize Max Bareiss for his help using cython to improve the performance of the simulation. We would also like to recognize the undergraduate interns who extracted the trajectories from the NASS/CDS scene diagrams: Katelyn Kleinschmidt, Kellie Matthews, Kyle Naddeo, Yvonne Teng, and Jacob Valente.

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RISK ASSESSMENT AND MITIGATION OF E-SCOOTER CRASHES WITH NATURALISTIC DRIVING DATA

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Paper Number 23-0143

ABSTRACT

Recently, e-scooter-involved crashes have increased significantly but little information is available about the behaviors of on-road e-scooter riders. Most existing e-scooter crash research was based on retrospectively descriptive media reports, emergency room patient records, and crash reports. This paper presents a naturalistic driving study with a focus on e-scooter and vehicle encounters. The goal is to quantitatively measure the behaviors of e-scooter riders in different encounters to help facilitate crash scenario modeling, baseline behavior modeling, and the potential future development of in-vehicle mitigation algorithms. The data was collected using an instrumented vehicle and an e-scooter rider wearable system, respectively. A three-step data analysis process is developed. First, semi-automatic data labeling extracts e-scooter rider images and non-rider human images in similar environments to train an e-scooter-rider classifier. Then, a multi-step scene reconstruction pipeline generates vehicle and e-scooter trajectories in all encounters. The final step is to model e-scooter rider behaviors and e-scooter-vehicle encounter scenarios. A total of 500 vehicle to e-scooter interactions are analyzed. The variables pertaining to the same are also discussed in this paper.

INTRODUCTION

Background

Electric scooters (e-scooters) have quickly spread in many towns and cities in the U.S. and across many countries in the world as a convenient, cost-effective, and clean mobility option. As early as 2017, 85 cities worldwide adopted e-scooter-sharing systems [1]. Soon after, e-scooter systems were more widely used than bike-sharing systems in the U.S., accounting for 63% of a total of 136 million shared micro-mobility trips in 2019 [2]. As one of the micro-mobility options, the primary use of e-scooters is to address the first and last mile problem, fill the gap between the rider's home or destination and public transport stops, or complete short trips [3], and replace ride-hailing services (39%) (Uber, Lyft, taxi), walking (33%), biking (12), bus (7%), or driving (7%).

In a survey of 7,000 people conducted by Populus in July 2018, 70% of the respondents had a favorable view of e-scooters. This result complies with a recent study published in January 2021 [3], in which researchers found that 73% of survey respondents would or may use e-scooters. Based on existing studies [3]-[9], potential factors affecting the attitudes toward the acceptance of e-scooters include gender, age, race, education level, income level, perceived hedonic quality, prior experiences of ride-hailing services, and familiarity with e-scooters. While economic benefits, locational benefits, and sustainability are driving e-scooter usage [4], infrastructure, weather, and safety might be the top concerns [3].

Rental e-scooters can usually run at a maximum speed of about 10~20 mph. In general, e-scooters are suggested to be ridden in bike lanes or share the road with cars. However, people may also ride e-scooters on sidewalks. Currently, e-scooters are required to follow all traffic rules, but there are no specified regulations established for this new type of transportation tool. This poses various safety concerns for both e-scooter riders and other road users.

For every 100k e-scooter trips, it is estimated that 20-25 injuries result in emergency room (ER) visits [10][11]. Based on this ratio, there might be around 17,000 – 21,000 ER-level injuries in 2019 nationwide. By summarizing news reports, a reporter found that 29 people worldwide have been killed and reported in e-scooter crashes from the summer of 2018 to the end of 2019, mostly in the U.S. Though most e-scooter crash victims are e-scooter riders, there are two pedestrians (including a 90-year-old woman) and one cyclist killed during the crashes too [12]. 169 e-scooter-involved crashes were identified between 2017 to 2019 from U.S. media reports [13]. However, media reports may not cover all cases and can be biased. According to [14], 65 e-scooter-related injuries at Virginia Beach were documented by emergency services during the research period. However, none of these cases were reported in the media. So, the number of severe e-scooter crashes is likely much more than the listed numbers. Based on a study in an emergency department [15], the researchers found that among the randomly sampled crashes causing the E.R. visits, the e-scooter-related crashes jumped from 0 to 25% among all the vehicle-related injuries from 2018 to 2019, when all other sources like cars, bicycles, and motorbikes remained unchanged. In an earlier study [16], the researchers also found a significant increase (500%) in e-scooter-related E.R. visits for two consecutive years after the launch of e-scooter rental services.

Related Studies

A naturalistic study was conducted to investigate the interaction of e-scooters and the riding environments, like surrounding objects and potholes, via mobile sensing data [17]. The researchers developed a mobile sensing system, including four low-end sensors: (1) GPS, (2) IMU, (3) 2D LiDAR (12m max distance, 5.5 Hz scan frequency), and (4) portable camera. All the sensing data were facing forward. The research used proximity to objects as the measurement of riding circumstances. Instantaneous proximity maps were aggregated for each trip as the riding complexity measurements. Riding complexity, vibration, and velocity were surrogate riding safety metrics. The main goal was to find the relationships between these safety metrics, riding locations, and surface conditions. Due to the data collection and analysis limitations, this research did not focus on risky interactions or e-scooter riders' behaviors. The study was not able to recognize surrounding objects, their movements, and their detailed interactions. In addition, the study did not record the behavior of the e-scooter riders. All data were aggregated to the whole riding duration for a coarse-level data analysis. The hardware also limited the data quality.

Although there has been very limited naturalistic study on e-scooters, there were some studies that were conducted on e-cyclists, mainly in Europe. Using e-bicycles instrumented with GPS, video cameras, IMUs, pedal sensors, and brake force sensors, the study in [18] collected 88 self-reported safety-critical events from 410 total trips (86 hours of data). Then each event was analyzed using video data about the environmental scenario and threats. The results showed that pedestrians (31%), light vehicles (21%), and bicycles (18%) are the main threats to e-cyclists in critical events. By comparing with the baseline data, the only significant factor affecting the existence of critical events is road location. The intersection is associated with more self-reported safety concerns.

Research Objectives and Methodology

Unlike vehicle crashes, there is no standard crash database available so far for e-scooter-related crashes [13]. The study collected detailed quantitative behavior data in a naturalistic riding setting. In addition, the effects of individual differences are also modeled and studied.

To our best knowledge, there has not been any systematic research that focuses on the moving behavior and crash scenarios related to e-scooters for public use in an open-road environment.

This paper will address the following important issues:

- Baseline moving patterns of e-scooters in diverse road environments and locations.
- Interaction of e-scooter riders with vehicles and other road users in different scenarios.
- The common scenarios for crashes or near-misses involving e-scooter riders at different risk levels.

DATA COLLECTION

Data Acquisition Systems

The primary purpose of the data acquisition system is to record real-time vehicle and e-scooter data. A vehicle-based and an e-scooter-based data collection systems were developed for data collection. Three types of sensors were used in vehicle-based and e-Scooter-based data acquisition systems: Cameras for video data, LiDAR for distance and IMU information, and GPS for latitude, longitude, and altitude data. For portability, the e-scooter system uses smaller-sized (and less quality) cameras and a computing platform compared to the vehicle-based system. The data acquisition system in both e-scooter and vehicle-based systems runs on Ubuntu/ROS platform.

Vehicle-based Data Collection System: The vehicle-based data collection system includes six FLIR cameras to cover 360-degree angles, one 64-beam 360-degree Ouster LiDAR, a Reach Emlid GPS, and a desktop computer. The complete system was described in detail a published paper [19]. ***Figure*** 1 shows the vehicle-based data collection system used in this project.

E-scooter-based Data Collection System: There are several constraints while choosing sensors and a data collection device to be mounted on an e-Scooter. Primary considerations are the weight and duration of operation of the system. Since the system is designed to collect data for the surrounding objects, the final system consists of three USB cameras, a 3D LiDAR with integrated IMU, an RTK GPS unit, and an NVIDIA Jetson Tx2 development computer board for data collection. A detailed explanation of the e-scooter-based data collection can be found in [20]. Figure 2 shows the e-scooter-based data collection system in operation.

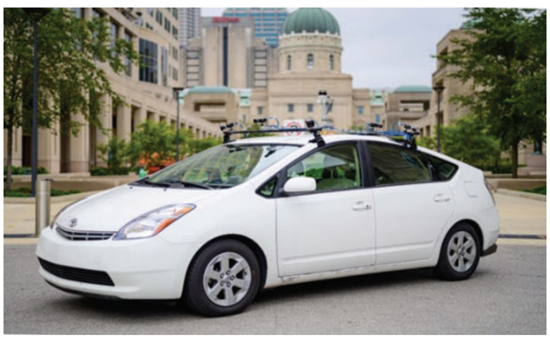


Figure 1. Vehicle-based Data Collection System.

Figure 2. E-scooter-based Data Collection System.

Summary of Data Collected – Vehicle-centered Data Collection

68 data collection sessions were completed, with 55 being external subjects. The data collection was mainly performed in Downtown Indianapolis. However, the subjects were given preferred locations to cover during the drive, and the route taken was up to the subject's discretion. Each session was about 20 – 40 minutes in length. The summary of the data collected is as follows:

1. Total time: 35.24 hours –an average of 31 minutes per session.
2. Total data size: ~7.52 TB of raw data.
3. Total number of frames: ~7.6 million (each frame has 6 camera images, LiDAR point cloud, and GPS).
4. Estimated total number of e-scooters: ~400.

Summary of Data Collected – E-scooter-centered Data Collection

A total of 14 e-scooter-centered data collection sessions were completed. The summary of the data collected is as follows:

1. Total time: 7.5 hours.
2. Total data size: ~1 T.B. of raw data.
3. Total number of frames: ~900,000 million (each frame has 3 camera images, LiDAR point cloud, and GPS).

The estimated nearby cars: >300

DATA PREPROCESSING

Figure 3 illustrates the data preprocessing pipeline used in this project. A brief explanation of the pipeline is below.

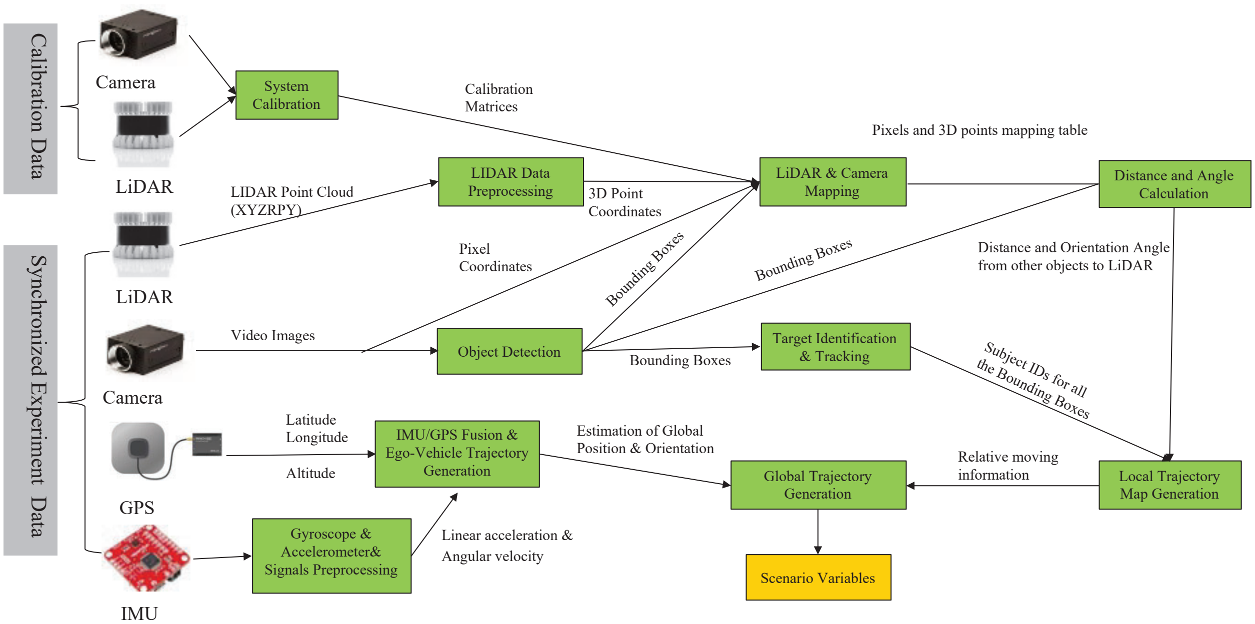


Figure 3. Data Preprocessing Pipeline.

1. LiDAR – Camera calibration. The two main components of the calibration are intrinsic and extrinsic matrices. The intrinsic matrix relies purely on the camera and projects 3D points to 2D pixel coordinates [21]. The extrinsic matrix is determined using the Levenberg-Marquardt algorithm and refined for accuracy using the designed user interface [22]. The complete process of system calibration can be found in [20].

2. Automatic object detection and tracking. The fusion output from the system calibration will be used to detect vehicles and humans. From frame to frame, the same vehicle or human will be recognized and connected to track their appearances through video frames. In addition, the 3D coordinates of each detected and tracked object, with respect to the data collection system location, are assigned at each time frame.

   a. A recent algorithm [23] has been successfully implemented to detect and track objects accurately and reliably. This algorithm uses the strategy to detect and track objects simultaneously, which is optimized for processing continued video data. The computational speed of this algorithm is also reasonable for the project at 6 FPS (frame per second).

   b. To detect e-scooter riders automatically, a computer-vision approach is developed in this project. The e-scooter detector structure is shown in Figure 4. This algorithm uses YOLO v3 [24] as the backbone to detect humans. First, the candidate regions on the video images are selected by enlarging the human bounding boxes from YOLO v3, which are then processed with Google MobileNet V2 [25] to obtain visual embeddings. A classifier based on a deep neural network is then trained to classify these humans and surrounding backgrounds into e-scooter-riders. The training and fine tuning are completed using the IUPUI-CSRC-E-Scooter dataset which is available to the public as a benchmark dataset for e-scooter rider detection via http://escooterdataset.situated-intent.net. The details about the algorithm and the training and evaluation process can be found in [26].

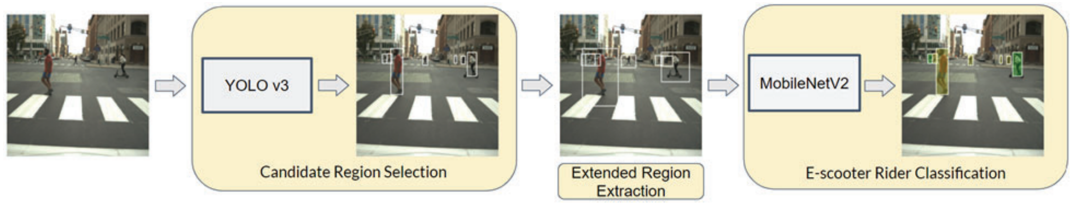


Figure 4. E-scooter Detector.

3. Local trajectory generation. Frame by frame, the relative positions of all the objects in the local coordinate system of the data collection platform are connected, filtered to remove outliers, interpolated to fill in missing data, and smoothened to reduce noise. Eventually, the local trajectories of these objects in the vehicle or e-scooter coordinate systems are generated.

4. The GPS-IMU fusion for ego-vehicle trajectory generation.

5. Global scene reconstruction. The global trajectories of the data collection platform and the local trajectories of all the surrounding objects relative to the data collection platform are fused. The reconstructed scene includes the global trajectories of the ego-car/ego-e-scooter and all the surrounding road users.

DATA ANALYSIS

Process

Cases with a time-to-collision (TTC) are defined as potential conflict cases. TTC indicates the potential crashes at a specific moment if both the ego vehicle and e-scooter maintain the current dynamic state (speed and heading direction). The complete data analysis process is explained in Figure 5.

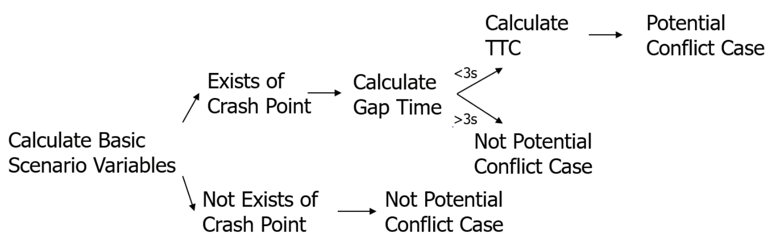


Figure 5. Data Analysis Process.

The minimum distance between the ego vehicle and e-scooter and their median speeds are first calculated. Based on the GPS coordinates of the current and previous points, the speed and heading angle are then calculated. Next, a crash point is determined in an intersection between the two trajectories. Finally, the cases with crash points are calculated for the gap time. A case with fewer than three (3) seconds of gap time is considered as a potential conflict case and used to compute the TTC. After the whole process, all cases are classified into non-potential and potential conflict cases. Moreover, from the vehicle-centric data the number of people wearing a backpack or helmet were also recorded.

Scenario Variables Calculation

<u>Gap Time and Time-to-Collision:</u> Given the E-scooter and vehicle's location, speed, and heading angle, they have potential conflicts if their coast trajectory intersect. If there is an intersection between the two coast trajectories, they must have a gap time, which is the time difference between their arrivals at the intersection. If the time difference between their arrival at the intersection is less than three seconds, it is defined as a possible crash. The definitions of gap time and time-to-collision are illustrated in Figure 6.

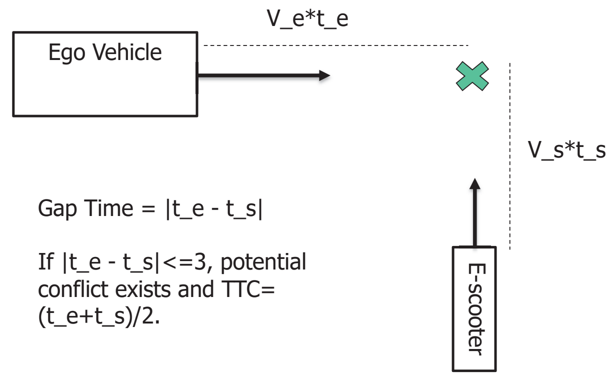


Figure 6 Gap Time and Time-To-Collision Calculation.

A threshold is set to filter out the gap time greater than 20 seconds. The main reason is that such a significant gap time indicates a low crash severity level but could contaminate the average gap time (by increasing it).

Closest Distance: Since we have the synchronized GPS coordinates for both the e-scooter and vehicle from previous preprocessing, we calculate the distance difference between them at each timestamp. The distance difference is then sorted to find the closest difference.

Median Speed: The speed of either the vehicle or the e-scooter is calculated by dividing the distance difference between two consecutive GPS coordinates by the corresponding time difference. This gives the estimated speed for each timestamp. Finally, the median speed is calculated for the whole trajectory. The reason for using median speed over average speed is the ability to remove outliers or noises from compromising the calculation.

RESULTS

Scenario variables were calculated for all cases, potential conflicting cases, and cases in different countering geometries. A total of 182 e-scooter-vehicle encountering cases were analyzed from the e-scooter-centered data.

Vehicle-Centered Data Analysis

A total of 203 vehicle-e-scooter encounter cases were analyzed from the vehicle-centered data. Table 1 shows the scenario variables analyzed from the vehicle-centered data. Some key findings are as below:

1. The average shortest distances are around 15-16m and the minimum distance is around 3m
2. During encounters, the average vehicle speed is about 12mph, while that of an e-scooter is 8.5mph.
3. Some cases highlight the possibility of fatal crashes at high speeds, 30mph and 20mph, respectively for vehicles and e-scooters.
4. The average minimum TTC calculated for all the potential conflict cases is 3.77 seconds, with the minimum TTC of about 1 second. Some of these cases are associated with small proximity and higher risks.
5. The minimum gap time for all cases has an average value of 3.09 seconds. The two entities keep about 10-15m apart when there is a need to cross each other's paths.

Table 1
Scenario Variables for all Vehicle-Centered Cases.

Variables	Average	Minimum	Maximum
Minimum distance (meters)	15.29	3.14	61.82

Ego-vehicle Median Speed (m/s)	5. 3	0	14.61
Ego-vehicle Median Speed (mph)	11.86	0	32.68
E-scooter Median Speed (m/s)	3.79	0	8.99
E-scooter Median Speed (mph)	8.48	0	20.11
Minimum TTC for Potential Conflict Cases (mTTC) (seconds)	3.77	0.96	13.85
Minimum Gap Time (Seconds)	3.09	0.03	16.91

<u>Analysis of Potential-Conflict Cases</u>: Among all the 203 encountering cases analyzed from the vehicle-centered data, 26.1% are potential conflict cases (Figure 7). Figure 8 shows the distribution of the minimum TTC for these cases. We have 10 cases in the range of 0-2 seconds, 28 cases in the range of 2-4 seconds, and the rest is more than 4 seconds.

Figure 9 shows the distribution of these potential conflict cases with the following defined risk levels:

- High risk: mTTC < 1 seconds
- Medium risk: mTTC < 2.5 seconds
- Low risk: mTTC >= 2.5 seconds

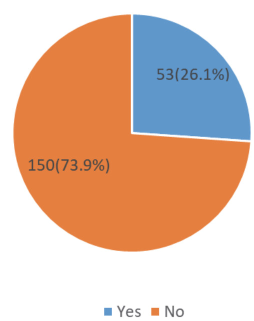


Figure 7 Distributions of Potential Conflict and Non-Potential Conflict cases

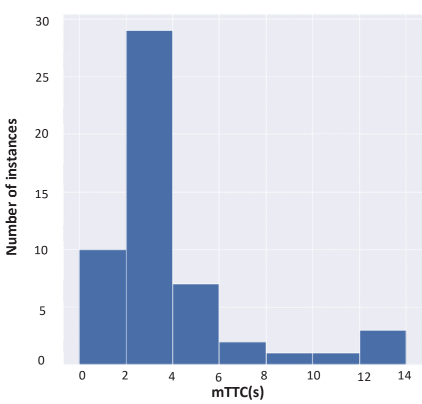


Figure 8 Distribution of mTTC for Potential Conflict Cases

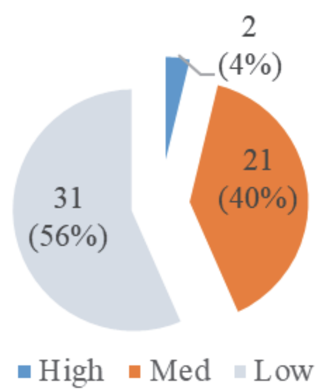


Figure 9 Distribution of Potential Conflict Cases with Different Risk Levels

<u>Comparison Between Baseline and Potential-Conflict Cases:</u> Table 2 compares potential conflict cases and baseline (non-potential conflict) cases in the key scenario variables.

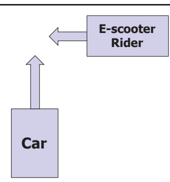
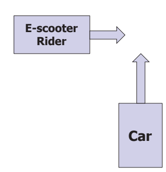
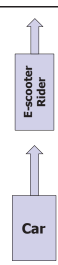
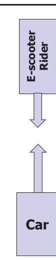
Table 2
Comparison of Scenario Variables for Potential and Baseline Cases

Scenario Variables	Potential Conflict Cases	Baseline Cases
Average Minimum Distance	16.22 m	14.94 m
Average Ego-Vehicle Median Speed	18.25 mph	9.51 mph
Average E-scooter Median Speed	8.43 mph	8.61 mph
Average Minimum Gap Time	0.77 s	5.54 s

The results show that the average minimum distance and the average e-scooter median speed among these two types of cases are similar. The average vehicle speed is much higher in the potential conflict cases at 18.25 mph, compared to 9.51 mph in the baseline cases. Not surprisingly, the average minimum gap time in the potential conflict cases is much shorter than the baseline cases. The potential conflict cases have a higher average minimum distance than the baseline cases. This is because, in baseline cases, the e-scooters riding on sidewalks tend to be near the driving lane and the coast trajectories do not intersect. In potential conflict cases, with some exception, the vehicle driver or the e-scooter rider tend to take necessary actions before their anticipated point of intersection to avoid a crash. The average median speed of the ego-vehicle is also much higher.

<u>Cases in Different Scenarios:</u> Table 3 shows the four encountering geometries analyzed in this project. All the cases are classified into these four geometries. If one case may be classified into multiple geometries, only one geometry is selected based on the main interaction phase. The results are shown in Figure 10. Most cases are parallel cases (about 73%), and the rest 27% are crossing cases, out of which more than half of the encounters (51%) are parallel cases with the same direction, and about 22% are parallel with opposite directions. E-scooter crossing from left cases stands for about 17% of all the cases, and the rest 9% are e-scooter crossing from right cases. Another important observation is that only 2-3% of e-scooter riders wear helmets when riding the e-scooters in the street.

Table 3
Four Geometries for Car and E-scooter Encounters

Crossing Cases	 E-scooter Crossing from Right to Left	 E-scooter Crossing from Left to Right
Parallel Cases	 Same Direction	 Opposite Direction

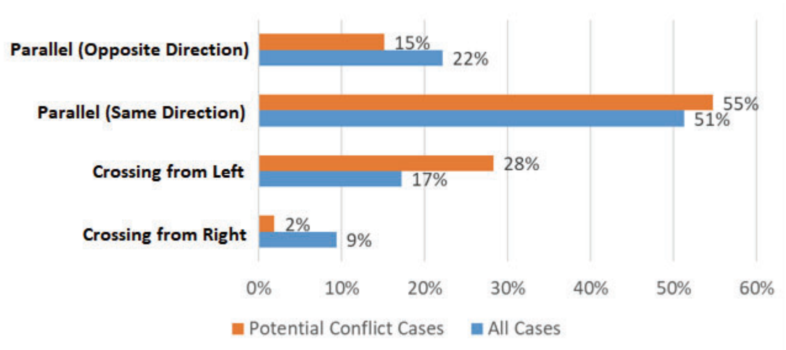


Figure 10. Distribution of Geometry Types for All Cases and Potential Conflict Cases

E-Scooter-Centered Data Analysis

A total of 182 e-scooter-vehicle encountering cases were analyzed from the e-scooter-centered data.

Table 4 shows the scenario variables for the e-scooter-centered data. Some of the key findings are:

1. Compared with the vehicle-centered data, the e-scooter-centered data can capture more cases with closer contact between cars and e-scooter riders.

2. Compared to the vehicle-centered data, the e-scooter-centered cases have higher speeds for both e-scooters and cars. This may be because most e-scooter-centered cases are collected at mid-block road locations, while many vehicle-centered cases happen at intersections.

3. The average minimum TTC calculated for all the potential conflict cases is 3.99 seconds, with the minimum TTC of about 1 second. All these numbers are like the numbers in the vehicle-centered analysis.

4. The minimum gap time for all cases has an average value of 2.26 seconds. This can illustrate the average time differences among vehicles and e-scooter riders to pass the common zones from the e-scooter-centered data.

Table 4

Scenario variables for all e-scooter-centered cases in comparison to vehicle-centered data.

	E-scooter-centered data			**Vehicle-centered data**		
Scenario Variables	Average	Minimum	Maximum	Average	Minimum	Maximum
Minimum Distance (meters)	7.27	2.35	21.68	15.29	3.14	61.82
Ego-vehicle Median Speed (m/s)	6.1	0	18.4	5. 3	0	14.61
Ego-vehicle Median Speed (mph)	13.65	0	41.16	11.86	0	32.68
E-scooter Median Speed (m/s)	4.8	0	10.60	3.79	0	8.99
E-scooter Median Speed (mph)	10.74	0	23.71	8.48	0	20.11
mTTC (seconds)	3.99	1.05	12.51	3.77	0.96	13.85
Minimum Gap Time (Seconds)	2.26	0.01	12.76	3.09	0.03	16.91

Analysis of Potential-Conflict Cases: Among all the 182 encountering cases analyzed from the e-scooter-centered data, 45.1% of them are potential conflict cases (Figure 11). Figure 12 shows the distribution of the minimum TTC for these cases. The minimum distance is considerably different between the vehicle-centric and e-scooter-centric data, with the e-scooter-based distance being significantly less than the vehicle-based distance. During the e-scooter-centric data collection, the subjects were advised to follow e-scooter riding rules in Indianapolis, which is to ride on the street, alongside other motorized vehicles (avoiding sidewalks wherever possible). During the vehicle-centric data collection, it was noticed that majority of e-scooter were ridden on the sidewalks. This explains why the minimum distance between the two is noticeably different.

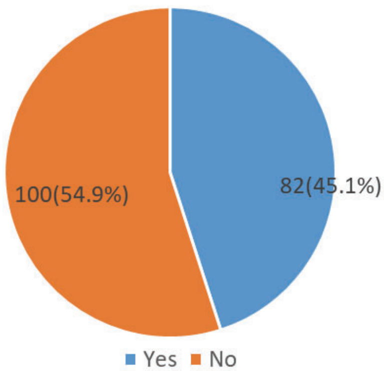


Figure 11. Distributions of Potential Conflict and Non-Potential Conflict cases

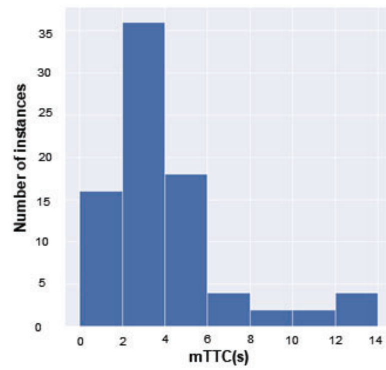


Figure 12. Distribution of mTTC for Potential Conflict Cases in E-scooter-centered Data

Comparison Between Baseline and Potential-Conflict Cases: Table 5 shows the comparison between potential conflict cases and baseline (non-potential conflict) cases e-scooter-centered data. One difference from the vehicle-centered data is that the average vehicle speed is comparable between potential-conflict and non-potential-conflict cases. The average e-scooter median speed is higher in potential conflict cases. This explains the difference in average minimum distance.

Table 5
Comparison of scenario variables between potential-conflict and baseline cases in the e-scooter-centered data

	Potential Conflict Cases	**Baseline Cases**
Average Minimum Distance	7.67 m	6.95 m
Average Ego-Vehicle Median Speed	13.60 mph	13.65 mph
Average E-scooter Median Speed	11.63 mph	10.07 mph
Average Minimum Gap Time	0.84 s	3.97 s

Cases in Different Scenarios: The results for the different geometries are shown in Figure 13. For e-scooter-centered data, most of them are parallel cases (about 75%), and the rest of them (25%) are crossing cases. More than half of the encounters (52%) are parallel cases with the same direction, and about 23% are parallel with opposite directions. E-scooter crossing from left side stand for about 9% of all the cases, and the rest 16% are e-scooter crossing from right side. These findings are quite similar as the results from the vehicle-centered data analysis. The only difference is that there are more crossing-from-right cases than crossing-from-left cases in the e-scooter-centered dataset.

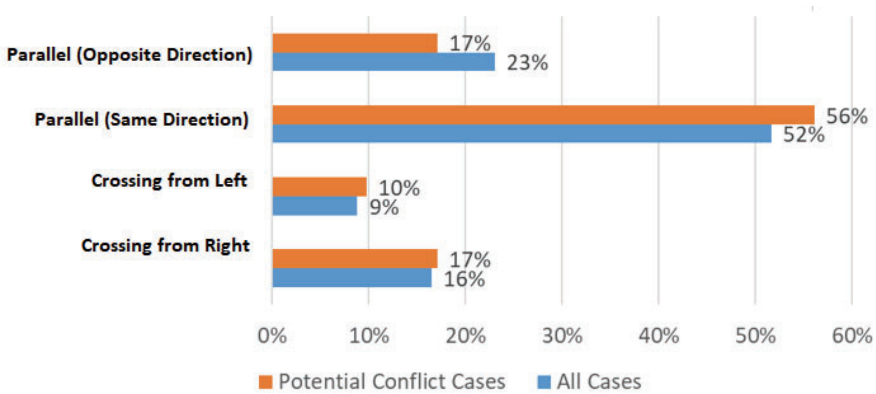


Figure 13. Distribution of Geometry Types for All Cases and Potential Conflict Cases

CONCLUSIONS

In this work, two data acquisition systems were developed to collect naturalistic data for vehicle-e-scooter-rider interactions. After carefully designing the routes and areas for vehicle-centered and e-scooter-centered data collection activities in the Indianapolis downtown area and IUPUI campus, 55 subjects with diverse demographic backgrounds were recruited to participate in the data collection experiments. 68 vehicle-centered data collection sessions and 14 e-scooter-centered data collection sessions were completed. To process the large-scale data collection, an efficient data preprocessing pipeline was developed. A state-of-the-art algorithm was adopted to detect and track vehicles and humans from the collected video data. Furthermore, a computer-vision approach was developed with a new benchmark dataset to detect e-scooter riders efficiently and automatically.

The study has shown the behavior metrics of e-scooter riders in different vehicle-e-scooter interactions. E-scooter rider detection benchmark dataset and classifier are also released publicly. The results of this study will help to fill the gap in quantitative empirical data about e-scooter rider behaviors, which can potentially support the development and testing of vehicle-e-scooter collision avoidance mitigation systems. In the follow up effort, the results can be further integrated with crash data to better model e-scooter crash risks and guide the training of e-scooter behavior prediction algorithms with more labels to the dataset.

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ESTIMATING THE CONTRIBUTIONS OF AUTOMATIC EMERGENCY BRAKING AND LANE SUPPORT SYSTEMS TO ACHIEVING VISION ZERO

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Paper No. 23-0146

ABSTRACT

Vision Zero is an approach to transportation safety that aims to eliminate all traffic-related fatalities and lifelong injuries. A common strategy to achieving Vision Zero is the safe system approach, which employs a multitude of transportation-related branches to create a safe system for all road users. The design and implementation of advanced driver assist systems (ADAS) is one way to contribute to Vision Zero. This study used real-world nationally representative crash data from the Crash Investigation Sampling System to estimate the contributions of two ADAS to achieving Vision Zero in the United States: an advanced automatic emergency braking system (A-AEB) and lane support systems (LSS). It was assumed A-AEB has crash avoidance capabilities for rear-end crashes, left turn across path opposite direction and lateral direction crashes, and straight crossing path crashes, as well as injury mitigation capabilities due to prevented crashes as well as due to delta-v reduction due to system-induced braking. It was assumed LSS has crash avoidance capabilities for head-on crashes, road departure crashes, and opposite direction sideswipe crashes. The combined contributions were estimated to prevent a cumulative 7,054,894 crashes and 869,456 moderate to fatal injuries by 2050. Despite this, over 125,000 moderate to fatal injuries are still estimated to occur each year, and the total number of crashes is not expected to decline. This emphasizes the need for continuous future contributions from all branches of transportation if the US is to someday achieve Vision Zero.

INTRODUCTION

Vision Zero

Vision Zero, officially adopted by the United States (US) Department of Transportation in 2022, is an approach to road safety that aims to eliminate all traffic-induced fatalities and lifelong injuries [1][2]. To achieve Vision Zero, a common strategy is the safe system approach, which considers the limitations and capabilities of human drivers [3]. Many factors contribute to achieving a safe system, including but not limited to: vehicle design, road design, traffic-related laws, and regulatory standards. One approach to Vision Zero is the development of advanced driver assist systems (ADAS), that are designed to assist drivers in performing normal driving and evasive maneuver actions.

Advanced Driver Assist Systems

ADAS are one way vehicle safety is improving to help achieve a safe system. ADAS are vehicle-mounted systems designed to aid the driver in performing driving tasks and reduce the occurrence and severity of crashes [4]. One example of an ADAS is automatic emergency braking (AEB) which uses forward-facing sensors to prevent and mitigate frontal crashes [5]. Similarly, lane support systems (LSS) systems are designed to assist drivers in staying within the lane boundaries. One LSS system, lane departure warning (LDW) uses a combination of auditory, visual, and haptic warnings to alert the drive they are encroaching upon the lane boundary and need to make a corrective maneuver [5]. A second LSS system, lane keep assistance (LKA) is an active safety system that makes minor steering adjustments, without driver input, to correct the vehicle's trajectory to prevent the vehicle from departing the lane boundaries [5]. Like LDW, LKA may also provide a combination of warnings to alert the drive the vehicle is encroaching upon lane boundaries. Additionally, some LKA systems assist the vehicle in remaining centered within the lane. AEB, LDW, and LKA all have the ability to help avoid crashes, while AEB and LDW have the additional ability to mitigate the severity of a crash by assisting or encouraging the driver to make corrective maneuvers.

Previous Work

Previous research has shown AEB [6]–[9] to be a very effective system in terms of crash prevention, such that several manufacturers have voluntarily committed to standardizing AEB on their vehicles by 2022 [10]. In addition to investigating the effectiveness of current AEB systems, some work has investigated the potential effectiveness of a future advanced AEB (A-AEB) system: an intersection advanced driver assist system (I-ADAS), equipped with AEB capabilities [11]–[13]. Similar to assessing AEB and A-AEB effectiveness, various approaches have been taken to assess the effectiveness of LSS [6], [14], [15]. To successfully achieve Vision Zero, it is necessary to understand the combined effect of AEB and LSS in not only crash prevention, but also in injury mitiation. Some of the aforementioned studies have estimated injury mitigation effectiveness of these systems using the KABCO scale [6][7]. The KABCO scale is a five-level injury scale developed by the Federal Highways Administration (FHWA) and is used by law enforcement to record injuries for persons involved in vehicle crashes [16]. Other studies used the abbreviated injury scale (AIS) to estimate injury mitigation effectiveness for AEB in various crash modes [9], [11]–[13]. The abbreviated injury scale (AIS) is a medically relevant scale designed by medical professionals that divides injuries into six levels [17]. Due to the medical relevance and the detail used to assign AIS scores, it is a more reliable injury scale than KABCO [18].

Automatic Emergency Braking Bareiss et al. [13] investigated the crash avoidance and injury mitigation effectiveness of an A-AEB system in left turn across path opposite direction (LTAP/OD) crashes. Injury mitigation effectiveness was estimated for occupants who sustained a serious injury: a maximum AIS (MAIS) score of 3 or greater, including fatalities (MAIS3+F). However, it is possible for permanent medical impairment to occur at the moderate injury level (MAIS2+F) [19], [20], so it is critical to investigate the ability of systems to mitigate MAIS2+F injuries to achieve Vision Zero. In a separate study, Bareiss et al. [12] assessed the crash avoidance and MAIS2+F injury mitigation effectiveness of an A-AEB system in straight crossing path (SCP) crashes. Prior to Bareiss et al.'s [12] study, Scanlon et al. [11] reported crash and MAIS3+F injury effectiveness values for an A-AEB system in SCP and left turn across path lateral direction (LTAP/LD) crashes. Two studies, one by Cicchino [7] and one by Kusano and Gabler [9] reported crash and injury effectiveness values for a traditional AEB system in rear-end crashes. Cicchino's study used the KABCO scale to assess occupant injury, while Kusano and Gabler assessed injury mitigation at the MAIS2+F level. Finally, like Cicchino, a study by Jermakian looked at crash and injury mitigation effectiveness of AEB using the KABCO scale [6].

Lane Support Systems Braking Dean and Riexinger [14] investigated both LKA and LDW real-world crash avoidance effectiveness but did not investigate injury mitigation effectiveness associated with the systems. Similarly, Riexinger et al. [15] investigated LKA crash avoidance capabilities but did not investigate injury mitigation effectiveness. Finally, Jermakian [6] investigated LKA crash avoidance effectiveness as well as injury mitigation effectiveness using the KABCO scale. Two additional studies, like Dean and Riexinger [14], investigated LDW crash avoidance effectiveness but did not investigate injury mitigation effectiveness: Holmes et al. [21] and Cicchino [22]. The study by Dean and Riexinger [14] investigated LKA and LDW effectiveness using the quasi-induced exposure method to obtain retrospective real-world effectiveness values. This method was similar to Jermakian's [6] study, as both used nationally representative data to form target populations and assess system relevance in various crash configurations. The work by Riexinger et al. [15] and Holmes et al. [21] employed a different method, using vehicle trajectory data to simulate crash scenarios with and without system intervention.

Table 1.
Crash and injury prevention effectiveness values for AEB and LSS computed in previous studies.

Safety System	Configuration	Effectivness	
		Crash	**Injury**
Automatic Emergency Braking			
AEB	Rear-End and Single Vehicle	20% [6]	9% (AB) 2% (F) [6]
	Rear-End	50% [7]	56% (KABC) [7]
	Rear-End	7.7% [9]	50% (2+F) [9]
A-AEB	SCP, LTAP/LD	25%-59% [11]	38%-79% (3+F) [11]
	SCP (one vehicle equipped)	57% [12]	75% (2+F) [12]
	SCP (both vehicles equipped)	63% [12]	85% (2+F) [12]
	LTAP/OD (one vehicle equipped)	18%-73% [13]	47%-86% (2+F) [13]
	LTAP/OD (both vehicles equipped)	36%-84% [13]	65%-93% (2+F) [13]
Lane Support Systems			
LKA	ROR, HO, SS (opposite and same direction)	3% [6]	5% (AB) 23% (F) [6]
	ROR, HO, SS (opposite direction)	60% ± 16% [14]	--
	ROR	51.1% [15]	--
LDW	ROR, HO, SS (opposite direction)	3% ± 33% [14]	--
	ROR	17.3%-37.3% [15]	--
	ROR, HO, SS	11% [22]	--
	Cross-centerline	22% [21]	--

Objective

The objective of this study was to use real-world crash data and two previously developed injury prediction models to estimate the potential contribution of A-AEB and LSS crash reduction and MAIS2+F injury mitigation capabilities to achieving Vision Zero in the US. The A-AEB system is assumed to function in both traditional AEB scenarios, such as rear-end collisions, and in intersection crash configurations, such as LTAP/OD crashes.

METHODS

Data Sources

In-depth, nationally representative, real-word crash data was selected from the Crash Investigation Sampling System (CISS) case year 2020. CISS is a probability sample of all US tow-away passenger vehicle crashes and records in-depth occupant and vehicle information that was necessary for this analysis, e.g., occupant age, occupant injury outcomes using the 2015 AIS, location of vehicle damage, and vehicle delta-v [23]. Delta-v in CISS is estimated using WinSmash, the crash reconstruction software developed by the National Highway Traffic Safety Administration [24]. To be nationally representative, cases in CISS are assigned weight values that can be used to estimate the national incidence of crashes. These weighted values were used in this analysis. The 2015 AIS is used to code injuries in CISS and was used in this study to define occupant injury severity [17].

Target Population

Distinct target populations were selected for the A-AEB and LSS analyses (Table 2). For both analysis datasets, only drivers and right-front passengers at least 13 years old [25] in tracking passenger vehicles were included. Vehicles needed to be tracking prior to the crash to be included in the analysis because it was assumed ADAS and/or the driver would not be able to regain control of a non-tracking vehicle. Additionally, vehicles were only included if the vehicle did not rollover, and occupants were only included if the occupant was not ejected. This is because the injury prediction models used to estimate A-AEB and LSS injury mitigation effectiveness were not trained to be able to predict injuries for ejected occupants and occupants in vehicles that rolled over. Additionally, the total delta-v of the vehicle must have been recorded in CISS for the vehicle to be included in the analysis, as this value is necessary to run the injury prediction models. Finally, cases with a weight value of 5,000 or greater were removed from the analysis so that a few cases with large weight values would not dictate the results for the subset of cases used in this study. While this is not typical practice for data selection within the CISS database, the injury prediction model was trained on NASS/CDS for which this was a common step [26]. If multiple occupants were in one vehicle, the vehicle was only counted once in the crash prevention analysis while every occupant was included in the injury mitigation analysis.

Automatic Emergency Braking Four two-vehicle A-AEB-applicable crash configurations were analyzed in this study: rear-end crashes, left turn across path opposite direction and lateral direction (LTAP/OD and LTAP/LD, respectively) crashes, and straight crossing path (SCP) crashes. These four crash configurations typically comprise the majority of front row occupant multi-vehicle crashes. In 2019, they comprised 75% of all front row occupants involved in multi-vehicle crashes. The front-striking vehicle in rear-end crashes was considered for analysis, as it was assumed an A-AEB system would not apply to vehicle being struck in this configuration. For the LTAP/OD, LTAP/LD, and SCP crash configurations, both vehicles were considered for analysis. This is because there is a potential increase in system effectiveness if both vehicles in these configurations are equipped with A-AEB [12], [13]. For an occupant to be included in the injury mitigation analysis, occupant belt status and age must have been known if the general area of damage was at the front of the vehicle. Occupant belt status only must have been known if the general area of damage was at the side of the vehicle. This is because belt status and age are significant predictors in the frontal and side crash injury prediction models used to estimate injury mitigation effectiveness.

Lane Departure Prevention Three LSS-applicable crash configurations were analyzed in this study: right and left side road departure (RD) crashes, head-on (HO) crashes, and opposite direction sideswipe (OD/SS) crashes. These crash modes were chosen for analysis because it is assumed the driver did not intend to leave their lane of travel. Same direction sideswipe crashes were excluded, as this crash scenario may present overlap between LSS and blind spot monitoring systems. The location of the damage on these vehicles was not restricted, since the LSS sensors are not responsible for detecting potential collision partners. No specific occupant information was required to be available for the LSS target population cases. This is because LSS does not have crash severity mitigation capabilities, and so an injury prediction model was not used on this population to determine injury mitigation effectiveness.

Table 2.
Case selection criteria for the analysis.

Inclusion Criteria	**Remaining Occupants**	
	A-AEB	**LSS**
CISS 2020 passenger vehicles towed for damage	3,432,288	
Drivers and right-front passengers	3,080,597	
At least 13 years old	3,062,195	
Vehicle tracking before crash	2,576,554	
Vehicle did not rollover	2,445,529	
Occupant was not ejected	2,442,182	
Relevant crash type	992,025	295,990
Two-vehicle crash	860,252	--
Recorded DV	608,852	93,551
Weight < 5,000	410,710	75,061
Unique vehicles within occupant population	345,004	60,487
Crash Analysis Dataset	**345,004**	**60,487**
Known occupant predictor variables	293,500	56,572
Occupant Analysis Dataset	**293,500**	**56,572**

Estimating Crash Prevention

The residual number of target population crashes for a given year ($RTP_{Y,C}$), after system intervention, was considered to be a function of vehicle miles travelled (VMT), system crash prevention effectiveness (E_p), and system market penetration (MP) (Eq. 1). In 2020, traditional AEB and LSS both had a non-zero market penetration, so the number of actual crashes was lower than the number of hypothetical crashes that would have occurred with no AEB or LSS intervention. To adjust for this, the hypothetical number of crashes in 2020 was included in the denominator of the estimated residual target population calculation (Eq. 1). $RTP_{Y,C}$ was computed once for each crash configuration, using independent system effectiveness values and TP_{2020} values. The sum of the $RTP_{Y,C}$ values for each configuration represented the total residual crash population.

$$\mathrm{RTP}_{\mathrm{Y,C}} = \frac{\mathrm{TP}_{\mathrm{Y}}(1 - \mathrm{E}_{\mathrm{P}} * \mathrm{MP}_{\mathrm{Y}})}{(1 - \mathrm{E}_{\mathrm{P}} * \mathrm{MP}_{20})} \#(1)$$

$$\mathrm{TP}_{\mathrm{Y}} = \mathrm{TP}_{2020} * 1.0101^{\mathrm{Y}-2020} \#(2)$$

It was assumed VMT increases 1.01% annually and therefore the number of target population crashes (TP_Y) increases 1.01% annually (Eq. 2) [27]. Predicted AEB and LSS market penetration was obtained from the IIHS-HLDI 2020 annual report that outlines predicted availability and prevalence of safety systems within the US vehicle fleet [10]. IIHS-HLDI's definition of LSS includes both warning systems (LDW) and lane keeping systems (LKA). It is expected that AEB will reach 50% and 95% market penetration by 2029 and 2046, respectively. LSS is expected to reach 50% and 95% market penetration by 2028 and 2045, respectively. A-AEB and LSS crash prevention effectiveness values (E_P) from previous studies were used (Table 3). Crash avoidance effectiveness was assessed separately for LDW and LKA. When confidence intervals were presented for an effectiveness value, the average effectiveness was implemented in the study.

Table 3.
Crash avoidance effectiveness values for A-AEB and LSS computed in previous studies used for this analysis.

System	Configuration	Crash Avoidance Effectiveness (E_P)
A-AEB	Rear-End	0.50 [7]
	SCP+LTAP/LD (one vehicle equipped)	0.57 [12]
	SCP+LTAP/LD (both vehicles equipped)	0.63 [12]
	LTAP/OD (one vehicle equipped)	0.45 [13]
	LTAP/OD (both vehicles equipped)	0.60 [13]
LKA	Head-on, road departure, opposite direction sideswipe	0.60 [14]
LDW	Head-on, road departure, opposite direction sideswipe	0.03 [14]

The number of A-AEB and LSS target population crashes in 2020 were used to compute the future residual crash population for each crash configuration (Table 4). When computing $RTP_{Y,C}$ for the LTAP/OD, LTAP/LD, and SCP crash modes, the possibility of both vehicles being equipped with A-AEB needed to be considered. The probability of one vehicle being equipped with AEB is expressed in Eq. 3. The probability of both vehicles being equipped with A-AEB is expressed in Eq. 4. The addition of both probabilities (Eq. 5) was substituted for the E_P*MP term when computing $RTP_{Y,C}$ for the specified crash configurations (Eq. 6).

$$\mathrm{P(1\ Vehicle\ Equipped)} = 2 * (\mathrm{MP})(1 - \mathrm{MP})\left(\mathrm{E_{p,one}}\right)\#(3)$$

$$\mathrm{P(2\ Vehicles\ Equipped)} = (\mathrm{MP})^2\left(\mathrm{E_{p,two}}\right)\#(4)$$

$$\mathrm{P(1) + P(2)} = 2 * (\mathrm{MP} - \mathrm{MP}^2)\left(\mathrm{E_{p,one}}\right) + (\mathrm{MP})^2\left(\mathrm{E_{p,two}}\right)\#(5)$$

$$\mathrm{RTP_{Y,C}} = \frac{\mathrm{TP_Y}\left(1 - \left(2 * (\mathrm{MP_Y} - \mathrm{MP_Y^2})\left(\mathrm{E_{p,one}}\right) + (\mathrm{MP_Y})^2\left(\mathrm{E_{p,two}}\right)\right)\right)}{\left(1 - \left(2 * (\mathrm{MP_{2020}} - \mathrm{MP_{2020}^2})\left(\mathrm{E_{p,one}}\right) + (\mathrm{MP_{2020}})^2\left(\mathrm{E_{p,two}}\right)\right)\right)}\#(6)$$

Table 4.
Number of A-AEB- and LSS-applicable crashes and MAIS2+F injuries in 2020.

System	Crash Type	2020 Crashes	2020 MAIS2+F Injuries
A-AEB	Rear-End	84,213	2,353
	SCP	78,749	3,196
	LTAP/OD (one vehicle equipped) LTAP/OD (both vehicles equipped)	132,034	4,944
	LTAP/LD	50,008	1,333
	AEB Total	**345,004**	**11,826**
LSS	Head-On	11,760	3,060
	Left Road Departure	18,062	4,531
	Right Road Departure	28,788	9,824
	Opposite Direction Sideswipe	1,877	1,062
	LSS Total	**60,486**	**18,477**
Both	**Total**	**405,490**	**30,303**

Estimating Injury Mitigation

Both A-AEB and LSS are capable of reducing the occurrence of injuries by avoiding potential collisions. To estimate the number of residual MAIS2+F injuries after accounting for crash avoidance effectiveness, the crash avoidance effectiveness values computed in previous studies (Table 3) were used alongside the number of target population MAIS2+F injuries in 2020 (Table 4) to compute a residual number of MAIS2+F injuries for each crash configuration (Eq. 7).

$$\mathrm{RTP}_{\mathrm{Y,I}} = \frac{\mathrm{TP}_{\mathrm{Y}}(1 - \mathrm{E}_{\mathrm{P}} * \mathrm{MP}_{\mathrm{Y}})}{(1 - \mathrm{E}_{\mathrm{P}} * \mathrm{MP}_{20})} \#(7)$$

In addition to injury mitigation due to crash avoidance, A-AEB has the ability to reduce the severity of a crash by reducing the vehicle's maximum delta-v. This in turn has the potential to reduce the maximum injury severity sustained by an occupant. To estimate the number of MAIS2+F injuries after accounting for both A-AEB crash avoidance and crash severity reduction, an injury mitigation effectiveness (E_M) value needed to be computed. An MAIS2+F injury mitigation effectiveness value (E_M) for A-AEB was computed for this study using two logistic regression (Eq. 8) crash injury prediction models previously developed by the authors: one for frontal crashes (Eq. 9) and one for side crashes (E. 10). The models were trained using real-world crash data from the National Automotive Sampling System Crashworthiness Data System (NASS/CDS), the predecessor database to CISS [28]. The frontal model uses maximum delta-v, occupant belt status (B), and occupant age (A) to quantify occupant risk. B was set equal to 0 or 1 if the occupant was unbelted or belted, respectively. A was set equal to 0 or 1 if the occupant was less than 65 or at least 65 years old, respectively. The side model uses maximum delta-v, belt status, and side impact type (ST) to quantify occupant risk. ST was set equal to 0 or 1 if the occupant was in a far-side or near-side impact, respectively. A far-side impact was defined as when the primary plane of damage is on the opposite side of the vehicle as where the occupant is seated. A near-side impact was defined as when the occupant is seated on the same side of the vehicle as where the primary damage occurs. Primary damage plane was determined using the CDCPLANE variable in CISS. Occupants in vehicles with frontal damage were evaluated using the frontal model. Occupants in vehicles with side damage were evaluated using the side model. The models were first run on the A-AEB target population occupants using the total delta-v recorded in CISS. Then, the models were run again on the same set of occupants with all the total delta-v values reduced by 34%, as this is the median delta-v reduction due to AEB [9]. The injury mitigation effectiveness was set equal to one minus the ratio of predicted injuries after the delta-v reduction to predicted injuries before the delta-v reduction (Eq. 11). The computed effectiveness value was then used to compute the residual number of A-AEB-applicable MAIS2+F injuries over time ($\mathrm{RTP}_{\mathrm{Y,I}}$) (Eq. 12). The sum of the $\mathrm{RTP}_{\mathrm{Y,I}}$ values for each A-AEB-application crash configuration represented the total residual injury population. LKA and LDW were considered to have injury mitigation capabilities due to crash avoidance only. They were not considered to have injury mitigation capabilities due to crash severity reduction.

$$\mathrm{P(MAIS2 + F)} = \frac{1}{1 + \mathrm{e}^{\mathrm{logit}}} \#(8)$$

$$\mathrm{P(MAIS2 + F)_{Front}} = \frac{1}{1 + \mathrm{e}^{-(-8.44+0.67(\mathrm{Max.DeltaV})-1.81(\mathrm{B})+3.47(\mathrm{A}))\#}} \#(9)$$

$$\mathrm{P(MAIS2 + F)_{Side}} = \frac{1}{1 + \mathrm{e}^{-2.95+0.39(\mathrm{Max.DeltaV})-2.60(\mathrm{B})+1.63(\mathrm{ST})\#}} \#(10)$$

$$\mathrm{E_M} = 1 - \left(\frac{\text{Predicted After MDV Reduction}}{\text{Predicted Before MDV Reduction}}\right) \#(11)$$

$$\mathrm{RTP}_{\mathrm{Y,I}} = \frac{\mathrm{TP}_{\mathrm{Y}}(1 - \mathrm{E}_{\mathrm{P}} * \mathrm{MP}_{\mathrm{Y}})(1 - \mathrm{E}_{\mathrm{M}} * \mathrm{MP}_{\mathrm{Y}})}{(1 - \mathrm{E}_{\mathrm{P}} * \mathrm{MP}_{20})(1 - \mathrm{E}_{\mathrm{M}} * \mathrm{MP}_{20})} \#(12)$$

RESULTS

Crash Prevention

The estimated number of A-AEB-applicable crashes with and without A-AEB intervention was plotted over time from 2020 to 2055 (Figure 1). The estimated number of LSS-applicable crashes with and without LSS intervention was plotted for the same range of years (Figure 2). The LSS plot depicts residual crashes after LDW and LKA intervention independently. Black vertical lines indicate when the system is expected to reach 95% market penetration. Since the A-AEB target population was much larger than the LSS target population, A-AEB is projected to prevent over 200,000 crashes in some years, while the maximum annual crash prevention due to LSS is approximately 40,000 crashes. While A-AEB and LKA had significant crash avoidance effects within their target population crashes, LDW had little to no crash avoidance effect. When looking at the combined effect of LKA and A-AEB on the total crash population, the scale of their contribution is much smaller than when looking at the system-applicable target populations (Figure 3). Their combined effect does not result in a decrease in the number of annual crashes for any of the projected years.

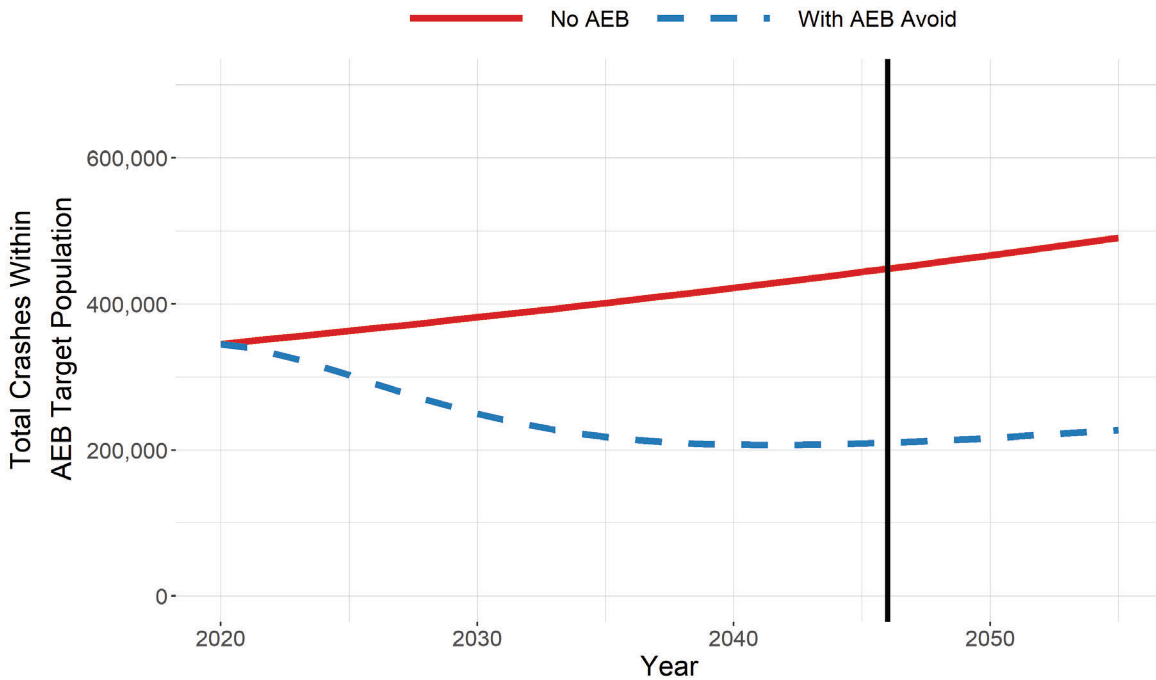

Figure 1. Total predicted A-AEB target population crashes over time with and without A-AEB crash avoidance effectiveness.

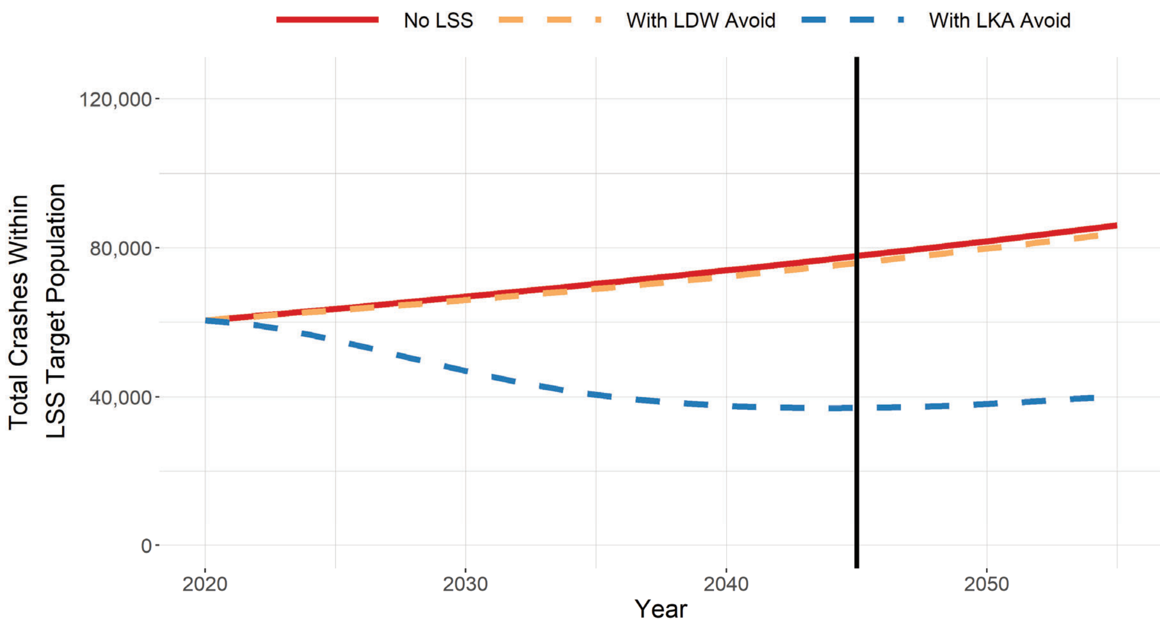

Figure 2. Total predicted LSS target population crashes over time without LSS, with LDW crash avoidance effectiveness, and with LKA crash avoidance effectiveness.

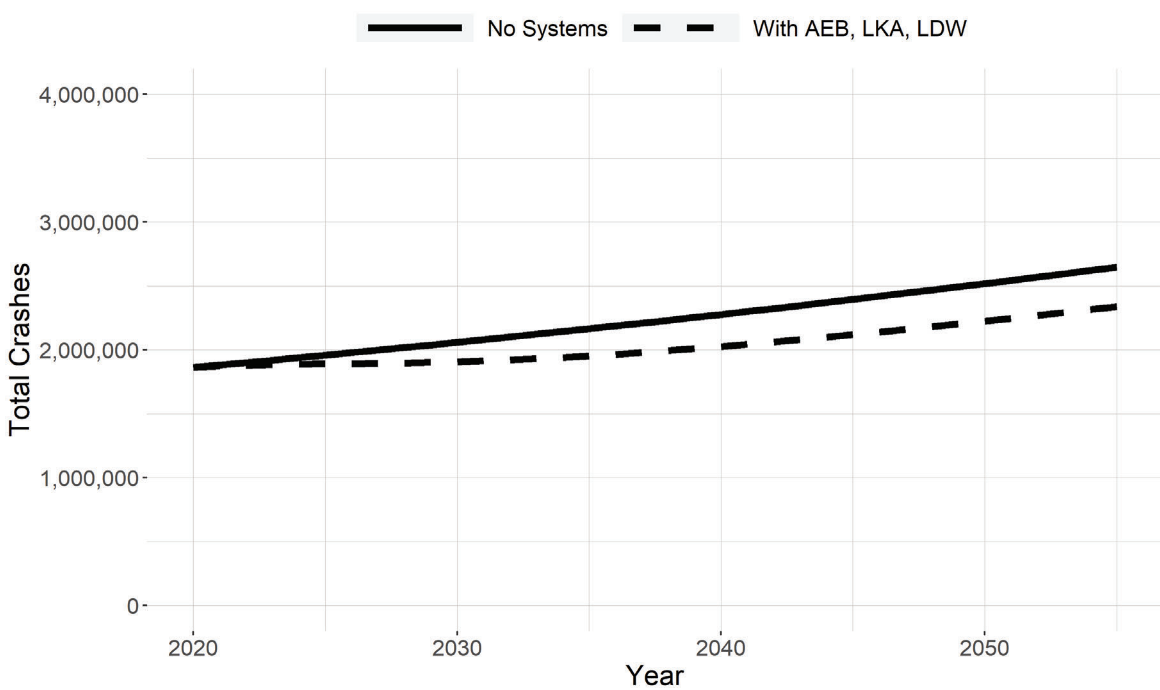

Figure 3. Total number of MAIS2+F injuries over time with and without AEB, LKA, and LDW.

Injury Mitigation

Within the A-AEB occupant target population, there were 15,163 ± 1,831 predicted injuries before the delta-v reduction and 5,802 ± 1,163 predicted injuries after the delta-v reduction (Table 5). The average predicted number of injuries using the recorded delta-v values overpredicted the number of injuries by approximately 3,000. The computed injury mitigation effectiveness was 62% ± 9% and the average effectiveness value, 62%, was used for analysis. The estimated number of A-AEB- (Figure 4) and LSS-applicable (Figure 5) MAIS2+F with and without A-AEB intervention were plotted over time from 2020 to 2055. A black vertical line indicates when the system is expected to reach 95% market penetration. Like seen with the crash avoidance analysis, LDW has little to no effect on injury mitigation, while A-AEB and LKA make significant injury mitigation contributions within their respective target populations. A-AEB is able to mitigate a larger overall number of injuries than LKA due to 1) the A-AEB target population being larger than that of LKA and 2) A-AEB is able to mitigate injuries through both crash avoidance and reducing crash severity. On the other hand, LSS only mitigate injuries via crash avoidance. Given these differences, A-AEB is able to prevent up to approximately 15,000 MAIS2+F injuries in a year, where the maximum number of prevented injuries due to LKA is approximately 13,000. Like seen with the crash avoidance analysis, the combined relative effect of these systems on the overall number of injuries is significantly smaller than the relative effect within the target populations (Figure 6). The total number of annual injuries is expected to remain mostly constant until the year 2040, when the number of injuries will begin to increase again.

Table 5.
Actual and predicted A-AEB-applicable MAIS2+F injuries and the computed A-AEB injury mitigation effectiveness.

Actual MAIS2+F Injuries	Delta-V	Predicted MAIS2+F Injuries	Injury Mitigation Effectiveness	Injury Mitigation Effectiveness Used in Analysis
11,827	Recorded	15,163 ± 1,831	62% ± 9%	0.62
	Reduced	5,802 ± 1,163		

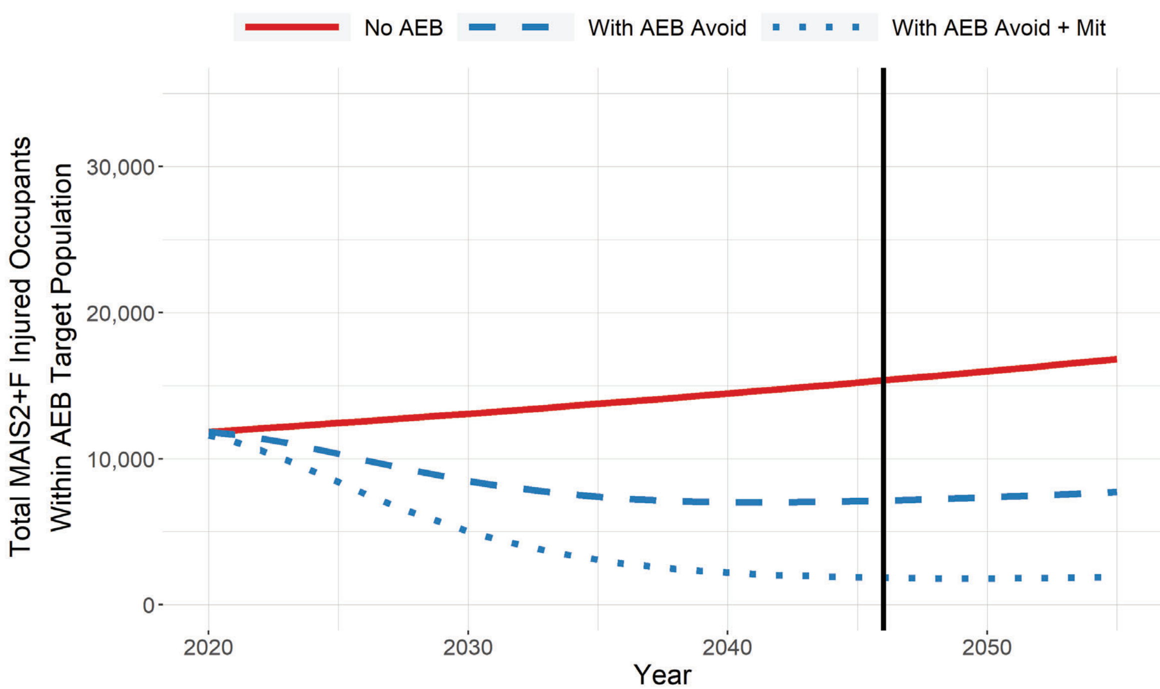

Figure 4. Total predicted AEB target population MAIS2+F injuries over time without A-AEB, with A-AEB injury avoidance effectiveness, and with A-AEB crash avoidance and injury mitigation effectiveness.

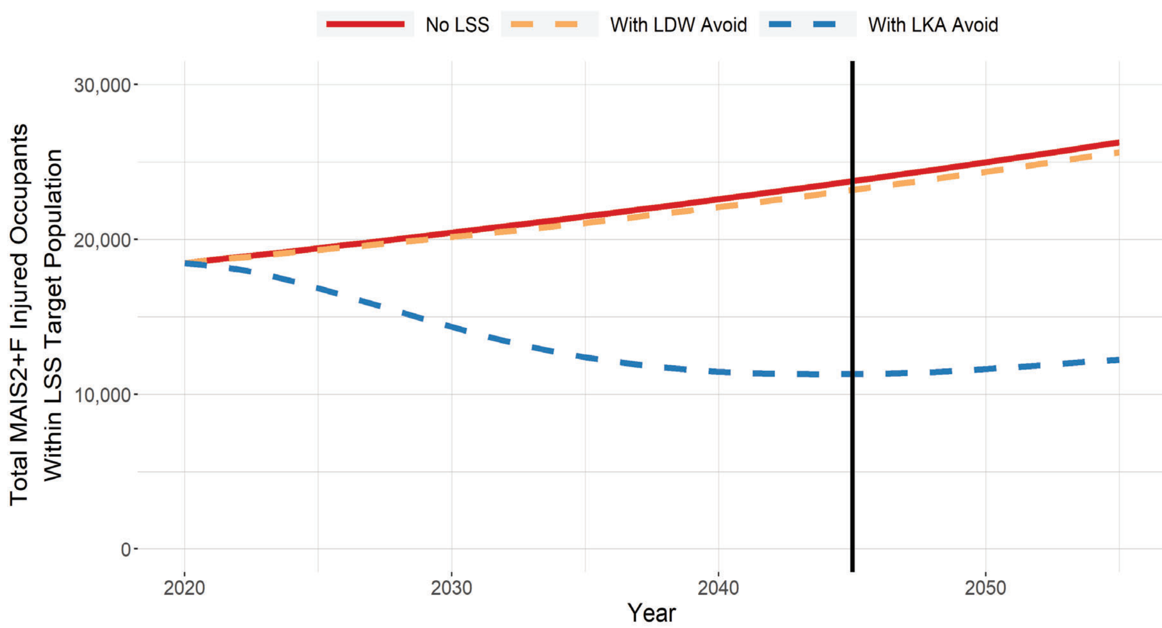

Figure 5. Total predicted LSS target population MAIS2+F injuries over time without LSS, with LDW injury avoidance effectiveness, and with LKA injury avoidance effectiveness.

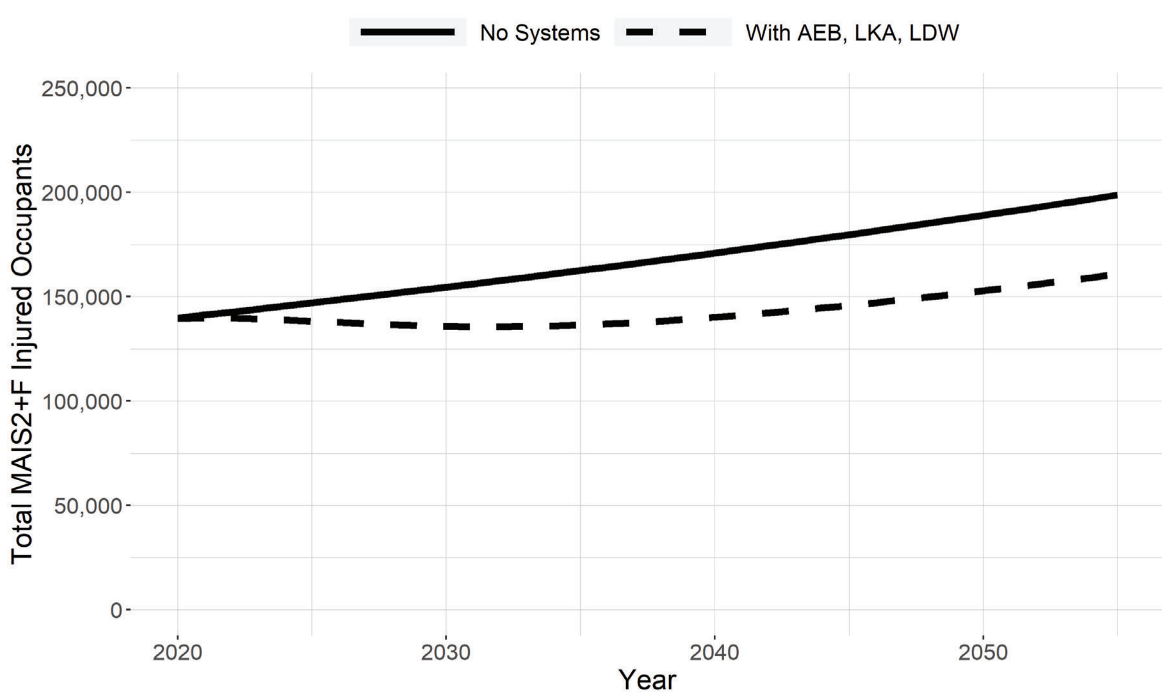

Figure 6. Total number of crashes over time with and without A-AEB, LKA, and LDW.

Overall, the combined effect of A-AEB and LSS are estimated to be able to prevent a cumulative 7,000,000 crashes and 869,000 MAIS2+F injuries by the year 2055 (Table 6).

Table 6. Predicted cumulative crash and MAIS2+F injury reductions due to A-AEB and LSS crash avoidance and injury mitigation effectiveness.

Year	Number Prevented	
	Crashes	MAIS2+F Injuries
2035	1,633,762	202,908
2045	4,121,638	508,438
2055	7,054,894	869,456

DISCUSSION

Due to the assumption that each crash configuration increases in incidence by 1.01% annually, the residual crash and MAIS2+F injury curves will always eventually trend upward again, assuming system effectiveness is less than perfect. Despite this, the number of injuries within the A-AEB target population are projected to level out around 2045 and remain constant until at least 2055. A similar trend is observed for the LKA target population between 2040 and 2050. Despite these significant contributions within each target population, the overall number of MAIS2+F injuries is expected to never dip below 125,000 and is to begin rising steadily again sometime between 2035 and 2040. This emphasizes the need for crash avoidance and injury mitigation strategies outside of just A-AEB and LSS development. Within LSS development, LKA advances and implementation should be prioritized over LDW since real-world LKA effectiveness for both crash avoidance and injury mitigation is significantly higher than that of LDW [14]. This low LDW system effectiveness is largely due to drivers deactiving the system [14], [29].

Additional active safety system development, traffic laws, and vehicle and infrastructure standards and design are all avenues for contribution to the safe system approach to meet the goal of Vision Zero. For example, shoulder, edge line, and center line rumble strips are effective in reducing lane departure crashes [30], [31]. Additionally, setting safe speed limits is one way to mitigate crash severity in all crash configurations and therefore mitigate occupant injury outcomes. Implementing traffic safety cameras, even when not active, has also been an effective method in reducing fatalities and injuries in Sweden, where Vision Zero was first conceptualized [32]. Further, designing roadside infrastructure to handle impact speeds relevant to the set speed limits is a necessary step in improving occupant safety. Currently, roadside hardware is crash tested at a maximum impact speed of 62 mph (100 km/h) [33], despite the maximum speed limit in the US being 85 mph (135 km/h) [34].

Limitations

One limitation of this study is that the A-AEB portion of the analysis assumes an advanced AEB system capable sensing and emergency braking for imminent collisions in typical intersection crash configurations (LTAP/OD, LTAP/LD, and SCP). Therefore, this study assumes that current traditional AEB technology will continue to advanced and merge with I-ADAS system. Additionally, this study uses the total delta-v value recorded in CISS to compute injury mitigation effectiveness. Total delta-v recorded in CISS is computed using WinSmash, NHTSA's crash reconstruction software. WinSmash is known to underpredict delta-v by up to 23% [35] prior to the 2008 version, which increased by only 8.1% for frontal crashes in the 2008 version [36]. The injury prediction model used to estimate injury mitigation effectiveness was trained using delta-v time series data from NASS/CDS vehicle EDRs, which would have been a more accurate representation of the true delta-v. This likely contributes to the model underestimating the actual number of MAIS2+F injuries in the CISS 2020 A-AEB target population. Further, since this analysis uses varying crash avoidance effectiveness values for the A-AEB crash configurations, this analysis assumes the proportions of the crash configurations within the A-AEB target population remains constant over time. Looking at CISS 2017 through CISS 2020 reveals this to be a reasonable assumption (Table 7). The most variation in any of the crash configurations analyzed is in head-on crashes, which comprised a low of 10.0% of the LSS target population crashes in 2019 and a high of 19.4% in 2020. However, since the same effectiveness value is used for all the LSS-applicable crashes, this does not alter the validity of the current results.

Table 7.
Comparison of A-AEB and LSS vehicle crash configuration proportions from CISS 2017 to CISS 2020.

CISS Case Year	A-AEB-Applicable Crash Configurations			LSS-Applicable Crash Configurations		
	Rear-End	**SCP and LTAP/LD**	**LTAP/OD**	**Head-On**	**Road Departure**	**Opposite Direction Sideswipe**
2017	23.9%	42.4%	33.7%	13.6%	81.5%	4.9%
2018	23.6%	41.2%	35.2%	10.6%	85.3%	4.1%
2019	21.5%	41.7%	36.8%	10.0%	85.9%	4.1%
2020	24.4%	39.5%	38.3%	19.4%	77.5%	3.1%

CONCLUSIONS

The crash avoidance and injury mitigation contributions of A-AEB and LSS have the ability to prevent 7,054,894 crashes and 869,456 MAIS2+F injuries by 2050. These are significant contributions within the A-AEB and LSS target populations, but a large number of crashes and injuries will still comprise the overall total residual crash and injury population. Contributions from other branches of the safe system approach will be necessary to achieve Vision Zero, in addition to the constant development and improvement of current and new ADAS.

ACKNOWLEDGEMENTS

The methods used in this study were largely inspired by previous work done by Dr. H. Clay Gabler and Max Bareiss from Virginia Tech, and Rini Sherony and Takashi Hasagawa from Toyota Motor Corporation. Dr. Douglas J. Gabauer assisted the authors in developing the frontal crash injury model used to estimate AEB injury mitigation effectiveness. Thank you to the New Horizon Graduate Scholars program at Virginia Tech for funding my time as a researcher for my final academic year.

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ADAPTIVE DISTANCE CONTROL – ROAD SAFETY POTENTIALS OF AN EXCITING NEW FEATURE IN EXISTING E/E ARCHITECTURE

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Paper Number 23-0169

ABSTRACT

The list of driver assistance features is getting longer and longer. All this assistance raises the question: Will driving still be fun in future? Adaptive cruise control (ACC) as SAE Level 1 system adds safety and comfort to the driver. Per definition, ACC takes over driving tasks and offers limited self-determination in terms of driving experience and enjoyment. On the other hand, Automatic Emergency Braking (AEB) systems are designed to prevent a potential collision at latest. Yet, an AEB system has operational constraints depending on its system capabilities and the type and complexity of the sensors used.

To expand SAE Level 0 safety systems like AEB, Bosch develops the feature Adaptive Distance Control (ADC). It transfers an early and comfortable distance control to self-driving situations. And it adapts to personal driving style to enable a natural driving experience with a comfortable and noticeable safety benefit. Thus, ADC links between ACC and AEB to relax traffic flow and to prevent incidents at an early stage.

The present study evaluates the effectivity of ADC in terms of the above-mentioned safety benefits. It is comprised of a thorough analysis of road traffic observation data (drone data) and the analysis of rear-end collisions involving M1-vehicles on German roads.

In the first part of the study, real-world traffic observation data (highD dataset) from six motorways in North Rhine-Westphalia in Germany was used to determine the time headway (THW) among cars. THW equals the ACC time gap between two vehicles. In the second part, data from the German in-depth accident study (GIDAS) was used to identify the number of relevant crashes which can potentially being positively influenced, i.e., the field of effect (FoE) for ADC.

The analysis of 89,139 passenger car observations reveals that ADC could support 1 out of 12 drivers to keep a THW $\geq$ 0.6s if lane changes are neglected. Furthermore, the FoE for ADC was estimated up to 5.3% of all crashes with casualties in Germany, depending on its system capabilities. This corresponds to about 16,100 addressable collisions annually if each car would be equipped with the ADC feature.

The present study reveals that ADC can prevent crashes. Moreover, the system maintains the balance between safety and comfortable driving experience and could support a relaxation of the traffic flow. All this in a standard E/E architecture without adaptations.

INTRODUCTION AND MOTIVATION

Feel safe, be comfortable, stay in control – these are the working principles of Adaptive Distance Control (ADC). It conveys a comfortable distance control and adapts it to personal driving styles enabling a natural driving experience with a comfortable and noticeable safety benefit. ADC is always on and works in the background. In other words, ADC links between an Adaptive Cruise Control (ACC) and an Automatic Emergency Braking (AEB) system.

The well-known and established Adaptive Cruise Control (ACC) system automatically adapts the vehicle speed to the current traffic environment by controlling the longitudinal distance to a preceding vehicle travelling in the same lane and direction. Without a preceding vehicle, the ACC system will keep its set cruise control speed. Its functionality allows the ACC to automatically slow down and speed up in accordance with the current traffic without intervention from the driver (SAE Level 1). ACC is deactivated once the driver brakes. From a hardware perspective, the ACC needs a reliable system to detect the lead vehicle's distance and speed, typically achieved by a radar sensor. Given all features and limitations, ACC adds some safety elements but is mainly a comfort system supporting the driver in their longitudinal control.

On the other hand, Automatic Emergency Braking (AEB) systems are designed to avoid or mitigate potential collisions. Consequently, the AEB system is a safety feature (SAE Level 0) and not a comfort system. Typically, the AEB system is adapted to different opponents, ranging from cars and trucks to cyclists and pedestrians. It observes the distance to potential collision opponents and continuously calculates the degree of vehicle deceleration required to avoid a collision. If the system detects that the driver has failed to apply a sufficient brake force, it may automatically initiate full braking. As a result, the collision is avoided or, in adverse conditions, mitigated due to a reduced collision speed. As the AEB system is constantly monitoring its environment, it is always active within its functional scope. In-fleet AEB system studies of indicate an avoidance rate (effectiveness) for rear-end injury crashes of 56 - 64% [1][2].

ADC offers functions linking ACC and AEB: at a first glance it is an ACC system where the driver is controlling the vehicle speed. The ADC system is keeping the longitudinal distance to a preceding vehicle, and it is always active, even after a braking intervention by the driver. It performs moderate braking maneuvers, de-escalating critical situations before they may become dangerous. To maintain the driver experience of actively controlling the vehicle, the driver may temporarily decrease the ADC inherent distance to the preceding vehicle, limited to a certain minimum (see Figure 1). Thus, the driver is in control and, at the same time, can rely on the system at times of comfortable cruises. Due to its capabilities of moderate braking maneuvers, the ADC system ensures a time gap to the preceding vehicle and may hand over to the driver or the AEB system in case of an imminent collision. Consequently, the ADC system adds some safety aspects, too.

This study aims to give an introduction of the ADC system and its working principles as well as an estimate of the potential comfort and safety benefit. In the following chapter, ADC will be introduced as well as its technological requirements and functional limitations. Thereafter, we share more insights about the comfort and safety benefit assessment, in particular for Germany. For the comfort aspects of ADC, we evaluate traffic observation data whereas for the safety benefit estimation we analyze German crash data. We close with a detailed discussion of the results and pointing out its limitations.

ADAPTIVE DISTANCE CONTROL

Description

The Adaptive Distance Control (ADC) system controls the longitudinal distance to the preceding vehicle while driving manually. The ADC system is designed to support the driver when driving on frequented roads, in normal traffic or within traffic jams.

As the ADC system keeps the distance to the preceding vehicle it acts as safety angel in the background and supports AEB interventions in advance or even avoids them. The system increases safety due to early distance control and supports the driver if necessary to avoid critical distances to a preceding vehicle. The driver is in full responsibility of the vehicle and can override the system.

The system is active on any road including urban area, rural area and motorway. The driver has the following adjustment possibilities:

- The initial distance with a safety margin to the preceding vehicle in form of a so-called time gap or time headway (THW). It can be set in the Human-Machine Interface (HMI).
- The desired distance can be adjusted by a changed accelerator pedal positioning. The adjustment is limited to a minimum safety distance.
- ADC can be deactivated manually by the driver via the HMI.

The initially set distance with a safety margin is a time featuring values between 1.0s and 2.5s. It is offered to the driver in e.g., three selectable steps. The ADC system is automatically active when the ignition is switched on. If the driver brakes, the system stays active. If the driver strongly pushes the accelerator pedal (e.g., kick-down), the ADC system is temporarily deactivated.

ADC can decelerate the vehicle down to standstill when the vehicle in front stops. ADC can automatically drive off, if the vehicle has stopped for less than 3s and if the driver still pushes the accelerator pedal. For safety reasons, the driver has to drive-off after longer stopping time periods by additionally increasing the accelerator pedal positioning.

Figure 1 visualizes the functional principle of ADC. If during free ride mode a slower preceding vehicle is detected, the ego vehicle adapts its speed to maintain the set THW (approaching mode). In case the preceding vehicle changes or leaves the lane, the ego vehicle accelerates to the speed requested by the accelerator positioning. If there is still a vehicle in front and the driver requests a higher acceleration by pushing the accelerator pedal, the system will reduce the longitudinal distance to the preceding vehicle until a safe minimum distance is reached (immersion mode). If a small distance is driven for a longer time, the driver is warned visually.

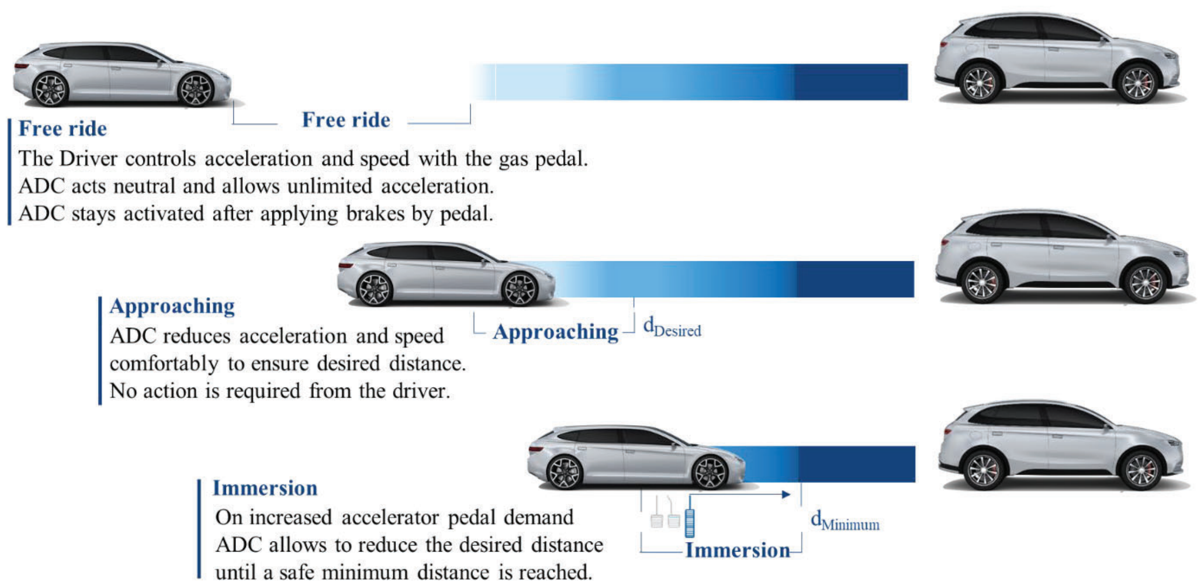

Figure 1: Functional principle of Adaptive Distance Control (ADC)

The availability of the ADC system depends on several conditions, which may deactivate or suppress an active system.

- Deactivation: The ADC system permanently monitors the operation parameter and will deactivate in certain situations. Depending on the situation the system will choose one of the following deactivation types:
    - Immediate deactivation: ADC will cancel immediately any engine or brake control without consideration of any comfort criteria. This applies in particular for fault entries in corresponding vehicle or transmission control units, if AEB or Evasive Steering Assist (ESA) are activated or either

Electronic Stability Control (ESC) or Antilock Braking System (ABS) are active for a longer time period.
- Soft deactivation: ADC will gradually release engine torque limit or release brake pressure to provide as much comfort as possible before cancelling. This applies for an ADC deactivation in the HMI or if object detection sensors are temporarily not available.

- Suppression: The ADC system permanently monitors the operation parameter and will be suppressed in several situations. For instance, if vehicle systems like, e.g., ABS, ESC, Parking Assist or Hill Descent Control are active. ADC is also suppressed if the engine is not ready or not running, if no forward gear is applied, if the vehicle is rolling backwards or driving faster than 250 km/h or if the slope is too steep.

E/E Architecture

The ADC system is a flexible and customizable software module which is responsible for managing the current values of time gap (THW). It allows changes to the value of THW through driver commands. These commands can be given using a suitable HMI, e.g., buttons and switches on the steering wheel or with a separate lever. The driver command is sent via the vehicle bus, which are then taken as an input for the ADC system. The buttons and switches are called driver input elements. Depending on the specific configuration, pressing these input elements causes changes in the time gap setting. These changes are managed and executed by corresponding ADC controllers.

Additional hardware elements of the E/E architecture required for the ADC system are a Vehicle Control Unit (VCU), Transmission Control Unit (TCU), Electronic Stability Control (ESC), and sensors like radar and video. All hardware elements and their respective tasks are displayed in Figure 2 and Table 1.

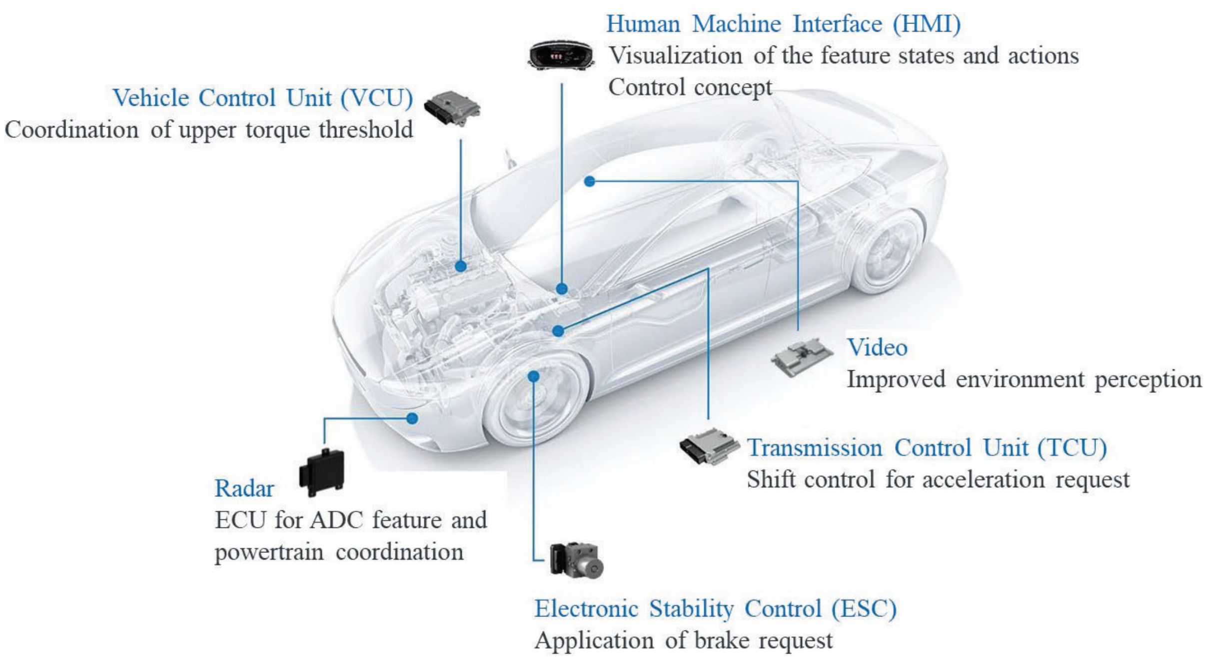

Figure 2: Overview of the E/E architecture for ADC

Table 1: Required technology elements

System/ Component	Function
Driver assistance system, e.g., front radar	Object detection and environment for ADC system
Brake system, e.g., ESC	Support of standstill management based on braking system e.g., Automatic parking brake for stop & go
Powertrain, e.g., VCU	Combustion engine or electric motor
Transmission, e.g., TCU	Automatic (for stop & go)
Human-Machine Interface (HMI)	Operation: Using existing driver assistance control elements or separate button (cp. operation concept) Visualization: No separate hardware needed

Functional limitations

The ADC system is parameterized according to ISO 15622 for ACC [3]. This addresses in particular to the maximum decelerations, the maximum change of deceleration, and the minimal time gap. All ADC characteristics are shown in the following Table 2.

Table 2: ADC functional parametrizations according to ISO 15622

Maximum ADC deceleration		
Vehicle speed	**ISO 15622**	**Implemented**
< 5.5 m/s	5.0 m/s²	4.5 m/s²
> 19.44 m/s	3.5 m/s²	3.5 m/s²
Maximum ADC change of deceleration		
Vehicle speed	**ISO 15622**	**Implemented**
< 5 m/s	5.0 m/s³	4.0 m/s³
> 20 m/s	2.5 m/s³	2.5 m/s³
Minimal ADC time gap without driver requested distance reduction		
Vehicle speed	**ISO 15622**	**Implemented**
all	1.0 s	1.0 s

Limitations by sensor technology performance results directly in a limitation of the ADC system. A non-availability of the ADC system is displayed to the driver.

SAFETY AND COMFORT EVALUATION APPROACH

Data sources

The data sources for our safety and comfort evaluations are two-fold: in the first part of the study, we use traffic observations from German motorways while for the second part of the study we use German crash data.

The traffic observations are based on the highD dataset which recorded naturalistic vehicle trajectories on six motorways in North Rhine-Westphalia in Germany in 2019 with an aerial drone. The dataset stores for each vehicle the trajectory, vehicle type, size, and maneuver. In addition, it was enriched with a lane-based time gap or time headway (THW) between two consecutive vehicles and a lane-based and simplified time-to-collision (TTC). In total, the dataset covers more than 110,500 vehicles (80.6% cars and 19.4% trucks). Further information can be found in Krajewski et al [4].

The crash data for this study is based on the data from German in-depth accident study (GIDAS) project. GIDAS records real traffic crashes with personal injuries and death and provides a reconstructed pre-crash sequence. Each recording contains detailed on-spot information of each participant including vehicle data, injury information, a scaled sketch of the accident site, and all environmental and road conditions [5]. For the present study, we use a subsample of the GIDAS database with more than 40,000 crashes. These data are weighted by type of crash, location, and injury severity to German national statistics of the year 2019 using additional data from the German Federal Statistical Office (DESTATIS) [6][7].

Methods

ADC comfort evaluation

For the ADC comfort evaluation, we analyze the number of vehicles that are affected in their regular driving by the ADC system. ADC controls the distance to the preceding vehicle based on time-headway (THW). The enriched highD traffic data directly provides for each vehicle and time step a THW in case there was a preceding vehicle in the same lane. Based on the functional limitations described earlier, we analyzed the highD dataset with the following requirements:

- Vehicle under investigation: passenger car (vehicle class "car")
- Preceding vehicle: all other motorized vehicles
- Maneuver: No lane change

For the analyses below, we investigated the share of affected vehicles as a function of the minimal THW. As a standard application, we assumed a minimal THW = 0.6 s.

ADC safety evaluation: field of effect in crashes

To cover the safety aspect of ADC, GIDAS data was assessed to estimate the ADC field of effect (FoE). The FoE regarding crashes describes the number of crashes which potentially can be positively influenced (mitigation or avoidance of the original crash) by the ADC system. In general, the ADC system addresses the same crash scenarios as an AEB system: a vehicle hits with its front another vehicle in the back (front-to-rear-end crash). Based on the functional limitations of the ADC and AEB systems, we analyzed the GIDAS data with the following criteria:

- Vehicle under investigation:
    - passenger car (M1 vehicle)
    - crash triggering vehicle (main causer)
    - no skidding before primary impact
    - first contact at vehicle front
- Preceding vehicle:
    - all motorized vehicles
    - first contact at vehicle rear-end
- Front-to-rear end crash relevant type of accident

All crashes fulfilling these criteria are analyzed by location (urban, rural, motorway) separately.

An AEB system has operational constraints, mostly to ensure an intervention only in an imminent crash situation. As a result, some crashes may still occur with an AEB system, partially with reduced collision speed. All crashes that have not been avoided by an AEB system could be positively influenced by the ADC system, i.e., are within the ADC field of effect. Consequently, within the AEB field of effect, we looked for crashes with adverse conditions for AEB that could be further addressed by the ADC system. We used the following criteria:

- The lateral overlap (offset) between both vehicles is less than 50%
- Road surfaces with a low friction coefficient, i.e., wet, snowy or icy roads
- Speed difference between both vehicles above 60 km/h

A symbolic representation to identify the ADC field of effect within the AEB field of effect is shown in Figure 3. Basically, we assume for ideal conditions for AEB that an imminent rear-end crash will be avoided by the AEB system. All other remaining cases due to adverse conditions for AEB – estimated by the three main criteria above – are in the field of effect of the ADC system.

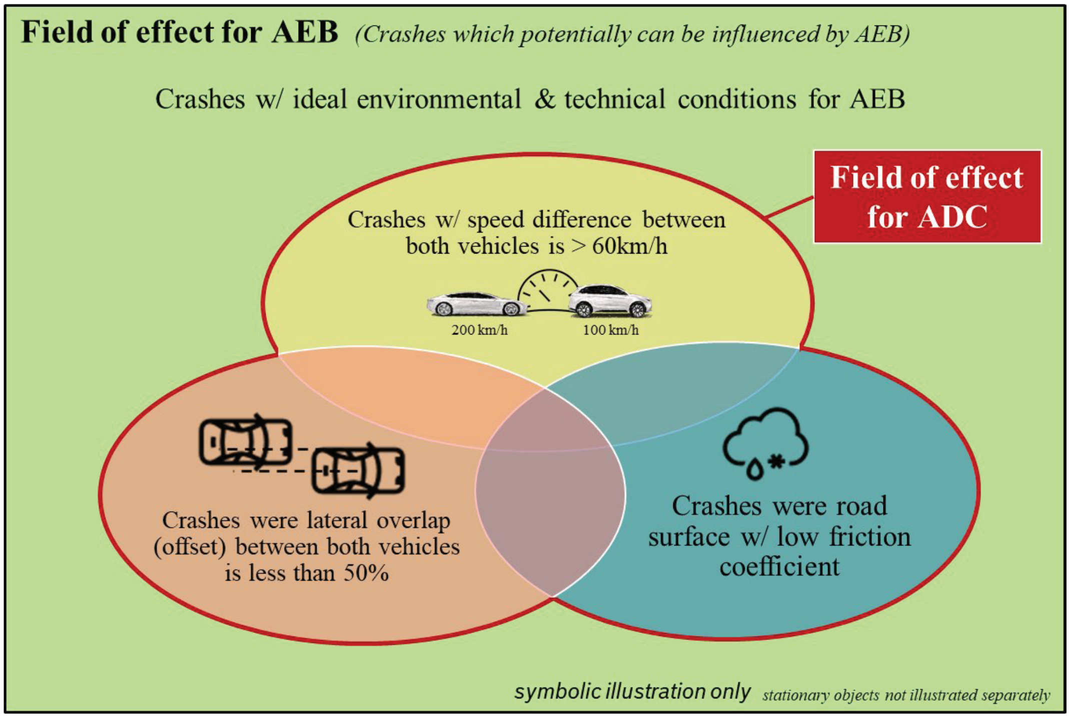

Figure 3: Symbolic illustration – ADC can increase effectiveness of AEB in which real-world constraints given

RESULTS

ADC comfort evaluation: Time headway analysis

Applying the selection criteria on the highD dataset described above, we find the number of vehicles that would be affected by the ADC system. As the ADC system actively prevents the driver to have a THW below the ADC minimum time gap settings t_{min}, every vehicle with a THW below t_{min} would be affected and kept at a distance representing t_{min} or above. For the first step, we assume an ADC system setting with an initial safety distance and minimum distance of $t_i = 1.0s$ and $t_{min} = 0.6s$, respectively, while for the second step, we keep t_{min} as a parameter.

Figure 4 shows the distribution of the minimal THW per passenger car for the highD dataset. The distribution has a maximum at $THW \approx 0.9s$ and is heavily skewed to the left. As a reference, we display THW = 1.8s as a vertical line in Figure 4 which is derived from the recommended driving distance on German roads (distance in m equals half travel speed in km/h). As a first result, we count the overall number of vehicles with a THW below the thresholds of 0.6 s and 1.0 s ending up in about 1 out of 12 cars and 1 out of 4 cars, respectively.

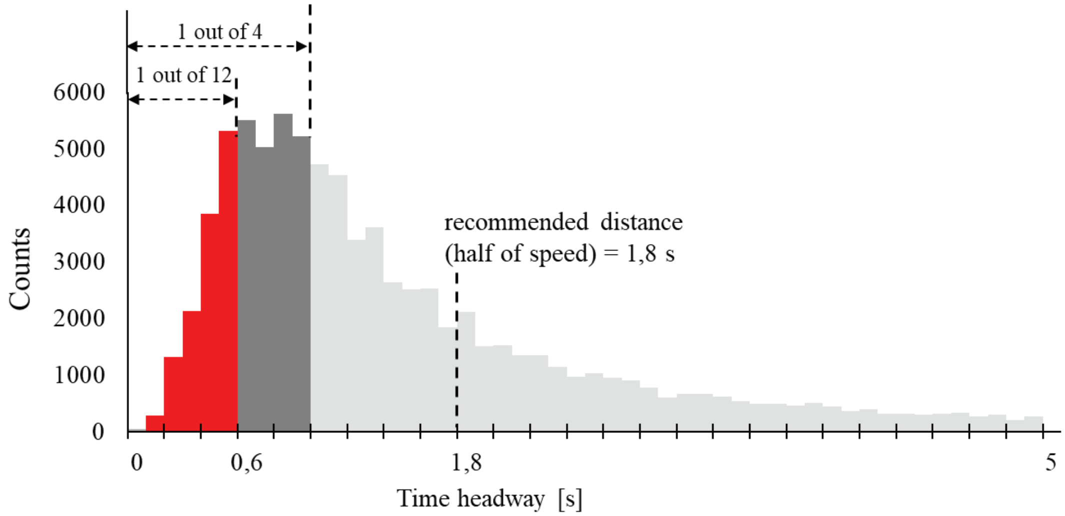

Figure 4: Time headway (THW) distribution of passenger cars on German motorways

In more detail, for an ADC system setting of $t_{min} = 0.6s$, the highD dataset reveals that 7,892 out of 89,139 passenger cars (8.9%) have a $THW \leq t_{min}$ for longer than one second. Table 3 summarizes the relevance for ADC in detail for the highD dataset and $t_{min} = 0.6s$.

Table 3: Relevance of ADC in the highD dataset

Criteria	Number of vehicles	Share
Vehicles in the enriched highD dataset	110,516	
... number of passenger cars	89,139	100%
… w/o lane change	78,722	88.3%
… THW ≤ 0.6s	9,308	10.4%
... THW ≤ 0.6s for more than 1s	7,892	8.9%

In a second step, we analyze the relative share of passenger cars that would be affected by a given ADC t_{min}. Sweeping t_{min} in the range $[0.1s, 1.2s]$ shows a strong sensitivity starting at $t_{min} \cong 0.5s$, i.e., a small increase in t_{min} results in a large number of additionally affected drivers. The full sensitivity curve is shown in Figure 5. We would like to point that driving at distances corresponding to $THW < 0.9s$ is penalized on German motorways. Thus, setting ADC $t_{min} \geq 0.9s$ could not only prevent the driver from potentially dangerous situations leading to front-to-rear-end crashes but also from being penalized due to insufficient safety distance.

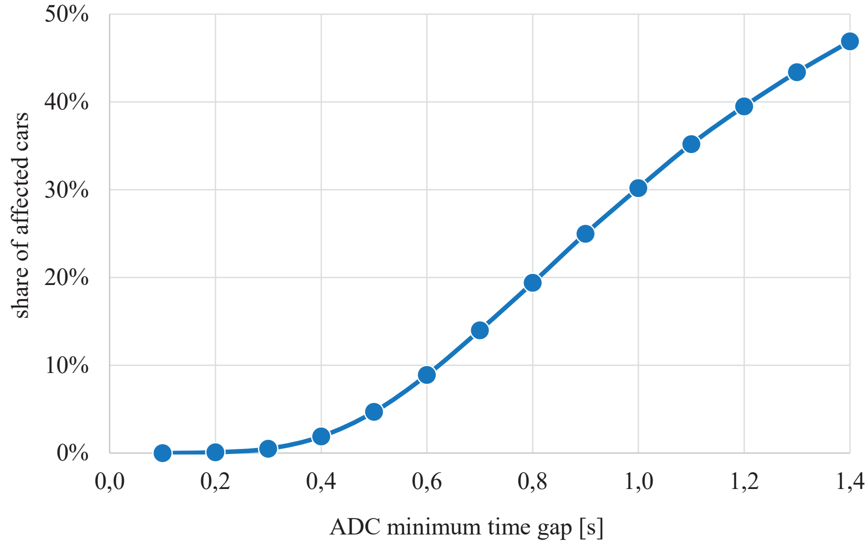

Figure 5: Sensitivity curve for ADC system parameter minimum time gap t_{min} according to highD data

Crash analysis
According to the national statistics (DESTATIS), there were a total of 300,143 crashes with personal injuries or death in Germany in 2019. Most of those crashes occurred on urban (207,625) and rural roads (72,538) whereas the remaining 19,980 crashes occurred on German motorways. Applying the criteria for the AEB field of effect in crashes, as motivated in the method section, to the GIDAS database and extrapolating towards German national statistics unveils a sum of about 40,200 annual crashes with personal injuries or death. Table 4 provides a more comprehensive overview. In the following paragraphs, we will estimate more specific numbers for ADC.

Table 4: AEB field of effect estimated for Germany

Criteria	Estimated number of crashes in Germany (2019)			Source
	Motorway	Rural	Urban	
Crashes with personal injuries or death	19,980	72,538	207,625	DESTATIS
... involving passenger car (M1) as crash triggering vehicle	15,200 (n=1,034)	53,000 (n=3,274)	131,000 (n=14,643)	GIDAS (weighted to Germany)
… w/o skidding before first collision	11,000 (n=695)	38,000 (n=2,001)	124,000 (n=13,832)	
… front-to-rear-end crash	6,100 (n=385)	10,100 (n=460)	24,000 (n=2,154)	
Share of initial still standing preceding vehicles within AEB FoE[1]	8%	27%	44%	

As discussed in the method section, ADC can contribute to increase the effectiveness of the AEB system especially in non-ideal or adverse conditions for the AEB system. Therefore, we additionally evaluate the number of crashes with a potentially reduced AEB system performance due to non-ideal or adverse conditions. Table 5 shows for each combination of the three main AEB limitations (overlap, low friction, and speed difference) per location the share of affected crashes.

[1] Share of initial still standing target objects (related to a probable classification by AEB/ADC-system) only reliable for motorway and rural streets currently – for accidents at these locations single case analyses were conducted. Share for urban roads was not evaluated in terms of a possible classification by the AEB/ADC-system, therefore system relevant share on urban roads is expected to be smaller.

Table 5: Conditions of ADC for injury crashes

GIDAS (2001-2020)						
	Lateral overlap between both vehicles is less than 50%	Road surfaces with a low friction coefficient, e.g., wet, snowy or icy roads	Speed difference between both vehicles above 60 km/h	Share within AEB field of effect		
				Motorway 6,100 (n*=365)	Rural area 10,100 (n*=430)	Urban area 24,000 (n*=2,085)
Ideal environmental & technical conditions for AEB	No	No	No	30%	32%	56%
Non-ideal or adverse conditions for AEB	No	No	Yes	27%	23%	3%
	No	Yes	No	5%	15%	21%
	No	Yes	Yes	7%	8%	1%
	Yes	No	No	15%	11%	13%
	Yes	No	Yes	13%	5%	1%
	Yes	Yes	No	2%	3%	5%
	Yes	Yes	Yes	1%	3%	<0.5%
	Subtotal			70%	68%	44%
	Subtotal projection to Germany			4,300	6,800	10,600
Total				100%	100%	100%

* number of crashes in GIDAS, cases with unknown overlap or road surface are excluded here

Based on Table 5 we derive[2]:

1) On German motorways, 70% of relevant crashes occur at non-ideal or adverse conditions for AEB. Main constraints are the difference in collision speed (relevant for 48%) and a too small lateral overlap between the colliding vehicles (relevant for 31%).
2) On rural roads, the proportion of relevant crashes is similar at 68%. The low friction coefficient (29%) has a considerably larger share than on motorways. Speed differences > 60 km/h (39%) and overlaps <50% (23%) are less relevant than on motorways.
3) On urban roads, the share of AEB relevant crashes in non-ideal or adverse conditions for AEB is at 44%. Speed differences > 60 km/h are considerably low at 6%. Proportions of low friction coefficient and of too small lateral overlap are comparable to rural roads.

Following the main results of Table 5, we find for non-ideal or adverse conditions for AEB in a total of 21,700 annual crashes with personal injury or death in Germany. A distribution by location (motorways, rural roads, and urban roads), is shown as a subtotal for non-ideal or adverse conditions for AEB in Table 5.

Based on US in-fleet insurance studies [1][2], we assume an average AEB avoidance rate of 60% within the AEB field of effect. Consequently, we expect about 24,100 avoided and 16,100 remaining crashes with personal injury or death annually in Germany (60% and 40% of 40,200 crashes, respectively). Estimating the ADC field of effect, we assume (i) all crashes under ideal AEB conditions are avoided by the AEB system, and (ii) the ratio of crashes not avoided by AEB to AEB-relevant cases under non-ideal conditions is independent of the location. With these assumptions, we apply the location distribution of AEB-relevant cases with non-ideal or adverse conditions to the total of 16,100 remaining cases not avoided by AEB (see Table 6) revealing the ADC field of effect by location for the remaining injury crashes.

[2] As shown in Table 5, there are overlaps in the boundary conditions, so the proportions listed cannot be summed up together

Table 6: ADC field of effect for injury crashes estimated for Germany 2019

	Motorway	Rural roads	Urban roads	All locations
Non-ideal / adverse conditions for AEB	4,300 (20%)	6,800 (31%)	10,600 (49%)	21,700 (100%)
	⇩		Applying the above percentages to the total ADC FoE of 16,100 crashes	
ADC field of effect for injury crashes	**3,200**	**5,100**	**7,800**	**16,100** (40% of AEB FoE)

In summary and based on accident numbers of 2019, with full market penetration for passenger cars, ADC could address up to 16,100 injury crashes in Germany annually, thereof up to 3,200 crashes on motorways, up to 5,100 crashes on rural roads and up to 7,800 crashes on urban roads. The possible crash avoidance rates by the ADC system within its field of effect depend on the ADC system design and the location.

DISCUSSION AND LIMITATIONS

After a thorough introduction of the new Adaptive Distance Control (ADC) system and its positive influence on traffic and crashes, we will discuss in the following section the results and potential limitations.

We assume ADC will be a very recognizable system. Unlike many safety systems as, e.g., AEB or ESC, which become active only in emergency situations, ADC will actively interact with the driver's car following control task in regular traffic. According to the drone-based traffic observation highD data, ADC would affect more than a quarter of all car drivers on German motorways for the lowest ADC standard time gap (safety distance) of 1.0s. Every day driving experience already shows a variation of individual time gaps to preceding vehicles in car following situations due to distraction, misjudgment of what a sufficient safety distance is at given speed, or misinterpretation of the situation. Consequently, over a vehicle's time of use, it can be expected that a very large proportion of all drivers will be supported by the system. While we may speculate of the large quantity of drivers keeping a sufficient time gap, we can conclude that the ADC system due to keeping an active state irrespective of regular driver inputs, it will be one of the assistance systems reminding the driver of its presence.

ADC is a comfortable system potentially affecting many drivers and in consequence impacting future traffic. For the active driver additionally pushing the accelerator in a car following situation, ADC may reduce the time gap to a minimal fixed value. Exemplarily setting the ADC minimal time gap to 0.6s would affect one out of twelve drivers on German motorways according to highD data. Yet, distances below the ADC minimal time gap are impossible within the ADC functional boundaries. Only very active drivers would still be able to undercut the ADC minimal time gap in a few cases by temporarily deactivating the ADC system (e.g., kickdown). As the ADC covers a huge range of regular driving situations, the ADC system will have a tremendous effect on the German motorway traffic pushing the time gap between two vehicles to a level above the ADC minimal time gap if every car would be equipped with ADC.

While ADC offers a subjective safety benefit and could transform motorway traffic entirely, the objective safety benefit is complex to assess. In principle, ADC is affecting potentially critical situations which could become relevant for an Automatic Emergency Braking system. Yet, the ADC system is designed to decelerate comfortably and, thus, influence the vehicle speed earlier than an AEB. Consequently, ADC is supporting the AEB system especially in non-ideal or adverse conditions for AEB. In particular, a detailed analysis of the respective shares based on German crash data using the GIDAS database shows that the speed difference is one of the biggest challenges for an AEB system on motorways and rural roads. ADC provides especially in those situations additional support by an early and comfortable deceleration. In all locations, an overlap below about 50% to the preceding vehicle is also a significant limitation of the AEB system. The share of overlap <50% that we see in crash data, among other things, may possibly also an effect of swerving before the collision. The ADC system may intervene in overlap <50% situations more reliably by system design than AEB systems can do.

The safety benefit results of this study are consistent with literature: in about 46% of AEB relevant cases there are ideal environment conditions. This share is smaller than the avoidance rate of about 60% determined by in-fleet studies [1][2]. For the difference (14 percentage points), several explanations are possible: (a) mitigation of injury crashes to property damage only crashes by AEB (b) differences in traffic and accident situations between US and Germany (speed limit, climate conditions, etc.) and (c) potential limitations in the GIDAS database.

We expect an improved avoidance rate of a combined ADC-AEB system if stationary objects are processed reliably. According to Table 4, the shares of still standing preceding vehicles is strongly dependent on the location. In addition, technical challenges in reliably processing those standing vehicles are well known [8] If the object detection subsystem for ADC can reliably process stationary objects due to, e.g., a fusion of radar and camera information, the avoided number of crashes within the ADC field of effect could be increased.

In addition to mitigating or avoid crashes with personal injury or death, ADC could mitigate or avoid property damage only crashes, too. Yet, besides the complexity encountered in the analysis above, the data sources for property damage only crashes are less sufficient regarding its depth of information than existing in-depth accident studies as, e.g., GIDAS. The additional potential for ADC to support in avoiding property damage only crashes is motivated by the fact that there are about eight times more property damage only crashes than injury crashes within police reported crashes in Germany [6][7]. This does not necessarily mean that the ADC field of effect for property damage only crashes is in the same range, yet it shows an idea of the possible extent. For a robust quantification, further analysis based on additional data sources is required.

CONCLUSIONS

The presented study introduces the so-called Adaptive Distance Control (ADC) system as a new driver assistance system enhancing the driving experience while using an existing E/E architecture. As a driver assistance system, it not only supports the driver in challenging situations, but it brings the driving experience to the next level: a regular driver will acknowledge the support in keeping a reasonable distance to the preceding vehicle in traffic, while the active driver may decrease this distance for his active participation in traffic. Yet, the ADC minimal distance is – within the system boundaries – fixed and may not be undercut. Consequently, the driver can rely in all normal driving situations on the ADC system to keep the distance to the preceding vehicle. Subjectively, ADC takes the rather tiresome task of car following, especially in dense traffic, and transforms it into a comfortable experience.

The ADC system is a recognizable system. It is typically active by default and interacts with the driver in car following situations by moderate deceleration interventions to ensure the ADC minimal time gap. Results of an initial user study with 30 participants shows very positive acceptance rates, particularly regarding an increased driving comfort and an increased subjective safety level resulting in a high willingness to use ADC in general.

Although the ADC system is commonly perceived as a driver assistance system to increase the driving experience, it also addresses a considerable share of crashes. We estimate the ADC field of effect, i.e., the number of crashes that may be positively influenced by the ADC system, up to 16,100 annual crashes with personal injury or death in Germany based on accident numbers for 2019 (~5.3%). The potential of ADC on property damage only crashes was not quantified, yet the ADC system may positively influence these crashes, too. In other countries, the ADC field of effect could be in a similar range.

In a future, with most cars being equipped with an ADC system, traffic could be shifted remarkably, especially for motorways. Driving could be more relaxed and safer. In addition, ADC together with other driver assistance systems could even influence the driver's mindset on the path to a vision of traffic without crashes.

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REAL-WORLD EFFECTIVENESS OF MODEL YEAR 2015–2020 ADVANCED DRIVER ASSISTANCE SYSTEMS

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ABSTRACT

In 2020, an estimated 2.3 million people were injured in traffic crashes, and 38,824 people were killed on U.S. roadways [1]. Advanced driver assistance systems (ADAS) in passenger vehicles hold the potential to reduce traffic crashes, prevent serious injuries, and save thousands of lives on our roadways each year. Given the growing rate at which auto manufacturers are equipping vehicles with ADAS [2], there is an increasing need to study and understand the safety benefits and potential limitations of these technologies. To address this need, the Partnership for Analytics Research in Traffic Safety (PARTS) was formed in 2018 as an independent, voluntary data sharing and analysis partnership among eight automobile manufacturers and the United States Department of Transportation (USDOT). The not-for-profit MITRE Corporation (MITRE) operates PARTS as the independent third party and conducted this study at the direction of and in collaboration with the PARTS partners.

The objective of this PARTS study was to explore the real-world effectiveness of ADAS features in reducing system-relevant crashes, specifically front-to-rear crashes for forward collision warning (FCW) and automatic emergency braking (AEB) and single-vehicle road-departure crashes for lane departure warning (LDW), lane keeping assistance (LKA), and lane centering assistance (LCA). This study combined 13 states' police-reported crash data (2016 to 2021) with vehicle equipment data from 47 million vehicles representing 93 vehicle models (model years 2015 to 2020), resulting in the study dataset of 2.4 million crash-involved vehicles. This study defined three crash severities (all, injury, serious) and estimated ADAS effectiveness for each using quasi-induced exposure and logistic regression, comparing vehicles equipped with ADAS against vehicles without those features.

For the population of all front-to-rear crashes, the study estimated that crashes were reduced by 49% (Wald 95% CI: 48 to 50%) when the striking vehicle was equipped with both FCW and AEB compared against striking vehicles that were not equipped with either. For FCW alone, the estimated reduction is 16% (13 to 20%). For the population of front-to-rear crashes involving injury, effectiveness estimates were slightly higher. The study estimated that front-to-rear crashes were reduced by 53% (51 to 54%) when the striking vehicle was equipped with both FCW and AEB. For FCW alone, the estimated reduction for crashes with injuries is 19% (13 to 25%). Altogether, this study shows that the combination of warning and active braking reduced more front-to-rear collisions than warnings alone. The study demonstrates that AEB performs well even when weather and lighting conditions are not ideal. This study investigated the effectiveness of Pedestrian AEB with non-motorists but was unable to detect an effect. For single vehicle road departure crashes, this study estimated that LDW and LKA reduced crashes by 8% (5 to 12%). When adding LCA, crashes are reduced by about the same amount (9%, 4 to 14%). This study did not find significant results for vehicles equipped with LDW alone.

INTRODUCTION

New safety features and advances in ADAS and ADS promise to reduce the number and severity of traffic crashes, prevent many serious injuries, and save thousands of lives annually. ADAS features are increasingly standard on new vehicles and their adoption is growing. Auto manufacturers (original equipment manufacturers, or OEMs) are equipping their U.S. vehicles with more ADAS features over time as both standard and optional equipment. Given the above, there is a need to investigate the real-world performance of these safety features, including their benefits and potential limitations, to drive innovation and continuous improvement. PARTS was formed to respond to this need by enabling collaborative data sharing and analysis among industry and government participants.

PARTS Overview

PARTS is an independent and voluntary partnership among automobile manufacturers and USDOT in which participants share relevant safety-related data solely for collaborative safety analysis. Established in 2018, the goal of this government-industry collaborative, operated by The MITRE Corporation (MITRE), is to gain real-world insights into the safety benefits and opportunities of ADAS and other emerging safety technologies. PARTS partners (see Figure 1) co-define the nature of their ongoing data sharing and analysis collaboration.

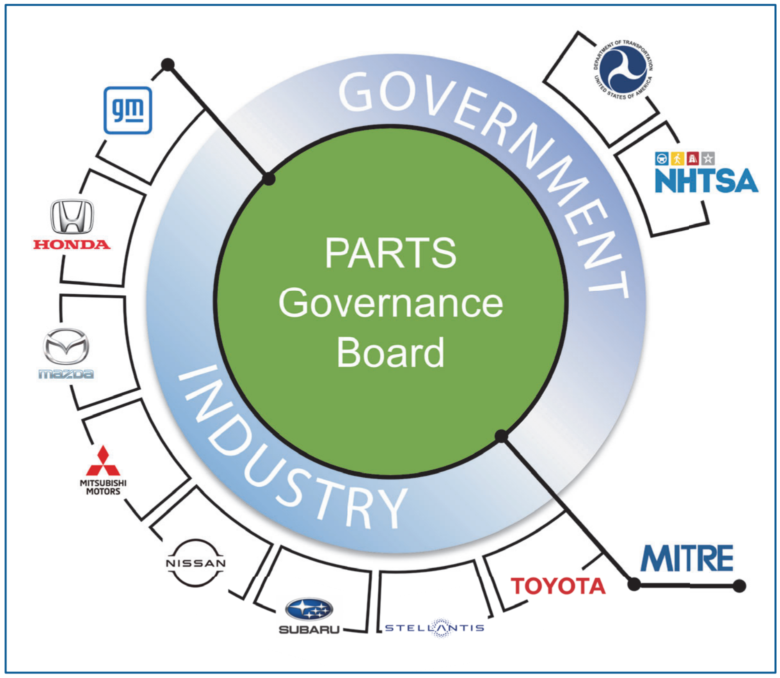


Figure 1. PARTS Partners.

PARTS operates under its own authority through a legally binding charter and cooperative agreements, shared governance, and consensus-based decision making. Given competitive and regulatory dynamics among partners, PARTS employs an independent third party (ITP) to ensure that partners' interests and sensitive data are protected from improper use and disclosure. MITRE fulfills the ITP role for PARTS by serving as a neutral convener and data steward, hosting the collaborative environment and analytic enclave, and performing analyses and studies according to partner direction.

The eight participating industry partners that provided vehicle data for this study are American Honda Motor Co., Inc., General Motors LLC, Mazda North American Operations, Mitsubishi Motors R&D of America, Inc., Nissan North America, Inc., Stellantis (FCA US LLC), Subaru Corporation, and Toyota Motor North America, Inc. These PARTS industry partners account for more than 65% of the 2021 U.S. market for sales of passenger cars and light commercial vehicles [3]. Since the conclusion of this study (see full report [4]), the Ford Motor Company has joined PARTS. Data used for PARTS are governed by binding legal agreements that specify permitted uses and leading privacy and security safeguards. PARTS results are anonymized to ensure that results are not attributed to an individual vehicle or OEM. The large number of PARTS participants allows for larger sample sizes and the potential identification of smaller effects, such as changes in ADAS effectiveness in different conditions.

Related Work

In preparation for conducting this study, PARTS conducted a literature review. This review focused on studies in the last 5 years that had comparable research objectives about real-world ADAS effectiveness and a large volume of data linking vehicle equipage to crashes. Many experts have contributed to the field of traffic safety upon which this study builds. Respected organizations have addressed aspects of ADAS performance, though not necessarily with the scope, sample size, or approach that this PARTS study did. For example, researchers with the University of Michigan Transportation Research Institute (UMTRI) [5] [6] [7] [8] and Impact Research/Toyota [9] [10] have studied the effectiveness of ADAS features but have done so for only a single automobile manufacturer and a more limited sample size. Researchers with the Insurance Institute for Highway Safety (IIHS) [11] [12] [13] have looked at effectiveness of ADAS features across a variety of automobile manufactures but with smaller sample sizes.

Through its literature review and consultation with principal investigators at UMTRI, PARTS decided to adopt methods that were similar to those used by UMTRI in related studies of ADAS. For example, like UMTRI, PARTS also linked similar states' crash data to a broader set of vehicles, used the method of quasi-induced exposure via a logistic regression, controlled for similar covariates, and made decisions about which covariates to include in logistic regression based on Bayesian Information Criterion (BIC). Other studies in the literature review were broadly consistent with this approach.

DATA AND METHODOLOGY

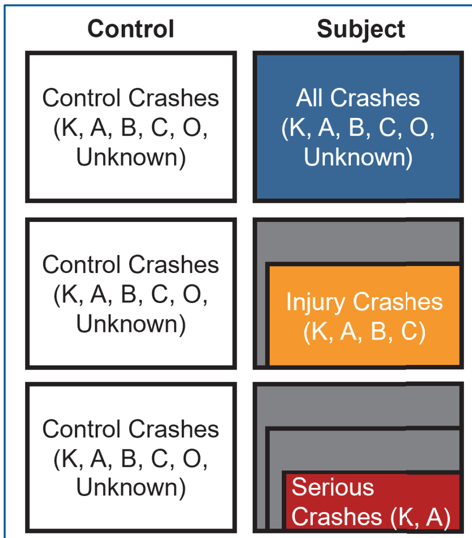
This PARTS study used real-world data to explore the effectiveness of six ADAS features to reduce system-relevant crashes. The primary research questions were, 1) To what extent do FCW and AEB reduce front-to-rear crashes? and, 2) To what extent do LDW, LKA, and LCA reduce single-vehicle road-departure crashes? A goal was also to determine if a given ADAS feature's effectiveness changed under different conditions (e.g., dark vs. daylight conditions; different speed limits; dry roads vs. wet roads) and/or for different populations of drivers (e.g., by age) and to quantify the magnitude of those changes in effectiveness. Please see the full report for more detail [4].

PARTS measured ADAS effectiveness in reducing crashes three ways: (1) in all system-relevant crashes, (2) in system-relevant crashes that had an injury of any severity, (3) in system-relevant crashes that had an injury that was serious or fatal. Injury types are based on KABCO scores using a nested structure. PARTS estimated the effectiveness of each ADAS feature for three nested sets of crash types based on the severity of injury of any participant in the crash. This nesting uses injury data recorded in the crash data based on KABCO scores (Figure 2) [14] as follows:

- **All Crashes:** System-relevant crashes that involve property damage only, have unknown injury level, or an injury of any severity (i.e., KABCO score of K, A, B, C, O, or unknown).
- **Injury Crashes:** System-relevant crashes that involve an injury of any known severity including fatality (i.e., KABCO score of K, A, B, or C).
- **Serious Crashes:** System-relevant crashes that involve a serious or fatal injury (i.e., KABCO score of K or A).

Each nested set of system-relevant crashes is compared against the same set of control crashes, which include all injury levels (i.e., control crashes can have a KABCO score of K, A, B, C, O, or unknown). The set of control crashes remains constant because it is simply meant to represent general exposure.

For each set of ADAS features in this study, PARTS fit separate logistic regression models for each of the three nested system-relevant injury sets (All Crashes, Injury Crashes, and Serious Crashes) along with the full set of control crashes for all three.



Code	Definition
K	Fatal Injury
A	Suspected Serious Injury
B	Suspected Minor Injury
C	Possible Injury
O	No Apparent Injury

Figure 2. Nested Injury Structure.

Data Overview

This PARTS study used two primary data sources: OEM-provided vehicle data on vehicles for select makes/models for 2015–2020 model years, at the Vehicle Identification Number (VIN) level; and NHTSA-provided police-reported crash data for select states during 2016–2021, at the 17-digit VIN level.

<u>Vehicle Data</u> includes the ADAS features on each vehicle, build date, sold or customer delivery date, sales market (used to filter U.S.-only car market), and sale type (retail or fleet). The data included 93 models from model years 2015–2020 and covered seven vehicle segments noted below.

- **Small Car (14):** Acura ILX, Honda Civic, Fit, & Insight; Mazda3 sedan & hatchback; Nissan Versa & Sentra; Subaru Impreza, WRX, & Crosstrek; Toyota Corolla, Prius, & C-HR.
- **Midsize Car (13):** Buick Regal & Chevrolet Malibu; Acura TLX, Honda Accord; Mazda6; Nissan Altima & Maxima; Alfa Romeo Giulia, Chrysler 200; Subaru Legacy & Outback; Lexus IS, Toyota Camry.
- **Large Car (8):** Buick LaCrosse, Chevrolet Impala; Chrysler 300, Dodge Charger & Challenger; Lexus ES & LS, Toyota Avalon.
- **Small SUV (19):** Buick Envision, Chevrolet Equinox, & GMC Terrain; Acura RDX, Honda HR-V & CR-V; Mazda CX3, CX5, & CX-30; Mitsubishi Outlander Sport & Eclipse Cross; Nissan Rogue; Fiat 500X, Jeep Compass, Renegade, & Wrangler 2DR; Subaru Forester; Lexus NX, Toyota RAV4.
- **Midsize SUV (22):** Buick Enclave, Chevrolet Traverse, Cadillac SRX & XT5, GMC Acadia; Acura MDX, Honda Pilot & Passport; Mazda CX-9; Mitsubishi Outlander; Nissan Murano, Pathfinder; Alfa Romeo Stelvio, Dodge Durango, Jeep Cherokee, Grand Cherokee, & Wrangler Unlimited; Subaru Ascent; Lexus RX & GX, Toyota Highlander & 4Runner.
- **Pick-Up and Large SUV (14):** Chevrolet Tahoe/GMC Yukon, GMC Sierra 1500; Honda Ridgeline; Nissan Armada, Titan, & Frontier; Ram 1500, Ram 2500, Ram 3500, Jeep Gladiator; Toyota Tundra, Tacoma, & Sequoia.
- **Minivan (3):** Honda Odyssey; Chrysler Pacifica; Toyota Sienna.

PARTS selected the models above based on the following guidelines: (1) A minimum of approximately 5,000 model sales per year, which helped ensure a sufficient sample size for analysis and reduced the costs of data ingest and processing; (2) At least one model year for each model was required to have at least one ADAS feature in scope for the analysis; (3) Among other data protection measures, PARTS required data from at least 3 OEMs to be included to produce a given analytic result, which excluded some models.

Crash Data was from 13 states provided by NHTSA through its Consolidated State Crash (CSC) database, which consolidates police-reported crashes received from states through the new Electronic Data Transfer (EDT) process. The data used is a census of all police-reported crashes in those states. It is limited by the information available in the original state-level crash report. Specific fields and data elements available for the crashes vary by state.

This study used crashes that occurred between January 2016 and August 2021 for the 13 states included in the analysis (see Table 1). While other states (California, Illinois, Kansas, Maine, Nebraska, Washington) were available in the EDT-driven CSC data, PARTS did not include them because they did not contain a historical archive within the study date range or were missing critical fields necessary for analysis.

Table 1.
Crash Data by State and Time Period Covered

State (Acronym)	Start Date	End Date
Arkansas (AR)	1/1/2016	8/2/2021
Connecticut (CT)	1/1/2016	7/30/2021
Florida (FL)	1/1/2016	8/1/2021
Indiana (IN)	1/1/2016	7/28/2021
Iowa (IA)	1/1/2017*	8/1/2021
Maryland (MD)	1/1/2016	8/3/2021
Nevada (NV)	1/2/2018*	8/3/2021

State (Acronym)	Start Date	End Date
Ohio (OH)	1/1/2019*	7/31/2021
Tennessee (TN)	1/1/2018*	8/1/2021
Texas (TX)	1/1/2018*	8/2/2021
Utah (UT)	1/1/2017*	8/2/2021
Virginia (VA)	1/1/2016	8/2/2021
Wisconsin (WI)	1/1/2018*	8/2/2021

** Asterisks indicate meaningfully different start dates*

Some limitations of police-reported crash reports are important to understand as a basis for interpreting results. KABCO [14], the framework for categorizing injury information used within the crash database, may not reflect precisely the injuries, injury type, or body region compared against the Abbreviation Injury Scale [15] [16] [17] [18]. Some information documented in the crash report is subjective by the police officer and may be reported inconsistently between officers and states (e.g., driver distraction at time of crash). Crash reports may have limited or no information on relevant factors (e.g., actual speed of the vehicle, road infrastructure that may impact the effectiveness of these systems). These limitations with police-reported crash data are known and generally accepted by this and other related studies, and do not present an outsize concern regarding the results.

Methodology – System-Relevant Crashes and Control (Exposure) Crashes

This study used quasi-induced exposure – comparing vehicles equipped with the set of ADAS features under study against vehicles without those features – and logistic regression to estimate the reduction in system-relevant crashes due to the presence of vehicles equipped with ADAS.

To assess ADAS feature effectiveness in reducing crashes using the quasi-induced exposure method requires that PARTS maps crashes that are relevant to that feature as well as crashes comprising the control group (i.e., indicating exposure). For each crash type, MITRE used this crash mapping to prepare data for the logistic regression model. Note that MITRE included vehicles involved in multiple separate crashes (e.g., a non-motorist crash and a different, front-to-rear crash) in the prepared datasets for each of those crash types.

Control crashes were defined for analysis of all ADAS features as the participating OEM vehicles that were the struck vehicles in front-to-rear collisions. This control group provided the indication of vehicle exposure in the quasi-induced exposure method noted above. PARTS identified these vehicles using all of the following selection criteria (logical AND):

- 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).
- Not crashes where more than two vehicles were reported (to reduce the potential for misattribution of striking and struck vehicles).

This control group definition is consistent with multiple studies and is an accepted practice for identifying exposure to collisions.

Front-to-rear crashes, which are FCW/AEB system-relevant, were defined as participating OEM vehicles that were the striking vehicle in front-to-rear collisions. PARTS identified these vehicles using all of the following selection criteria (logical AND):

- Manner of crash was identified as front-to-rear.
- Initial point of contact was on the front 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 non-system-relevant cases).
- Not crashes where more than two vehicles were reported (to reduce the potential for misattribution of striking and struck vehicles).

Single-vehicle road-departure crashes, which are LKA/LDW/LCA system-relevant, were defined as participating OEM vehicles that were in single-vehicle road-departure collisions. PARTS identified these vehicles using all of the following selection criteria (logical AND):

- Crashes where exactly one vehicle was reported.
- First event reported was ran off the road, cross centerline, cross median, collision with fixed objects, or rollover.
- Vehicle maneuver at the time of crash was either: going straight, negotiating a curve, leaving traffic lane, or ran off road.

Note that PARTS also considered sideswipe same-direction and opposite-direction crashes to be system-relevant for lateral ADAS features but did not include them here due to data limitations. Specifically, the crash data did not, with certainty, identify the vehicle that left its lane. As a result, both vehicles in a sideswipe collision would be included in the system-relevant set. This is an issue because it does not allow the study to isolate the vehicle where the ADAS feature was truly relevant. Therefore, PARTS focused on single-vehicle road-departure crashes as providing more reliable effectiveness estimates.

Methodology – Preparing and Linking Data Sources

MITRE processed vehicle data for this study to harmonize vehicles by segment as well as to map OEM-specific terms for specific ADAS features to standard definitions of the six features under study. This data processing represented a substantial and collaborative effort among PARTS partners, resulting in a uniquely robust and consistent dataset about ADAS equipage and model segmentation.

MITRE also worked closely with PARTS partners to harmonize crash data to mitigate inconsistencies across states. NHTSA worked to standardize a number of fields in the crash data it provided, such as the highest injury level and whether alcohol or drugs were involved. MITRE processed the crash data to standardize/reclassify additional fields needed for this analysis, such as the first vehicle event in the sequence of events, environmental conditions, and collision point of contact. PARTS also recognized that states have different crash reporting practices, some of which cannot be fully accounted for in the analysis, such as when a field (e.g., rural/urban) was not available for certain states, or when state definitions vary for the same field (e.g., the definition of driver impaired in one state may be illegal drug/alcohol intoxication, while another state may include both illegal and prescription drug use, alcohol use, and drowsiness; the dollar threshold triggering property damage crashes varies). Notwithstanding these caveats, the efforts of MITRE and the PARTS partners to harmonize crash data resulted in a large-scale and sufficiently consistent dataset that was sufficiently robust for this analysis.

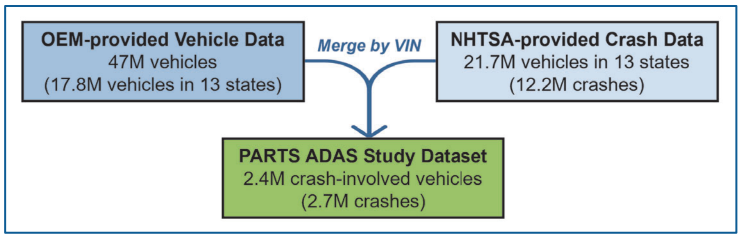


Figure 3. Joining Crash Data and Vehicle Data.

MITRE prepared the crash data and vehicle data for analysis by using VINs to join the datasets. The study included crashes that had at least one participating OEM vehicle in the analysis. The joined data resulted in a total of 2.4 million crash-involved vehicles and 2.7 million crashes. This statistic separately counts vehicles that are involved in multiple crashes at different times, and multiple vehicles that are in the same crash. MITRE safeguarded the pooled data from view by any partner and conducted analysis so that results are not attributed to any OEM (see **Error! Reference source not found.**).

PARTS deleted observations from the study dataset if they were missing any of the variables expected for the logistic regression. These deleted observations represented about 10% of the data.

Methodology – Quasi-induced Exposure

This PARTS study measured the effectiveness of each ADAS feature (or combination of ADAS features) with respect to reducing a relevant crash type. The PARTS study dataset lacked a reliable traditional exposure measure (e.g., vehicle miles traveled) and therefore relied on the quasi-induced exposure method. Quasi-induced exposure uses control (i.e., exposure) crashes within the crash dataset to gain insights into exposure. These control crashes should be unaffected by the ADAS feature being studied and occur at a similar rate in both equipped and unequipped populations [7]. The effectiveness of the ADAS feature is determined by looking at the rate of system-relevant crashes to the control crash (referred to as odds) comparing equipped to unequipped vehicles. For the simplest case, when the ADAS feature is effectively reducing crashes, the rate of system-relevant to control crashes is lower for equipped compared to unequipped vehicles. This method of quasi-induced exposure has been widely used when studying ADAS feature effectiveness. IIHS [19], Impact Research/Toyota [9], and UMTRI [8] (which has a particularly accessible explanation of quasi-induced exposure) have all used quasi-induced exposure to study ADAS feature effectiveness.

Methodology – Logistic Regression Model Design

PARTS used logistic regression to estimate the effectiveness of sets of ADAS features in reducing relevant crashes while controlling for several key factors (or covariates) that could affect the ADAS effectiveness estimate. Logistic regression provides a convenient way to incorporate factors that could potentially affect the rate of crashes (e.g., driver age, driver gender, weather) while maintaining enough statistical power to detect an effect (e.g., crash reduction due to ADAS feature). PARTS set the binary outcome variable of the logistic regression as system-relevant crashes (coded as 1) and control crashes (coded as 0). PARTS included sets of ADAS features as an explanatory variable to enable estimates of effectiveness.

To measure the uncertainty of the estimates, PARTS calculated Wald confidence intervals (CIs) at the alpha = 0.05 level for the coefficients. To formulate ADAS effectiveness more intuitively, where a higher value indicates more effectiveness, PARTS calculated the percentage reduction of equipped vehicles odds compared to unequipped vehicles odds.

The described calculations result in effectiveness weighted across the OEMs, vehicle models, environmental conditions, and driver populations as they appear in the dataset. Along with sets of ADAS features, PARTS included several covariates in the logistic regression to control for their influence on crash outcome, and thus on effectiveness (if not accounted for, those factors' influence could bias the estimate of effectiveness). PARTS transformed continuous variables into categorical variables, which effectively allows for non-linear relationships. Table 2 describes the driver, vehicle, environmental, and crash-related covariates PARTS identified for the logistic regression models.

Table 2.
Logistic Regression Model Covariates

Variable	Explanation	Specification in Logistic Regression	Additional Notes
Driver Age	Driver age as reported in CSC	14–24, 25–34, 35–54, 55–64, 65–74, 75+	Set to *None* if age <14 or >115.
Driver Alcohol/ Drugs	Drug or alcohol use attributed to driver in CSC	Boolean – True if either drugs or alcohol reported	Not always marked and different from state to state. *Not a number (nan)* and *unknown* set to False due to some states note only when alcohol present.
Driver Distracted	If driver was reported as being distracted in CSC	Boolean – True if driver distracted reported	Not always marked and different from state to state. *Nan, unknown*, and *NOT DISTRACTED* set to False.
Driver Gender	Reported in CSC	Female, Male	Limited number of entries were *unknown*, *nan*, etc. Such entries were removed.
Vehicle Model	Each individual vehicle model	See above	Likely correlated with specific driver behavior, which is not perfectly represented in the logistic regression
Vehicle Model Year	MY of vehicle manufacture	2015, …, 2020	Limited to model years 2015 through 2020
Vehicle Sales Type	If vehicle was fleet or retail at time of sale	Fleet, Retail	At time of initial sale, but do not know if vehicle was still a fleet vehicle at time of crash
Weather	If atmospheric conditions were *clear* or *overcast*, from CSC reporting	Boolean – True if weather was bad	*Not Reported*, *Reported as Unknown*, and *Unknown* were removed. Various other values were *precipitation; frozen precipitation; fog or smoke; blowing sand, soil, or snow; strong wind…*
Road Surface	Was road dry or not dry at time of crash, from CSC reporting	Boolean – True if road was not dry	*Not Reported*, *Reported as Unknown*, and *Unknown* were removed. Various other values were *wet, snow/slush, ice/frost, mud/dirt/sand/gravel…*
Light Condition	Light condition from CSC reporting	Daylight, Dark, Dawn/Dusk	*Unknown* and *nan* were ignored.
Road Alignment	Reported road alignment in CSC	Straight, Curve	Only if curved or straight not amount of curve. *Unknown*, *other*, *nan* were removed.

Variable	Explanation	Specification in Logistic Regression	Additional Notes
Intersection	Whether the crash occurred at a roadway intersection	Boolean – True if crash marked as occurring at an intersection	*Intersection* set to True, all else set to False.
Crash State	State where crash occurred	AR, CT, FL, …	
Crash Year	Year in which crash occurred	2016, 2017, 2018, 2019, 2020, 2021	
Crash Posted Speed Limit	Reported speed limit of roadway where crash occurred, in miles per hour	Under 25, 25–34, 35–44, 45–54, 55–64, 65 or over	Posted speed limit, not actual speed of vehicle

Covariates as Main Effects were selected by PARTS within the logistic regression models through:

1. Surveying literature on past research to identify factors previously important to control for in ADAS effectiveness.
2. Conducting discussions with partners to identify other potential factors that could affect the performance of ADAS.

PARTS included candidate covariates as main effects in a logistic regression model for front-to-rear crashes, the crash category containing the largest number of crashes. PARTS conducted a BIC backward selection process to determine which candidate covariates should remain in the model. PARTS then made various revisions (e.g., more precisely dividing the covariate, which effectively adds categories) to construct categorical variables, such as driver age and speed limit, to fine-tune the enumerated categories. The set of covariates above were selected for inclusion by BIC (i.e., BIC was lower with the covariate included) for front-to-rear crashes and were included as main effects in the logistic regression model. Given the conservative nature of BIC in adding parameters (whether as main effects or interactions), a factor being identified by BIC is a strong indication that that factor should be controlled for when studying ADAS feature effectiveness.

Of note is that BIC selected crash year for inclusion. The odds ratio, regardless of equipage, showed a general upward trend with respect to crash year. The causes of the upward trend with crash year could be several factors, with one logical explanation being that control crashes decrease in later years due to the increasing prevalence of AEB-equipped vehicles on the road. Inclusion of crash year as a main effect allows us to appropriately control for this influence.

PARTS generally included covariates as main effects. This helps control for these factors in influencing ADAS feature effectiveness estimates [20]. PARTS adopted the following approach to strengthen confidence in the logistic regression results:

1. Including factors selected for all front-to-rear crashes in the logistic regression for injury front-to-rear crashes and serious front-to-rear crashes.
2. Including factors selected for all front-to-rear crashes in the logistic regression models for single-vehicle road-departure and non-motorist crashes (including all, injury, and serious crashes) based on the assumption that the factors were likely to be important for other crash types.

By including the same covariates across the logistic regressions, researchers minimized the likelihood of this study missing an important factor to control for, due to limited statistical power driven by the smaller sample sizes associated with the single-vehicle road-departure and non-motorist crash datasets. PARTS included blind spot warning (BSW) not to estimate its effectiveness but rather to control for BSW influence while estimating effectiveness for LDW, LKA, and LCA. The study did not account for the presence of other ADAS features.

Covariates as Interactions were included given PARTS also sought to examine whether ADAS feature effectiveness changed for different conditions or populations. To find where effectiveness changes may be present with respect to a factor, this study included the covariates in the logistic regression model as an interaction with the ADAS features on an individual basis, with all covariates as main effects. This study used BIC to determine if each interaction was contributing meaningful information to the logistic regression model (i.e., BIC was lower with the interaction included). If BIC identified an interaction as adding meaningful information, then PARTS interpreted that as an indication that ADAS effectiveness is changing with respect to that covariate. PARTS applied a Bonferroni correction to the CIs to control for false positive rate by covariate (i.e., divided the false positive error by the number of levels for the covariate).

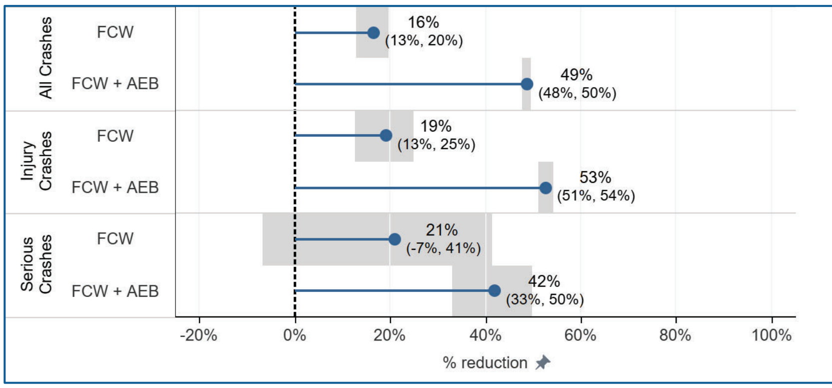
Changes in effectiveness could be due to confounding factors rather than the actual interacted variables. Additionally, the interactions, and effectiveness in general, could be influenced by incorrect specification of the model. Evidence exists that single-vehicle road-departure and non-motorist logistic regressions are more sensitive to incorrect specification than front-to-rear. Please see the full report [4] for more details on methodology.

RESULTS

FCW/AEB Reduction in Front-to-rear Crashes

This section highlights results from the PARTS analysis of front-to-rear crashes when the striking vehicle is equipped with FCW or FCW + AEB compared to vehicles not equipped with either, for all front-to-rear crashes, injury front-to-rear crashes, and serious front-to-rear crashes.

Overall FCW/AEB results are that vehicles equipped with FCW + AEB showed a substantial crash reduction of about half, as shown in Figure 4 (associated sample sizes are shown in the data table).



		System Relevant	Control
All Crashes	Neither	171,409	251,957
	FCW	5,769	12,893
	FCW + AEB	39,297	137,157
Injury Crashes	Neither	41,440	251,957
	FCW	1,289	12,893
	FCW + AEB	8,598	137,157
Serious Crashes	Neither	1,918	251,957
	FCW	67	12,893
	FCW + AEB	440	137,157

Figure 4. Results for FCW/AEB and Associated Sample Sizes.

FCW/AEB results for all crashes show FCW + AEB had an estimated reduction of 49% (48 to 50%) in all front-to-rear crashes compared against vehicles not equipped with FCW or AEB. FCW had an estimated reduction of 16% (13 to 20%) compared against vehicles not equipped with FCW or AEB. These estimated crash reductions of FCW and FCW + AEB are in line with past research, especially when considering the uncertainty associated with the estimates. This study found that there is a higher reduction for vehicles equipped with both FCW and AEB than vehicles equipped with FCW alone. This indicates that having an active system together with a warning is better than a warning system alone, at least for front-to-rear collisions.

FCW/AEB results for injury crashes were based on a dataset that was about 20% of the total system-relevant crashes, as shown in Figure 4. This study estimated reductions for injury front-to-rear crashes that were slightly higher than for all crashes. FCW + AEB had an estimated reduction of 53% (51 to 54%) for injury crashes compared to vehicles not equipped with FCW or AEB. FCW had an estimated reduction of 19% (13 to 25%) for injury crashes.

FCW/AEB results for serious crashes were based on a further subset of system-relevant crashes –only those where any participant suffered a serious or fatal injury. The dataset of serious front-to-rear crashes was only about 1% of the total system-relevant crashes, as shown in Figure 4. FCW + AEB had an estimated reduction of 42% (33 to 50%) for serious crashes. FCW had an estimated reduction of 21% (-7 to 41%) for serious crashes. Due to the much more limited sample sizes of serious crashes, the uncertainty in the estimate is much larger. The FCW case resulted in a CI that covered zero reduction in crashes (i.e., may not necessarily be effective).

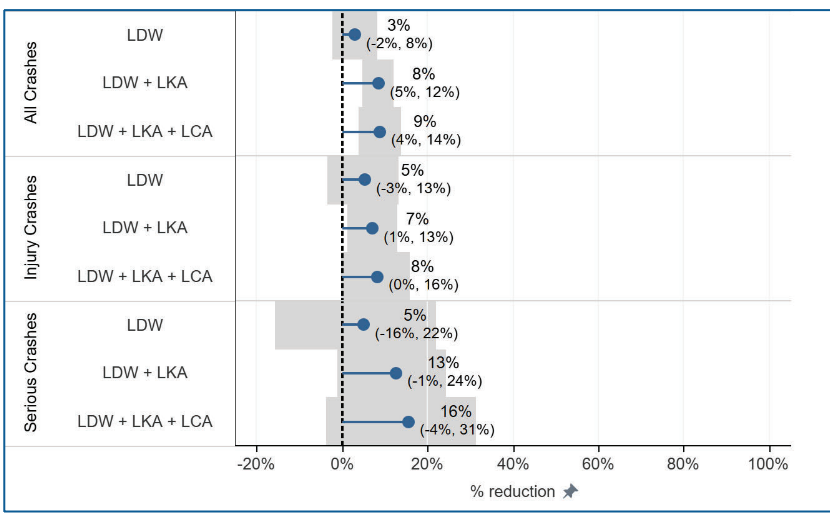
FCW/AEB results by condition were generally effective even in poor conditions. For the all front-to-rear crashes model, this study had eight interactions of FCW + AEB with covariates identified by BIC (driver age, weather, road surface, light, roadway alignment, intersection, speed limit, and sales type), while FCW did not have any interactions with a covariate identified by BIC. This study also found that the crash reduction effectiveness of FCW + AEB changes with respect to several conditions; its effectiveness was:

- Lower for dark at 42% (39 to 44%) and dawn/dusk at 44% (38 to 48%) light conditions than for daylight at 50% (49 to 52%).
- Lower for speed limits under 35 mph than 35 mph and above, with speed limits 25–34 at 44% (42 to 47%) and speed limits under 25 mph at 24% (16 to 32%).
- Lower as driver age increased, with effectiveness for age 55–64 at 44% (41 to 46%), age 65–74 at 42% (39 to 45%), and age 75 and older at 34% (29 to 38%).
- Lower for wet roads at 44% (42 to 47%) and bad weather at 42% (39 to 45%) than dry roads at 49% (48 to 51%) and good weather at 49% (48 to 51%).
- Lower for fleet vehicles at 43% (40 to 45%) than retail vehicles at 50% (48 to 51%). Note this categorization of fleet vs. retail is based on time of sale.
- Lower for crashes occurring at an intersection at 45% (43 to 46%), and lower for crashes occurring on curved road segments at 34% (30 to 38%) than straight road segments at 50% (49 to 51%).

In the injury front-to-rear crashes model, FCW + AEB had interactions with five covariates identified by BIC (weather, road surface, light condition, roadway alignment, sales type), while FCW did not have any interactions with a covariate identified by BIC. The overall trends for injury FCW + AEB interactions with covariates (see **Error! Reference source not found.**) were similar to the interactions noted above for the all front-to-rear crashes model. In the serious front-to-rear crashes model, no interactions were identified by BIC for FCW + AEB or FCW. The magnitude and direction of how interactions caused FCW/AEB effectiveness estimates to change generally aligned with PARTS partner expectations for many of the covariates.

LDW/LKA/LCA Reduction in Single-vehicle Road-departure Crashes

PARTS estimated the reduction in single-vehicle road-departure crashes when the vehicle is equipped with LDW (no LKA, no LCA), equipped with LDW + LKA (no LCA), and equipped with LDW + LKA + LCA, compared against vehicles equipped with none of these lateral ADAS features. Comparing LDW + LKA and LDW + LKA + LCA against LDW provides information about the inclusion of active systems over just a warning system. When comparing LDW + LKA against LDW + LKA + LCA, the differences can be attributed to the combination of vehicles equipped with both LCA and LKA systems and the estimated effectiveness, which is confounded by usage and technical specification of both systems.



		System Relevant	Control
All Crashes	No Lateral ADAS Features	54,090	275,178
	LDW	3,428	22,162
	LDW + LKA	9,417	70,007
	LDW + LKA + LCA	4,300	34,660
Injury Crashes	No Lateral ADAS Features	16,324	275,178
	LDW	1,046	22,162
	LDW + LKA	2,801	70,007
	LDW + LKA + LCA	1,326	34,660
Serious Crashes	No Lateral ADAS Features	2,718	275,178
	LDW	163	22,162
	LDW + LKA	423	70,007
	LDW + LKA + LCA	197	34,660

Figure 5. Results for LDW/LKA/LCA and Associated Sample Sizes.

Overall LDW/LKA/LCA results are that when combined with LDW, active lane keeping ADAS features (LKA and LCA) reduced the likelihood of all crashes by about a tenth, as shown in Figure 5, when accounting for the presence of BSW. However, study limitations did not support this finding of effectiveness in all cases of feature/crash/condition testing; further research may be required.

LDW/LKA/LCA results for all crashes are that vehicles equipped with LDW + LKA had the highest crash sample sizes. LDW and LDW + LKA + LCA had lower crash sample sizes that were similar. This study found that LDW + LKA had an estimated reduction in all single-vehicle road-departure crashes of 8% (5 to 12%) when compared against vehicles equipped with none of LDW, LKA, or LCA. Similarly, LDW + LKA + LCA had a reduction of 9% (4 to 14%) when compared against vehicles equipped with none of LDW, LKA, or LCA. Both preceding active lane management ADAS feature sets had similar crash reductions, and both had CIs above zero, indicating high confidence that those ADAS feature sets are reducing all single-vehicle road-departure crashes. LDW had an estimated crash reduction of 3% (-2 to 8%), which is not necessarily different from zero. Though these effectiveness estimates were for vehicles equipped with the features, whether the features were in use at the time of crash is unknown. Therefore, the effectiveness estimates assume usage of the feature. If the feature is being used less, then the effectiveness will reflect that by being lower. The usage (and non-usage) of the feature is believed to have a bigger impact on lateral features' effectiveness than FCW and AEB [21] [22].

LDW/LKA/LCA results for injury crashes are based on reduced sample sizes (by about 70%) as shown in see Figure 5. This study found that the estimated reductions in injury single-vehicle road-departure crashes were very consistent for all feature sets but with widened CIs. LDW + LKA had an estimated reduction of 7% and, similarly, LDW + LKA + LCA had an estimated reduction of 8%. Although the estimates were very similar, the CI for LDW + LKA + LCA covered zero (i.e., was not necessarily effective), likely due to the reduced sample size. LDW had an estimated reduction of 5%, which was not necessarily different than zero.

LDW/LKA/LCA results for serious crashes are based on about 5% of the total system-relevant crashes (see Figure 5). As expected, single-vehicle road-departure crashes (5% involve serious or fatal injury) lead to more severe injuries than front-to-rear crashes (1% involve serious or fatal injury). The subset of system-relevant crashes involving a serious or fatal injury produced a more limited sample size. For serious single-vehicle road-departure crashes, this study estimated reductions of 5% for LDW, 13% for LDW + LKA, and 16% for LDW + LKA + LCA, all of which were not necessarily different from zero. This is likely from the widening of the CIs due to more limited sample sizes.

LDW/LKA/LCA results by condition did not find interactions for LDW. For LDW + LKA, only sales type (fleet or retail) was identified by BIC for the all single-vehicle road-departure crashes and injury single-vehicle road-departure crashes models. This study found no interactions for LDW + LKA + LCA.

DISCUSSION

The focus of this study was on crash avoidance rather than crash mitigation. In many cases – almost half for FCW + AEB in front-to-rear crashes – the presence of ADAS features do prevent the crashes from happening. In many other cases, the crash is unavoidable and still occurs. Yet, ADAS can still assist by potentially making the crash less severe, with fewer and less serious injuries. In the future, PARTS will estimate crash mitigation separately from avoidance.

AEB/FCW (Front-to-rear Crashes)

This study estimated that when vehicles are equipped with FCW + AEB, they are 49% less likely to strike another vehicle in a front-to-rear crash. FCW + AEB effectiveness increases to 53% for crashes involving injury and was slightly reduced, to 42%, for the most serious (including fatal) crashes. The avoidance of about half of front-to-rear crashes across crash types is a remarkable achievement and demonstrates industry's voluntary and proactive commitment to safety [23]. Because drivers likely have FCW + AEB enabled at high rates [24] compared with other ADAS features, these estimates show the real-world effectiveness of AEB as a safety technology.

When vehicles are equipped with FCW and not AEB, they are 16% less likely to strike another vehicle in a front-to-rear crash, indicating that safety technologies that actively intervene and automatically brake to help avoid a collision are much more effective than just alerting drivers of potential collisions ahead. The estimated reductions found in this study align well with past literature, especially once accounting for CIs.

Because of the significant size and scope of the dataset, this study was able to assess effectiveness in a variety of environmental conditions and driver characteristics. The study demonstrated that AEB performs extremely well in all conditions, even when roadway, weather, and lighting conditions are not ideal. For example, AEB effectiveness is only reduced from 49% to 42% when comparing crashes that occur in daylight versus at dark. In addition, AEB effectiveness is only reduced from 49% to 44% when used on wet roads in bad weather as compared to on dry roads in good weather.

The goal of this study was not to explain the differences identified, but rather to indicate areas that require further research. The covariate analysis identified several areas that PARTS will explore in future iterations:

1. This study indicated that AEB effectiveness is lower for speed limits under 35 mph, particularly those under 25 mph, as compared to speed limits 35 mph and above. Lower-speed crashes are less likely to be police-reported in some states, and vehicles in lower-speed crashes may not have reached their minimum activation speed for AEB. In the future, PARTS may incorporate information about the operational design domains for ADAS features to analyze only those situations in which the systems are designed to function.
2. This study indicated that AEB effectiveness is lower as the age of drivers increased, 44% for drivers aged 55–64, 42% for drivers 65–74, and down to 34% for drivers over 75. More research is needed to understand these differences, though reasons could vary from driver adoption of ADAS, to driving behaviors, to types of crashes that younger vs. older drivers tend to be involved in.
3. This study indicated that AEB effectiveness is lower for all crashes occurring on curved road segments (34%) as compared to straight road segments (50%). This is an intuitive result, as vehicles may not be able to detect and classify the lead vehicle depending on the curvature of road. In the future, PARTS may integrate additional data sources that provide more accurate roadway information, including amount of curvature, to determine the type of curvature situations in which AEB is most and least effective.

In general, this study also found that the set of covariates analyzed were generally relevant, helpful in controlling for influential factors, and useful in detecting condition-specific effects. Based on their utility, the covariates used in this study should be included in future studies and refined as appropriate given additional data and model maturation. In particular, other studies using quasi-induced exposure should include crash year as a controlling factor.

Partners identified a number of priorities for expanding the FCW+AEB analysis in future iterations beyond those listed above. These include the following: (1) Understand unintended consequences, such as whether AEB-equipped vehicles are more likely to be in front-to-rear crashes; (2) Understand the distribution of the striking vs. struck vehicle, including by body type and/or mass, and explore how the severity of injuries vary with these differences; (3) Better understand how driver behavior, including risky behaviors, may impact results; (4) Determine how AEB effectiveness changes over the vehicle's lifecycle, especially accounting for vehicle service, maintenance, recalibrations of ADAS, or changing ownership; and (5) Consider effectiveness in other types of system-relevant crashes, such as head-on crashes and left turn across path crashes, as AEB functionality is expanded.

LDW/LKA/LCA (Single-vehicle Road-departure Crashes)

The analysis found that ADAS features such as LDW + LKA, when working together, provide some safety benefit in reducing single-vehicle road-departure crashes. The study estimated that lane management feature sets (LDW + LKA and LDW + LKA + LCA) reduced crashes by about a tenth for all single-vehicle road-departure crashes (8% and 9% respectively). These feature sets had similar estimated reductions for injury single-vehicle road-departure crashes, although after accounting for uncertainty, there was a possibility of no effect for LDW + LKA + LCA on reducing injury crashes. For crashes with a serious injury, estimates of reduction were slightly higher (13% and 16%), but once accounting for uncertainty there was still the possibility of no effect, possibly due to limited sample sizes. This study also estimated that LDW reduced single-vehicle road-departure crashes by about 5%, but accounting for uncertainty there was the possibility that LDW had no effect.

A significant limitation of the study is an assumption that if a vehicle is equipped with a feature, the driver has enabled that feature and it is activated at the time of crash. One possible reason for the lower effectiveness of LDW and LKA is that drivers may be turning off the systems 50% of the time [24] – if true, it shows that LDW and LKA effectiveness could be higher if people used them more. In the future, it is important to assess effectiveness once actual feature usage can be accounted for, and to explore why drivers are turning the systems off, including the types of alerts that are most and least nuisance, and what can be done to encourage adoption.

Another limitation is that the study did not incorporate information about OEM-specific implementations of lane management systems, to include the type of warning systems (e.g., auditory vs. haptic feedback) or the ODD that defines the limits of that feature's functional capability. For example, PARTS partners recognized that systems are not designed to work at lower speeds.

This analysis was limited by lack of roadway information at the time of crash – for example, there was no information about the existence or condition of lane markings, the number of lanes, or the exact amount of road curvature to understand how these lane management features perform in the real world under different roadway conditions. In the future, PARTS may investigate ways to incorporate more information about the roadway into the analysis.

STUDY LIMITATIONS

This study:

1. Accounts for vehicles that were equipped with ADAS features at the time of manufacture and does not account for actual ADAS usage. It does not capture when drivers have enabled or disabled ADAS features at the time of crash. These limitations likely affect effectiveness estimates of LDW, LKA, and LCA much more than FCW/AEB and PAEB.
2. Does not directly account for different driving behaviors and their effect on ADAS effectiveness. While the exact individual driver risk-taking profile and behaviors are unknown, PARTS included proxies, such as driver age, gender, and even vehicle model, as indicative of driver behavior.
3. Does not capture the variability in ADAS implementations across different OEMs, models, model years, and trimline-specific design and specifications. Further, this study did not incorporate data on each vehicle feature's ODD that defines the limits of that feature's functional capability to operate; rather, it assumed that if equipped, ODD parameters were met at the time of the crash.
4. Uses police-reported crash reports as a primary source of data, which presents a series of well-known challenges. KABCO [14], the framework for categorizing injury information used within the crash database, may not reflect precisely the injuries, injury type, or body region compared against the Abbreviation Injury Scale [15] [16] [17] [18]. Some information documented in the crash report is subjective by the police officer and may be reported inconsistently between officers and states (e.g., driver distraction at time of crash). Crash reports may have limited or no information on relevant factors (e.g., actual speed of the vehicle, road infrastructure that may impact the effectiveness of these systems). These limitations with police-reported crash data are known and generally accepted by this and other related studies, and do not present an outsize concern regarding the results.
5. Has results that may not be representative of the United States. While PARTS took care to capture census data from a diverse set of 13 states and many vehicles, this data on state-level crashes and associated vehicles may not be nationally representative. In the future, once sample sizes are sufficient, PARTS may analyze ADAS effectiveness using data from a national representative database, such as NHTSA's Crash Report Sampling System (CRSS).

SUGGESTIONS FOR FUTURE RESEARCH

In this iteration of analysis, the sample sizes were too small to detect a statistically significant result for PAEB effectiveness. This is due to the limited number of these incidents in crash reports and the lower level of market penetration for PAEB as compared to AEB, particularly in recent model years. More research is needed to understand contributing factors to crashes involving non-motorists, such as how poor lighting and insufficient infrastructure intersect with driver behaviors (e.g., speeding, impairment) and pedestrian factors (e.g., wearing dark clothing, impairment). Understanding the trajectories of vehicles and pedestrians prior to a collision is essential for understanding crash outcomes. In the future, PARTS may expand its dataset and investigate the effectiveness of PAEB by incorporating more information about the non-motorist (type of non-motorist, child vs. adult, and their actions, condition, and visibility prior to crash), vehicle (e.g., headlight implementation, ODD for PAEB, weight, grill height), and the crash (e.g., speed, kinematics of the pedestrian strike) to improve the analysis.

In future iterations, PARTS will seek to incorporate more vehicle equipment data from its OEM partners, including from its newest partner (Ford). Industry partners may provide data from more vehicle models and model years, on more ADAS features, as well as information about OEM-unique implementations of those features. PARTS will integrate additional police-reported crash data, from more states, to expand the sample sizes and increase the representativeness of the study. As sample sizes increase, especially for injury and serious crashes, it is expected that uncertainty in the estimates will decrease, which could cause an increase of power in detecting effectiveness.

In addition to expanded crash data and OEM-provided vehicle equipment data, a key opportunity is to explore and potentially incorporate other data sources, such as vehicle-based telematics, to better understand actual ADAS feature usage and activation, including whether and how features intervene in various situations. In addition, PARTS and traffic safety researchers may seek better, more comprehensive injury outcome data, to include relevant

Emergency Medical Services (EMS) and hospital record data for both drivers and passengers involved in crashes, to enhance understanding of outcomes in a variety of situations.

In future iterations, PARTS may also adjust its analytic methodology to address the challenges of estimating effectiveness that come once ADAS features become standard equipment on vehicles. In the PARTS study, the difference between the set of equipped and unequipped vehicles became starker as the model year increased, which made it more challenging to accurately estimate effectiveness without confounding factors influencing results.

PARTS, as a data sharing public-private partnership, is one-of-its-kind and innovative, continuously proving out new approaches for collaborating on safety. Learnings from PARTS will support improvement in ADAS technologies to have maximum impact on roadway safety. Working together, government and industry can contribute to enhancing the safety of our roads.

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EFFECTS OF A BICYCLIST DETECTION SYSTEM ON POLICE-REPORTED BICYCLE CRASHES

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Paper Number 23-0192

ABSTRACT

Research Question/Objective
Automatic emergency braking (AEB) is effective at preventing vehicle-to-vehicle rear-end crashes and pedestrian crashes. Subaru's driver assistance system that includes AEB, called EyeSight, could detect bicycles in parallel configurations in the United States in its first and second generations, and added bicyclist detection in perpendicular configurations in its third generation. The purpose of this study was to evaluate whether the first and second generations of EyeSight reduced bicycle crashes in the real world.

Methods and Data Sources
The presence or absence of EyeSight was identified through Vehicle Identification Numbers for model year 2013–2020 Subaru models where the system was optional. All bicycle crashes and single-vehicle single-bicyclist crashes with parallel and perpendicular configurations involving these vehicles were extracted from the police-reported crash databases of 16 U.S. states during calendar years 2014–2020.

The association of EyeSight with bicycle crash rates per insured vehicle year was examined with negative binomial regression controlling for calendar year, state, vehicle model year and series, and driver age group and gender. Quasi-induced exposure analyses using logistic regression compared involvement in a bicycle crash to the nonsensitive crash types of being rear-end struck or side-struck, using the same covariates as the negative binomial regression models. These analyses included crash data from 14 states where rear-end-struck and side-struck vehicles could be identified.

Results
Study vehicles were involved in 856 bicycle crashes, of which 283 had parallel configurations and 387 had perpendicular configurations. EyeSight was associated with a statistically significant 29% reduction in parallel crash rates per insured vehicle year (Rate ratio [RR], 0.71; 95% confidence interval [CI], 0.53–0.96, $p = 0.03$), and nonsignificant reductions of 5% in perpendicular crash rates (RR, 0.95; 95% CI, 0.74–1.21, $p = 0.66$) and 9% in overall bicycle crash rates (RR, 0.91; 95% CI, 0.77–1.08, $p = 0.28$). Effects of similar magnitudes were seen in the quasi-induced exposure analyses.

Discussion and Limitations
An early version of EyeSight reduced bicycle crashes in the parallel configurations it was designed to detect but did not have much effect on bicycle crashes overall. Crash configuration was identified by bicyclist and vehicle direction of travel when they were available. In states where direction of travel was unavailable, bicyclist precrash actions of cycling along the roadway with or against traffic and crossing were used as proxies for parallel and perpendicular configurations, respectively. The actual configurations of crashes in these states were unknown.

Conclusions and Relevance to Session Submitted
Although it is promising that an initial bicyclist detection system prevented crashes in parallel configurations, a minority of bicycle crashes are of this type. AEB systems will need to increase functionality and detect perpendicular crash configurations to meaningfully reduce bicycle crashes.

INTRODUCTION

Automatic emergency braking (AEB) systems, which typically warn drivers of an impending collision and apply the brakes if they do not respond to the warning, have been demonstrated to be effective in reducing vehicle-to-vehicle rear-end crashes [1-4] and crashes with pedestrians [5]. Because of its effectiveness, 20 U.S. automakers committed to make vehicle-to-vehicle AEB a standard feature on virtually all new passenger vehicles as of September 2022 [6], and the United States Department of Transportation [7] has pledged to begin rulemaking by 2024 to mandate AEB with pedestrian detection on new passenger vehicles.

Bicyclist detection is another feature that is being added to AEB. In the United States, this functionality is needed as a tool to potentially curb the increase in bicyclist fatalities that has occurred over the past decade. An estimated 985 pedalcyclists were killed in U.S. motor vehicle crashes in 2021 [8], which represents a 58% increase from the 623 cyclists who lost their lives in 2010. The number of U.S. bicyclists treated in emergency departments and admitted to hospitals has similarly risen over time [9].

Studies have estimated the potential benefits of AEB systems that detect cyclists [10,11], but little is known about their real-world effects on crashes. Recently, Kullgren et al. [12] reported that AEB with bicyclist detection was associated with a 21% reduction in bicyclist crash risk in Sweden. The goal of the current study was to investigate the effects of the first and second generations of Subaru's EyeSight, an AEB system that includes bicyclist detection, on bicyclist crash risk in the United States.

METHODS

Two approaches were used to examine the effects of EyeSight on bicyclist crash risk. First, the relationship of the system to bicycle crash rates per insured vehicle year was investigated. The second approach used the quasi-induced exposure technique to compare involvement in a bicycle crash with involvement in a crash type not relevant to EyeSight between vehicles that were and were not equipped with the system. The nonsensitive crash type in quasi-induced exposure is used as a proxy for driving exposure [13] and is thought to better account for differences in driving distance and conditions that are not captured when using insured vehicle years as the exposure measure.

EyeSight System

Study vehicles were model year (MY) 2013–2020 U.S. Subaru models that offered the first- or second-generation versions of EyeSight as an optional feature, including the MY 2013–2018 Legacy and Outback, 2014–2018 Forester, 2015–2019 Impreza, 2015–2020 Crosstrek, and 2016–2020 WRX. In its first and second generations in the United States, EyeSight was designed to detect cyclists in parallel scenarios but not in perpendicular ones. EyeSight is a feature that is discernable from the Vehicle Identification Number (VIN), and its presence or absence on vehicles was identified from decoding the VINs associated with crashes and insured vehicles.

Crash Data

Key variables from the crash databases of 16 U.S. states during calendar years 2014–2020 were coded into a common format for analysis (Appendix, Table A1). Bicycle crashes were defined as crashes involving one or more bicyclists in which the subject vehicle was not backing. Single-vehicle single-bicyclist crashes were further classified as having parallel or perpendicular crash configurations in two ways, depending on variable availability in each state. Configuration was based on the vehicle and bicycle directions of travel prior to the crash in the eight states where these variables were available. The crash had a parallel configuration if both the vehicle and cyclist were traveling along the same path (e.g., both east/west or both north/south), and a perpendicular one if they were traveling in intersecting paths (e.g., the vehicle was traveling north/south and cyclist east/west, or the vehicle was traveling east/west and the cyclist north/south).

The bicyclist's action prior to the crash was used as a surrogate for configuration in other states, with crashes where the cyclist was riding along the roadway with or against traffic categorized as parallel scenarios, and crashes where the cyclist was crossing considered to be perpendicular scenarios. When both variables were available, the configuration was established by the direction of travel, and bicyclist precrash action was considered when direction was missing. Nearly all single-vehicle single-bicyclist crashes were classified as having perpendicular or parallel configurations in states where vehicle/bicycle direction of travel were available unless direction was unknown. In states where bicyclist precrash action was used as a proxy for configuration, about one fourth of the bicyclists were coded with another precrash action (e.g., cycling on the sidewalk, adjacent to the roadway, playing in the roadway) and weren't included in analyses of crash configurations.

Rear-end-struck and side-struck crash involvements were also identified for use in the quasi-induced exposure analyses. A vehicle was considered rear-end struck if the manner of collision was a rear end and the point of impact was to the rear (5-, 6-, or 7 o'clock), and was side struck if the subject vehicle was impacted on the side (2-, 3-, 4-, 8-, 9-, or 10 o'clock) in a two-vehicle crash where the manner of collision was not a rear end by another vehicle with a frontal impact (11-, 12-, or 1 o'clock).

Insured Driver Data

Data on the number of days vehicles were insured were obtained from the Highway Loss Data Institute. Crash rates are expressed as crashes per insured vehicle year, with a single vehicle insured for 1 year or two vehicles insured for si6 months each equaling one insured vehicle year. Insured driver data included the state, age, and gender of the rated driver on the insurance policy and were matched to the crash data by vehicle, state, calendar year, driver age group, and driver gender.

Analyses

Analyses examining the relationship of EyeSight to bicycle crash rates per insured vehicle year used negative binomial regression models that controlled for vehicle model year and series combination, state, calendar year, driver age group (< 25, 25–64, 65 years and older), and driver gender.

Quasi-induced exposure analyses were performed using logistic regression with the same covariates as the negative binomial regression models. These analyses were limited to 14 states with variables for vehicle point of impact so that struck vehicles could be identified. The two states without these variables were large (New York and Washington), and so sample sizes were considerably smaller without them.

Rear-end-struck crash involvements were initially selected as the nonsensitive crash type. This crash type has been shown to vary close to linearly with exposure [13] and has been used in other quasi-induced exposure analyses examining the crash effects of AEB [2,3,5,12]; however, Cicchino [1] found that AEB was associated with a 20% increase in rear-end-struck crash-involvement rates per insured vehicle year, possibly due to more instances of hard braking when AEB is activated. If AEB increases the risk of being struck in the rear, treating that crash type as nonsensitive in the quasi-induced exposure analyses could result in biasing effect estimates towards showing a benefit. EyeSight was associated with a small (3%) but statistically significant increase in rear-end-struck crash rates per insured vehicle year in the current data set (Rate ratio [RR], 1.03; 95% confidence [CI], 1.00–1.06, $p = 0.04$). Thus, a second crash type, side-struck crash involvements, was used as the nonsensitive crash type in an additional set of quasi-induced exposure analyses.

Both methods were used to separately examine the association of EyeSight with (1) all bicycle crashes, (2) single-vehicle single-bicyclist crashes with parallel configurations, and (3) single-vehicle single-bicyclist crashes with perpendicular configurations. Vehicle series/model year combinations were removed from an analysis if they were involved in no bicycle crashes of the type examined (e.g., vehicles involved in no bicycle crashes with parallel configurations were excluded from analyses of parallel crash scenarios). Model parameters were exponentiated and interpreted as rate ratios (RRs) from negative binomial regression models and odds ratios (ORs) from logistic regression models, and percent changes in these rates and odds associated with AEB were expressed by $100(\exp(x)-1)$, where x is the parameter estimate for EyeSight.

RESULTS

Study vehicles were involved in 856 bicycle crashes. A total of 822 of these were single-vehicle single-bicyclist crashes, of which 283 (34%) had parallel configurations and 387 (47%) had perpendicular configurations. Crash rates per insured vehicle year were lower for vehicles with EyeSight than without, with the largest difference seen in parallel-configuration crashes (Table 1).

Table 1.
Bicycle crash rates per insured vehicle year among Subaru vehicles with and without EyeSight

System	Parallel configuration		Perpendicular configuration		All bicycle crashes	
	Number	Rate (x 100,000)	Number	Rate (x 100,000)	Number	Rate (x 100,000)
With EyeSight	68	4.2	113	6.9	242	14.8
Without EyeSight	215	5.9	274	7.6	614	16.9
Total	283	5.4	387	7.4	856	16.3

Negative binomial regression revealed that when accounting for covariates, bicycle crash rates in parallel configurations were 29% lower among vehicles with EyeSight compared with the same models without the system (RR, 0.71; 95% CI, 0.53–0.96, $p = 0.03$; Table 2). In contrast, there were smaller and nonsignificant differences of 5% in rates of perpendicular (RR, 0.95; 95% CI, 0.74–1.21, $p = 0.66$) and 9% of all (RR, 0.91; 95% CI, 0.77–1.08, $p = 0.28$) bicycle crashes per insured vehicle year between vehicles with and without EyeSight.

Table 2.
Model results of association of EyeSight with bicycle crash risk

Analysis	Parallel configuration	Perpendicular configuration	All bicycle crashes
	RR (95% CI)	RR (95% CI)	RR (95% CI)
Negative binomial regression	0.71 (0.53, 0.96)*	0.95 (0.74, 1.21)	0.91 (0.77, 1.08)
	OR (95% CI)	OR (95% CI)	OR (95% CI)
Quasi-induced exposure (rear-end-struck nonsensitive crash type)	0.72 (0.49, 1.05)$^{+}$	0.99 (0.73, 1.35)	0.93 (0.76, 1.15)
Quasi-induced exposure (side-struck nonsensitive crash type)	0.69 (0.47, 1.00)$^{+}$	0.95 (0.70, 1.29)	0.87 (0.71, 1.08)

Abbreviations: CI, confidence interval; OR, odds ratio; RR, rate ratio.
$^{*}p < 0.05$. $^{+}p < 0.10$.

Analyses using quasi-induced exposure included 571 total bicycle crashes, 181 with parallel configurations, and 259 with perpendicular configurations. Study vehicles in the quasi-induced exposure states were involved in 34,593 rear-end-struck crashes and 10,105 side-struck crashes. Effect sizes in quasi-induced exposure analyses were similar to models examining crash rates per insured vehicle year (Table 2), but the association of EyeSight with parallel configurations was no longer statistically significant ($p = 0.09$ for analysis using rear-end-struck crashes as nonsensitive crash type, $p = 0.05$ for analysis using side-struck crashes). The smaller sample sizes in the quasi-induced exposure analyses limited statistical power, especially when examining crash configurations.

DISCUSSION

The first and second generations of EyeSight were effective in the United States at reducing bicycle crashes in the parallel configuration they were designed to detect, but this did not translate into a consequential decline in bicycle crashes overall. It is well-documented that while parallel scenarios are overrepresented in fatal bicycle crashes, they are not the most frequent scenario when considering bicycle-motor vehicle crashes of all severities. MacAlister and Zuby [14] reported that in the United States during 2008–2012, the cyclist was in-line or against traffic in 28% of single-vehicle crashes involving the fronts of passenger vehicles and was crossing traffic in 54%. Crossing crashes similarly make up the majority of bicycle-motor vehicle crash scenarios in Europe [15,16]. AEB with bicyclist detection will need to respond in perpendicular scenarios as well as parallel ones to reduce bicycle crashes meaningfully.

Fortunately, systems with this functionality currently exist in production. The third generation of EyeSight, which was introduced in the United States on the MY 2022 Forester and WRX, adds detection of cyclists traveling in a path perpendicular to the vehicle. The MY 2023 Subaru Outback, Legacy, and Ascent are available with a third mono camera that expands the field of view of EyeSight and could potentially detect cyclists sooner in crossing scenarios. Euro NCAP [17] tests AEB with bicyclist detection in both crossing and longitudinal scenarios, which encourages automakers in the European market to equip vehicles with systems that perform well in both configurations. Future research can examine the real-world effects of these systems in the United States when enough crash data amass to study them.

AEB has been shown to struggle in some challenging vehicle-to-vehicle and pedestrian crash circumstances, which could also limit the potential effectiveness of AEB with bicyclist detection. Cicchino [5] found that AEB with pedestrian detection is not associated with pedestrian crash risk reductions in the dark, and Kullgren et al. [12] reported that a lack of efficacy in the dark extends to AEB with bicyclist detection in Sweden. Like with pedestrians, bicyclist fatalities disproportionally occur in the dark [14], and so AEB systems will need to work well in the dark to prevent deaths. Cyclists are at a greater fatality risk when involved in crashes with higher vehicle speeds, which has also been associated with lower efficacy for AEB with pedestrian detection [5]. Crashes where the subject vehicle is turning are challenging for vehicle-to-vehicle and pedestrian AEB [5,18], and while this scenario is not associated with increased injury severity, it is common; in U.S. national crash data, vehicle-turning scenarios make up more than 40% of single-vehicle bicycle crashes involving the fronts of passenger vehicles [14].

The constraints on situations where AEB with bicyclist detection may be effective underscore the need to implement other vehicle features, policies, and roadway design modifications that improve safety for cyclists. Better headlights [19] and roadway lighting [20] make it easier for drivers to see cyclists at night and lower nighttime crash risk. Treatments that lower vehicle speeds, such as traffic calming or lowering speed limits in urban areas, have been demonstrated to reduce injury risk for cyclists [21,22]. Geometric design features, like smaller curb radii, and pavement markings can decrease driver conflicts with cyclists while turning at intersections [23]. Raised bicycle crossings are associated with fewer bicycle-motor vehicle crashes at unsignalized intersections [24] and could reduce bicycle-motor vehicle crashes in perpendicular scenarios. Multiple types of countermeasures need to be used so that bicyclists can operate within a safe system.

Limitations

Data elements collected in police reports vary by state in the United States, and information pertaining to bicycle crashes is known to be inconsistent among states [25]. The classification scheme for identifying bicycle crashes as having occurred in parallel and perpendicular scenarios was meant to be an approximation for the actual crash configuration to focus the analysis on crash types that were likely (parallel) and unlikely (perpendicular) to be detected by the first and second generations of EyeSight. It is expected, though, that there were errors in these classifications. For example, direction of travel is meant to capture the cyclist's and vehicle's direction prior to the crash, but the direction recorded when the cyclist or vehicle was turning may not be consistently coded. Codes for bicyclist action prior to the crash do not account for the driver's action, and while it seems logical that crashes where the police coded the bicyclist as crossing were unlikely to be in parallel configurations, in-depth information on actual crash configurations was not available in state crash databases. The percentage of single-vehicle single-bicyclist crashes in this study that were categorized as parallel was higher than what would be expected from U.S. national crash statistics, and the percentage categorized as perpendicular was lower, suggesting that parallel configurations were overcounted and perpendicular ones undercounted. If this were the case, the effect estimate for EyeSight in parallel scenarios may have been underestimated.

EyeSight was an optional system on the vehicle models studied in this analysis, and drivers who chose to purchase it may drive differently than those who did not. Using the quasi-induced exposure technique and controlling for driver demographic characteristics in the analyses may have accounted for some aspects of driving exposure differences between these groups. Although rear-end-struck crashes are frequently used as the nonsensitive crash type in quasi-induced exposure analyses of AEB effects, Subaru vehicles with EyeSight experienced a rear-end-struck crash rate per insured vehicle year that was 3% higher than vehicles without the system, which may have inflated effect size estimates in the analysis using this crash type. It is encouraging that corroborating results were found in the analysis examining bicycle crash rates per insured vehicle year and in the quasi-induced exposure analysis using side-struck crash rates as the nonsensitive crash type. The small sample size by crash configuration is an additional limitation, especially in the quasi-induced exposure analysis, which restricted statistical power.

CONCLUSION

AEB systems that detect bicyclists have great potential to prevent motor vehicle crashes with bicyclists, but they need to be able to detect the most common crash configurations to make a difference in the overall crash picture. Currently available systems that can detect cyclists in perpendicular scenarios, including the third generation of EyeSight in the United States, should be more effective at reducing bicycle crashes as a whole than the first and second generations of EyeSight.

ACKNOWLEDGEMENTS

This work was supported by the Insurance Institute for Highway Safety. Thank you to Aimee Cox for compiling state crash data and Bingling Wang for providing data on insured drivers.

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APPENDIX

Table A1.
Police-reported crash data availability with variables for vehicle and bicyclist direction of travel, bicyclist action prior to the crash, and vehicle point of impact by state and year

U.S. state	Years available	Vehicle and bicycle direction of travel	Bicyclist action prior to crash	Vehicle point of impact
Connecticut	2017–2020		X	X
Florida	2014–2019		X	X
Idaho	2014–2020	X	X	X
Illinois	2014–2020		X	X
Maryland	2014–2020		X	X
Minnesota	2016–2020		X	X
Missouri	2014–2020	X		X
New Jersey	2014–2020	X		X
New Mexico	2014–2020	X		2019–2020 only
New York	2014–2019	X	2014–2015 only	
Ohio	2017–2020	X		X
Pennsylvania	2014–2020	X		X
Utah	2014–2019		X	2014–2016, 2018 only
Washington	2014–2020		X	
Wisconsin	2014–2019	2014–2016 only	2017–2019 only	X
Wyoming	2014–2020		X	X

ANALYSIS OF THE EUROPEAN CAR ROAD CRASHES FOR THE IDENTIFICATION OF THE MAIN USE CASES FOR A SIGNIFICANT ROAD SAFETY IMPROVEMENT THROUGH V2X

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ABSTRACT

Research question

In pursuit of Vision Zero towards traffic-related fatalities and injuries in Europe, the SECUR project (Safety Enhancement through Connected Users on the Road) was initiated in a Euro NCAP context. SECUR aims to study the potential of V2X communications to improve road safety. This paper illustrates the main European crash cases involving Passenger Cars as ego vehicles and their parameters. The following opponents were considered: Passenger Cars, Powered Two-Wheelers, Bicyclists and Pedestrians.

Methods and Data Sources

An initial study of crashes at a high level was done to draw a general picture based on German (DESTATIS), French (BAAC) and European (CARE) crash databases. Then, an in-depth study was performed to select and define the SECUR crash cases and their characteristics. As part of this in-depth analysis a generic scenario catalog was developed, covering traffic crash situations, that the driver of a passenger might encounter. The most relevant scenarios regarding accidentology were determined providing the baseline to develop a test environment for a useful V2X-system. Based on the German Insurance Association crashes classification (GDV) and the German in-depth crash database (GIDAS), this catalog clusters all the GDV crash types in 28 categories, each crash being analysed from the perspectives of both participants and considering all different opponent types. The data of the most relevant 15 crash scenarios were provided through a GIDAS-based in-depth study, considering a set of 16 parameters.

Results

According to the in-depth crash analysis, 15 out of 112 crash scenarios were identified as the most relevant ones regarding the number of Killed and Severely Injured (KSI) and the relevance of V2X. These 15 scenarios consider the 4 types of road users and cover 71% of all the KSI crashes from the catalog. Among them Straight Crossing Paths, Left Turn Across Path and Rear-End crash situations. The parameters study has shown that the most significant crash blackspot is at intersections with structural view obstruction.

Discussion and Limitations
This study is subject to certain limitations. First, it is expected to be European representative, so the study was based on GIDAS and complemented with analyses of CARE and the in-depth database (IGLAD). However, the European representativity is still limited by the GIDAS-weighting upon CARE.

Moreover, it is complex to draw conclusions for new vehicles as the current databases naturally include old information and are representative of a past context (vehicle without state-of-the-art safety systems). Therefore, in order to have a dataset more representative of the current context, crashes involving a vehicle without ESC were filtered out.

Conclusion
The main crash cases to be ruled out for a significant road safety improvement through V2X are illustrated in this paper. The results have shown that significant white spots that are not addressed by ADAS due to physical sensor limitations (e.g., obstruction) remain. And it is precisely where V2X benefits sit, standalone or fused with current systems. SECUR results will feed Euro NCAP V2X introduction into the protocols and also further NCAP developments in other regions.

INTRODUCTION

SECUR project resume

Through its 2030 roadmap, the European New Car Assessment Programme (Euro NCAP) aims at encouraging, by a consumer approach, even more safety on the roads, in particular thanks to the use of new inter-vehicle communication solutions.

The aim of the SECUR project is to study the potential of communication to improve the safety of different road users. SECUR ensures technological neutrality in a complex and multi-faceted context. Coordinated by UTAC, the SECUR project outlines a coherent proposal for V2X testing and assessment protocols to Euro NCAP. To this end, an industrial consortium brings together about twenty international stakeholders, from the automotive and V2X ecosystem – automotive OEM, Tier1 manufacturers, V2X-market-stakeholders, and automotive test systems providers.

First, the most common crash situations on European roads were studied. Then, the current knowledge on V2X communication systems was summarized. Thereafter, the potential of V2X systems was studied, either alone or combined with ADAS systems. Finally, multi-technologies connected targets and protocols for evaluating these V2X systems, were developed. The results of this paper are coming from the SECUR crash data study (WP1).

Research questions

This paper aims at answering the two following research questions:

> Question 1: What are the main crash scenarios leading to severely injured or killed persons described by road configuration, types of opponents, pre-crash manoeuvres and their relative frequencies?
> Question 2: What are the main other criteria linked to V2X that characterise each of these injury crash scenarios?

To complete them the following question will be discussed:

> What are the important characteristics of these injury crashes that could be addressable by V2X technology solutions in addition to conventional ADAS sensors?

To answer these questions this paper will go through the following sections: notes on V2X, method and data sources, results, discussions, limitations and conclusion. [1] [2]

Crash study scope

The geographical scope of the SECUR Project is Europe. Considering that vehicle connectivity is relatively recent, offering a wide range of possibilities and benefits to all road users the following actors were considered as opponents: Passenger Car, Power Two-Wheelers (PTW), Bicyclist and Pedestrian. However, in this study the ego vehicle is always a Passenger Car.

General view on road traffic crashes in Europe

According to the SECUR high level analysis [1] on the European crash database CARE, severe injury and fatal crash occupants decreased between 2012 and 2018. Most died as occupants in passenger cars. While generally the numbers of killed pedestrians and bicyclists are decreasing, the proportion of these kind of road users in the accident scenarios are getting more important. Most people were injured in a crash in urban areas. About one third of the injured people had a crash in rural area. However, the percentage of injured people in crashes on motorways increased since 2012 and decreased in urban areas. The highest percentage of all killed and severely injured people can be found in rural areas crashes.

NOTES ON V2X

V2X can be seen as a new type of sensor for perceiving the environment. Unlike conventional sensors where it is required to actively sense and obtain information from the environment, a V2X station passively receives the information from other V2X stations. Hence, V2X could be a reliable source of information in situations where other sensors may not be able to function properly. For example, conventional sensors, including cameras and radars, rely on a line of sight between the vehicle and other objects. They fail to detect hazards and objects which are invisible to the driver, e.g., objects at an intersection or vehicles blocked by other vehicles. V2X is not only able to “see” the objects in such situations but can also provide much more detailed information impossible to be obtained by other sensors. For instance, in harsh weather conditions where the camera may not be able to determine the state of the traffic light, such information with much more detail, including traffic light state change time, can be obtained from V2X messages. [3] [4]

Communication forms

There are different forms of communications for a V2X station, The main ones are as follows

- **V2V - Vehicle-To-Vehicle**: Direct communication between vehicles.
- **V2VRU - Vehicle-To-Vulnerable Road User:** Direct communication between a vehicle and a VRU, e.g., pedestrian and bicyclist.
- **V2I - Vehicle-To-Infrastructure**: Direct communication with connected infrastructure, e.g., road gantries and traffic lights.
- **V2N - Vehicle-To-Network**: Indirect communication between V2X stations via a mobile network using cloud-based services.

V2V and V2VRU can address all types of use cases, even safety-critical ones that require low latency communications. Today V2N, due to the latency of current mobile networks, has less or partial applications in safety and delay critical use cases [5]. This may change in the upcoming years. The main benefit of V2N is its large coverage area. Unlike direct communications, e.g., in V2V, that, depending on the situation, may have a coverage area of a few hundred meters, the coverage of V2N can be unlimited if a connection to the mobile network is established. This makes V2N especially suitable for long range communication. For instance, informing the V2X station over a large distance about a crash, traffic jam or road blockage can help the station in making or updating its plan.

V2X-related crash countermeasures

Based on ETSI [6] and defined by SECUR in [7] V2X could be involved in six different crash countermeasures to reduce the frequency and severity of crashes:

Driver information, to provide static (or semi-static) information about the In-Vehicle Signage (IVS) for a safe and comfortable drive (e.g., dynamic speed limit and dynamic lane management). No driver action required.

Driver awareness, to point the driver’s attention to a situation ahead on its vehicle trajectory (e.g., local hazards and Vulnerable Road User (VRU) presence) that has the potential to become dangerous or critical if overlooked by the driver. No driver immediate action required other than to be attentive and to adapt driving behaviour to the situation.

Driver warning, to issue alerts to the driver requiring an immediate action to avoid a crash (e.g., emergency braking and lane keeping). V2X could be used as an additional sensor.

Vehicle action. V2X could be used as an additional sensor for mitigation and crash avoidance by active safety systems. This category could be divided into non-safety-critical and safety-critical actions. Today V2X cannot provide Automotive Safety Integrity Level (ASIL) [8]. Non-safety-critical Vehicle Action is not subject to ASIL requirements due to the low consequence severity (e.g., speed reduction, acceleration limitation, system parameter/sensitivity update, etc). Safety-critical Vehicle Action is subject to ASIL requirements due to the high consequence severity. V2X should ensure enough safety confidence (ASIL level) before data fusion with those applications like Autonomous Emergency Braking (AEB).

Pre-crash countermeasure, to bring additional information to the vehicle active systems in case of an upcoming crash.

Post-crash countermeasures, triggered by passive safety systems after a crash to bring information to the surrounding road users to reduce the risk of another crash.

METHODS AND DATA SOURCES

The method consists in two mains steps which answer research question 1 and 2 respectively:

1. Generic crash scenario catalog: creation of a generic scenario catalog considering all types of crashes and all main road users (Passenger Car (PC), Powered two wheelers (PTW), Bicyclist (BC) and Pedestrian (PD))
2. In-depth crash scenarios study: deep study of selected parameters for the most frequent and severe crash scenario to build SECUR use cases.

To define the SECUR test scenarios and their parameters, a generic crash scenario catalog was created based on the German Insurance Association (dt. Gesamtverband der Versicherer; GDV) crash classification. The latter clusters all crashes involving a passenger car by categories. Thus, it is possible to determine the most frequent and severe crash scenarios and create a foundation to develop a test environment for a useful V2X-System via an in-depth crash study of a selection.

Definitions

In the following analysis, the terms category, crash scenario, use case and test scenario are used as defined in Table 1.

Table 1.
Definition table

Key words	Definition
CATEGORY	Described by the crash-causing conflict situation regardless of the participant.
CRASH SCENARIO	Described by road layout and basic motion parameters of vehicles participating in an injury road traffic crash. A crash scenario is a combination of a category with a kind of road user.
USE CASE	Derived from crash scenarios by adding detailed information for example about road layout, right-of-way and vehicle trajectories prior to the collision. Note: Use Cases serve as an intermediate step between the Crash Scenarios and the Test Scenarios.
TEST SCENARIO	Final testing conditions.

Crash datasets for the analysis

For the development of the SECUR generic crash scenario catalog [1], the data of the German In-depth Crash Study (GIDAS) were used. GIDAS is a collaborative project of the Federal Highway Research Institute of Germany (BASt) and The Research Association of Automotive Technology of Germany (FAT). Each case is encoded with about 3,400 variables. Following the documentation, most of the crashes are reconstructed by an experienced engineer. For all the analyses the GIDAS database with a status of June 2021 was used.

For this analysis it was necessary to create at first a target-oriented master dataset, which is a filtered version of the whole GIDAS dataset. The following selection criteria have been applied:

1) Only completely coded and reconstructed crashes were considered
2) The ego vehicle had to be a passenger car

3) The ego vehicle had to be equipped with an Electronic Stability Control system (ESC)
4) The crash severity had to belong to the following two injury severity groups:
    a. Killed and/or Seriously Injured (KSI)
    b. Injured

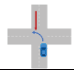
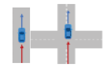
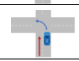
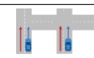
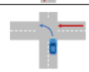
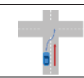
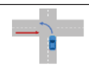
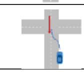
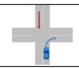
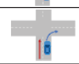
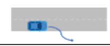
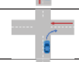
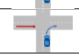
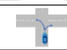
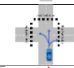
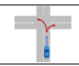
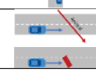
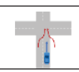
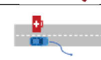
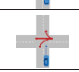
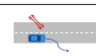
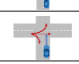
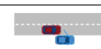
The two first criteria are explained by the need of complete crashes and by the scope of the project which is focus only on a passenger car as the ego vehicle. The third criteria, limits the number of vehicles that are too old in the master dataset. Indeed, the fact to eliminate vehicles without Electronic Stability Control (ESC) allows results that are more in line with the current car market. Two injury severity groups were studied separately. However, all the selection and decisions were done based on KSI crashes. Injured road users should be considered as a complementary information.

Generic crash scenarios catalog

This catalog was developed to group all possible injury crash scenarios into well summarized categories with the main road users with the aim to select the main ones in a second step. The approach was based on a method described by Feifel and Wagner to create harmonized scenarios based on the crash pre-crash description [9]. The method is based on GDV crash types that identify the conflict situation of the traffic participants leading to the crash. The crash types are also used for specifying the causer and non-causer in each crash. Only the first two conflicting partners such as vehicles or vulnerable road users are defined in each crash even if further participants are involved. The proposed scenario catalog contains all degrees of freedom for the ego and opponent participants, such as longitudinal, crossing or turning. All crashes are considered from the causer and non-causer perspectives; therefore, the number of scenarios is twice the number of crashes. This allows for developing a holistic picture of the traffic crash distribution between two participant types, such as car versus car. The catalog provides for a description of the target population in question, in research projects as well as throughout all phases of system development.

Two sources were used to define the categories of the catalog, MUSE project [10] and the scenario catalog in [9]. Additional categories were defined by accidentology experts. These ones are content-related based on the crash type. The crash types of the German Insurance Association (GDV) were mapped to those categories. The crash type is defined as the crash-causing situation. The overall catalog is described in [1].

Table 2.
Category list of the generic crash scenario catalog

Category					
1		Left Turn Across Path – Opposite Direction	15		Rear End - Previous Vehicle
2		Left Turn - Same Direction	16		Parallel Driving
3		Left Turn - Right Direction	17		Lane Change - Same Direction
4		Left Turn Across Path – Left Direction	18		Lane Change - Opposite Direction
5		Right Turn - Opposite Direction	19		Reverse
6		Right Turn - Same Direction	20		Loss Of Control in Straight Line
7		Right Turn - Right Direction	21		Loss Of Control in CUrve
8		Right Turn - Left Direction	22		Loss Of Control - Turning
9		Oncoming	23		Rail Vehicle
10		Straight - Same Direction - Turning	24		Animals / Objects
11		Rear End - Following Vehicle	25		Break Down
12		Straight - Same Direction - Lane Change	26		Inability
13		Straight Crossing Path – Right Direction	27		Sudden Vehicle Damage
14		Straight Crossing Path – Left Direction	28		Dooring

To address all the crash cases included in the GDV classification, the perspectives of all participants (participant A and participant B) were considered in each case. Therefore, a safety measure will not only assist one participant but both and the crash could also potentially be addressed form both sides. Table 3 show the total numbers by occupants and severity considered in the catalog.

Table 3.
Numbers considered in the catalog by occupants and severity (from GIDAS)

Total number of … (in GIDAS)	**Passenger Car**	**Powered Two-Wheelers**	**Bicyclist**	**Pedestrian**	**Other kind of participants**	**Total**
Injured persons	13.140	1.248	3.575	1.121	245	19.329
KSI persons	2.091	421	690	497	21	3.720

To validate the results coming from the catalog at the EU level, a target population study was done. The objective was to estimate for each catalog category the number of KSI occupants, who could be potentially saved thanks to system. For this the catalog categories were estimates based on CARE database 2020 with the methodology describe in [11]. CARE dataset 2020 is extrapolated from CARE 2018. This extrapolation ensures that the covid did not disrupt the data.

Detailed analysis of crash scenarios

Analysing all the 28 categories in combination with all four types of possible opponents would have meant to analyse 112 combinations. This detailed analysis was performed on the most frequent and severe crash scenarios of the catalog. The selection contains 15 crash scenarios selected by the number of KSI.

The 16 parameters chosen are listed in Table 4. However, not all the parameters were analysed for each scenario as not relevant in that case [2]. Those parameters were studied based on GIDAS database.

Table 4.
Parameters description

Parameter	Description
Weather condition [NIED]	E.g., rain, hail or snow
Road surface [STROB]	E.g., dry, damp, wet or hoarfrost
Light condition [LICHT1]	Daylight, darkness and dawn/twilight
Illumination of the road [STRABEL]	Illumination status of the road in the darkness and dawn/twilight cases
Percentage of view obstruction [SICHTBV]	Yes/No
Kind of view obstruction [SICHTV]	E.g., driving vehicle or structural circumstances
Topology of road / intersection [FSTREIF1]	E.g., straight road or intersection one lane
Radius of curve [KRADIUS]	E.g., 101-200m
Kind of traffic regulation [VKREG]	E.g., Traffic lights or observe right-of-way
Traffic density [VSTUFE]	E.g., light traffic, dense traffic or traffic jam
Crash cause [HURSU]	E.g., ability to drive or speed
Human failure [EINFKAT1]	Influence of the driver on the crash (e.g., distraction)
Initial speed [V0]	Ego and opponent speed driven prior the first crash critical situation
Deceleration [BV]	Ego and opponent deceleration prior to the crash

RESULTS

The results of the previously presented methodology are divided between two parts, one by research questions.

Research question 1: what are the main crash scenarios leading to severely or killed persons described by road configuration, types of opponents, pre-crash manoeuvres and their relative frequencies?

Figure 1 shows the frequency of severely or fatally injured people by the categories considered in the catalog.

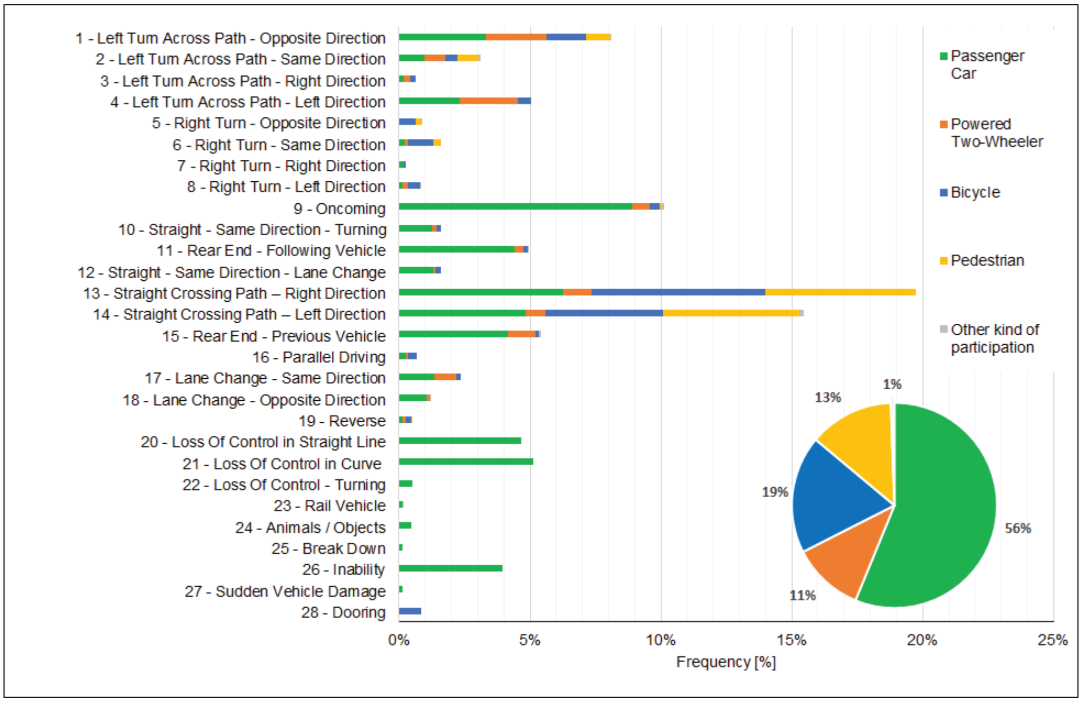


Figure 1. Frequency of severely or fatally injured people by catalog categories.

Table 5 provides a ranking on the 15 most frequent crash scenarios identified through the catalog. Crash scenarios describe a combination of category and road user type (e.g., "Reverse" is a category and "Reverse for bicyclist" is a crash scenario). The category "26 – Inability" contains all the situations, where the driver of the ego vehicle had a physical problem. This category got removed because of V2X systems would not provide assistance in case of inability. With these 15 crash scenarios, 71% of all the KSI occupants are covered and 84% of all injured occupants of the catalog.

This table also the EU target population results based on CARE database. Please note that because of the similarity of the categories 20 and 21 (LOC in Straight Line / LOC in Curve) they got combined to one category "Loss Of Control", see "*" in the table. Example of interpretation for the column "EU target population (CARE)": With a countermeasure which addresses the SCP-RD BC scenario, potentially 8% of the KSI bicyclists could be saved.

In addition, the EU project OSCCAR led to an estimation of reduced casualties and an identification of future accident configurations which ADAS equipped vehicles would be exposed to in 2025. It can be seen in [12], [7], how the selected scenarios of the SECUR analysis are aligned with the findings in OSCCAR project.

Table 5.
Main crash scenarios sorted by KSI frequency

KSI Ranking	**Catalog category**	**Crash scenario name**	**Description**	**Opponent**	**Crash scenario catalog coverage (GIDAS-2020)**				**EU target population (CARE-2020)**	
					KSI [n]	**KSI [%]**	**Injured [n]**	**Injured [%]**	**KSI [%]**	**Injured [%]**
1	9	Oncoming	Face to face impact between two passenger cars.	Passenger car	332	9%	1326	7%	6%	5%
2	13	Straight Crossing Path – Right Direction (SCP-RD)	Crossing bicyclist from right side at an intersection.	Bicyclist	248	7%	1162	6%	8%	9%
3	13	Straight Crossing Path – Right Direction (SCP-RD)	Crossing passenger car from right side at an intersection.	Passenger car	233	6%	1598	8%	4%	6%
4	13	Straight Crossing Path – Right Direction (SCP-RD)	Crossing pedestrian from right side.	Pedestrian	214	6%	497	3%	9%	10%
5	14	Straight Crossing Path – Left Direction (SCP-LD)	Crossing pedestrian from left side.	Pedestrian	194	5%	360	2%	9%	7%
6	21	Loss Of Control in CUrve (LOC-CU)	/	Ego single	190	5%	493	3%	6% *	3% *
7	14	Straight Crossing Path – Left Direction (SCP-LD)	Crossing passenger car from left side at an intersection.	Passenger car	179	5%	1230	6%	3%	5%
8	20	Loss Of Control in Straight Line (LOC-SL)	/	Ego single	174	5%	393	2%	6% *	3% *
9	14	Straight Crossing Path – Left Direction (SCP-LD)	Crossing bicyclist from left side at an intersection.	Bicyclist	167	5%	747	4%	5%	6%
10	11	Rear End - Following Vehicle (RE-FV)	Rear-end braking crash between two passenger cars.	Passenger car	164	4%	2051	11%	3%	8%
11	15	Rear End - Previous Vehicle (RE-PV)	Rear-end braking crash between two passenger cars	Passenger car	154	4%	2382	12%	3%	9%
12	1	Left Turn Across Path – Opposite Direction (LTAP/OD)	Passenger car turning left across the path of another vehicle coming from the opposite direction.	Passenger car	123	3%	828	4%	2%	3%
13	1	Left Turn Across Path – Opposite Direction (LTAP/OD)	Passenger car turning left across the PTW path coming from the opposite direction.	PTW	87	2%	188	1%	4%	3%
14	4	Left Turn Across Path – Left Direction (LTAP/LD)	Crossing passenger car from left side at an intersection.	Passenger car	86	2%	583	3%	1%	2%
15	4	Left Turn Across Path – Left Direction (LTAP/LD)	Crossing PTW from left side at an intersection.	PTW	82	2%	218	1%	4%	4%
				TOTAL	2627		14056			

Research question 2: What are the main other criteria linked to V2X characterising each of these injury crash scenarios?
The in-depth analysis was performed on the 15 crash scenarios identified before. As example, two relevant use cases are presented in this work. Full results are available in the SECUR Deliverable D1.2 [2] and the summary table in the appendix.

Straight Crossing Path – Right Direction (SCP-RD) Passenger Car

The SCP-RD PC crash scenario is a collision in which a vehicle travels forwards along a straight path across a junction, towards a vehicle crossing the junction on a perpendicular path, from the right direction.

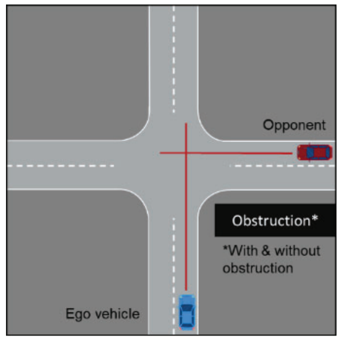


Figure 2. SCP-RD PC pictogram.

Table 6.
Detail analysis results for SCP-RD PC

Parameter	**Description**
Weather condition	In 13% of the cases, the crash happened during rainy conditions.
Light condition	26% of the crashes happened in the darkness or during dawn/twilight.
Illumination of the road	In those cases, 75% of the roads were illuminated with street lighting.
Percentage of view obstruction	in 30% of the crashes there was a view obstruction for the ego participant.
Kind of view obstruction	In the cases with an existing view obstruction, it was due to structural circumstances in 50% of the cases. And in 46% of the cases the view obstruction was due to vehicles. Most of them were parking (33%) during the time of the crash.
Topology of road / intersection	In the majority of the cases, the ego vehicle drove on a road towards an intersection, which had one lane for all directions (46%). In nearly every fifth crash the lane was for straight and right direction only.
Kind of traffic regulation	In 52% of the crashes, the ego had to observe the right-of-way.
Traffic density	During nearly four out of five crashes the traffic density was either light or only sporadic vehicles. Stop-and-go traffic or traffic jams are very uncommon for this type of crashes.
Crash cause	In more than 86% of the crashes one participant failed in observing the right-of-way.
Initial speed ego	In the majority of the cases (58%), the initial speed of the ego vehicle was between 36 kph and 65 kph (81% between 21 kph and 70 kph). The initial speed of the opponent vehicle was most frequently between 0 kph and 50 kph (86%). The ego vehicle was most of the times faster than the opponent before a critical situation was recognised.
Initial speed opponent	

Figure 3 shows the distribution between the different types of obstruction under the condition that a visual obstruction was present at the crash site. Structural circumstances are the main type of obstruction. Obstruction by vehicles is also an important factor; however, it is spread between several driving status.

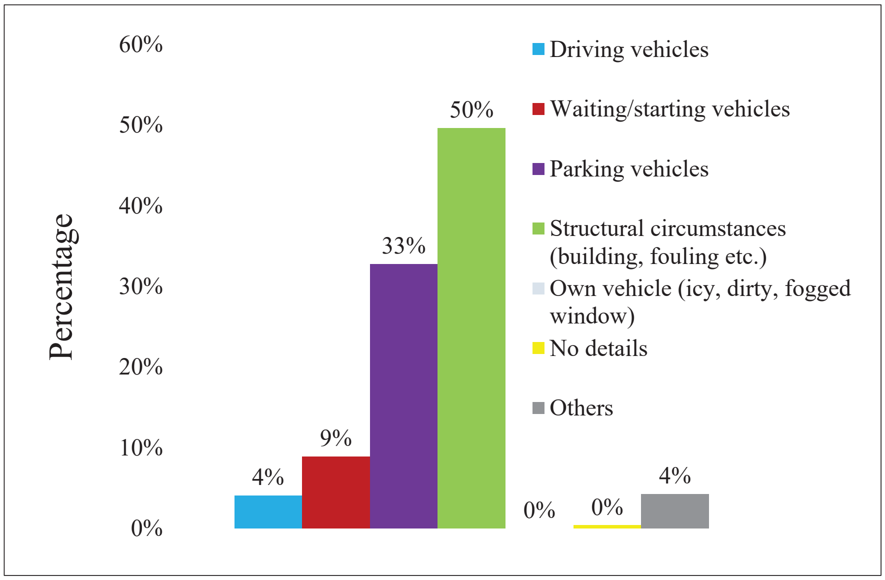


Figure 3. Kind of view obstruction – Ego.

Figure 4 shows that in 52% the traffic regulation is “observe right-of-way” and in 26% of these cases the ego vehicle is the main causer of the crash. The ego vehicle is mostly responsible in intersection regulated by traffic light and “right has right-of-way”.

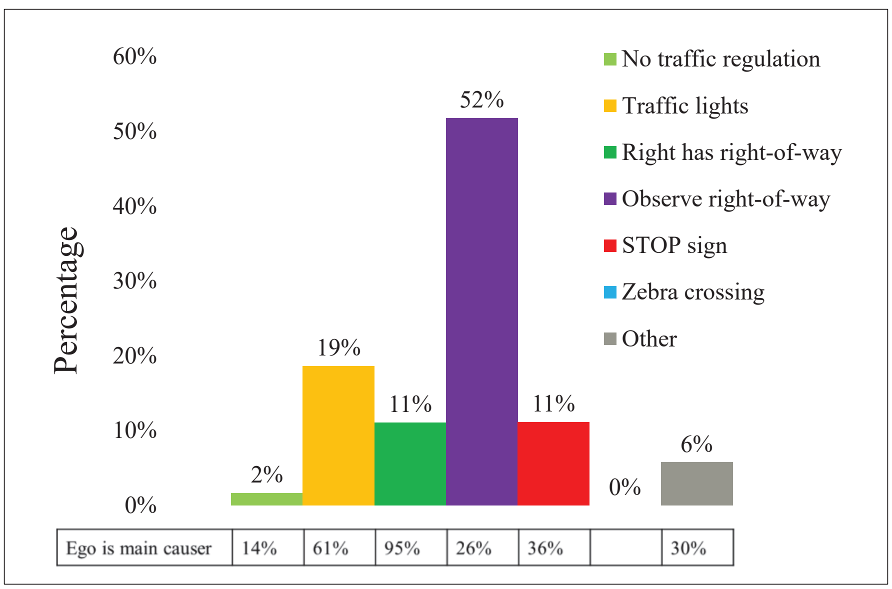


Figure 4. Kind of traffic regulation – Ego.

Table 7 shows the speeds distribution, the ego vehicle initial speed is rather concentrated while for the opponent it is more spread on an important range.

Table 7.
Initial speed - Ego vs. Opponent

Initial speed Ego [kph]		Initial speed Opponent [kph]																
		0	6	11	16	21	26	31	36	41	46	51	56	61	66	71	76	From
From	To	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	…	To
0	5	16	1	1	3	2	2	6	11	11	26	13	8	5	3	2	3	5,0%
6	10	3			2	1	3	1	3	6	3	4	2	1	1			1,3%
11	15	1	2	1	3	2	1	3	7	4	9	5	2	2	1	2	3	2,1%
16	20	2	2	4	3	2	8	6	9	7	15	9	5	1	2	1	9	3,7%
21	25	4	1	4	5	9	11	14	5	11	15	4	8	3	3		4	4,4%
26	30	19	9	12	10	9	19	16	22	11	20	12	9	5	5	1	9	8,2%
31	35	11	16	11	8	11	20	16	15	18	22	10	6	3	3		2	7,5%
36	40	28	18	10	14	19	24	22	25	16	17	12	11	1	5	2	4	10,0%
41	45	50	24	28	22	12	32	21	10	24	27	13	2	2	4	4	1	12,1%
46	50	86	51	42	32	26	32	33	23	18	47	13	6	3	4	2	2	18,4%
51	55	39	14	26	8	16	15	6	12	5	9	7	6	5	2	1	1	7,5%
56	60	33	11	17	8	8	8	10	2	6	7	5	2		4	1	2	5,4%
61	65	23	12	6	10	8	8	5	7	5	7	2	3	1	1		1	4,3%
66	70	14	6	10	8	9	7	5	4	1	3		2	1		1		3,1%
71	75	16	6	5	6	1	2	3		1	1	2			1		1	2,0%
76	80	5	8	4	4	2	2	2	4		4	1	1	1	1			1,7%
81	85	2	2	5	1	3	2	1	1		2	1	1					0,9%
86	90	3	4	4	2		3	2										0,8%
91	95	2	1	2	1		1			1				1				0,4%
96	100	3		1	1	2			1		3							0,5%
101	…	2	1		1	1	3									1		0,4%
		15,9%	8,3%	8,5%	6,7%	6,3%	8,9%	7,5%	7,1%	6,4%	10,4%	5,0%	3,2%	1,5%	1,8%	0,8%	1,8%	**Total**

Less than 10 cases
10…20 cases
More than 20 cases

Straight Crossing Path – Right Direction (SCP-RD) Bicyclist

The SCP-RD BC is a collision in which a vehicle travels forwards along a straight path across a junction, towards a bicyclist crossing the junction on a perpendicular path, from the right direction.

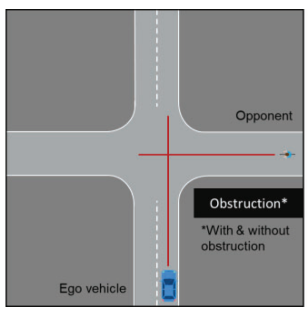


Figure 5. SCP-RD BC pictogram.

Table 8.
Detail analysis results for SCP-RD BC

Parameter	**Description**
Weather condition	In the majority of the cases (92%) there was no precipitation.
Light condition	With a share of 87%, the majority of crashes happened during daylight conditions.
Illumination of the road	In 71% of the named group of cases, the road was illuminated with street lighting.
Percentage of view obstruction	In 35% of the crashes with cyclists there was a view obstruction for the ego participant.
Kind of view obstruction	The view obstruction was due to structural circumstances in 69% of the obstructed cases. In 20% the view obstruction was due to parking vehicles.
Topology of road / intersection	In most of the cases, the ego participant was driving towards an intersection on a single lane for either left or right direction only (24%), all directions (23%), right direction only (22%) or right or straight only (5%).
Kind of traffic regulation	In 55% of the crashes one of the participants had to observe the right-of-way. In 81% of these cases, the crash was mainly caused by the ego.
Traffic density	During four out of five crashes the traffic density was either light, or only sporadic vehicles. Around every fifth ego had a crash during dense traffic.

Crash cause	Nearly 60% of the crashes happened mainly, because one participant made a failure at observing the traffic signs regulating the priority. The second big type of main crash causation were mistakes at entering the flow of traffic (16%).
Initial speed ego Initial speed opponent	In the majority of the cases (63%), the initial speed of the ego vehicle was less than 21 kph and 0 kph to 35 kph represent 80%. The initial speed of the opponent was most frequently (82%) between 6 kph and 20 kph, which are typical speeds for cyclists.

Figure 6 shows the distribution between the different types of obstruction. Structural circumstances the main type of obstruction with 69%. Complementary, vehicle obstruction is also a notable type of obstruction.

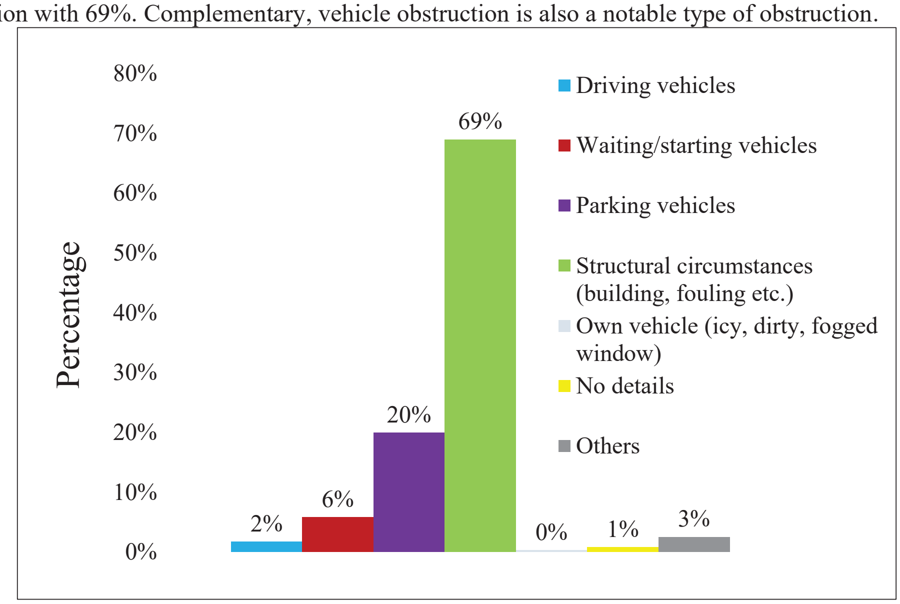


Figure 6. Kind of view obstruction – Ego.

Figure 7 shows the kind of traffic regulation. In 56% the kind of traffic regulation is "observe right-of-way" and in 81% of these cases the ego vehicle is the main causer of the crash. The ego vehicle is also mostly responsible in "stop sign" and "right has right-of-way" regulation.

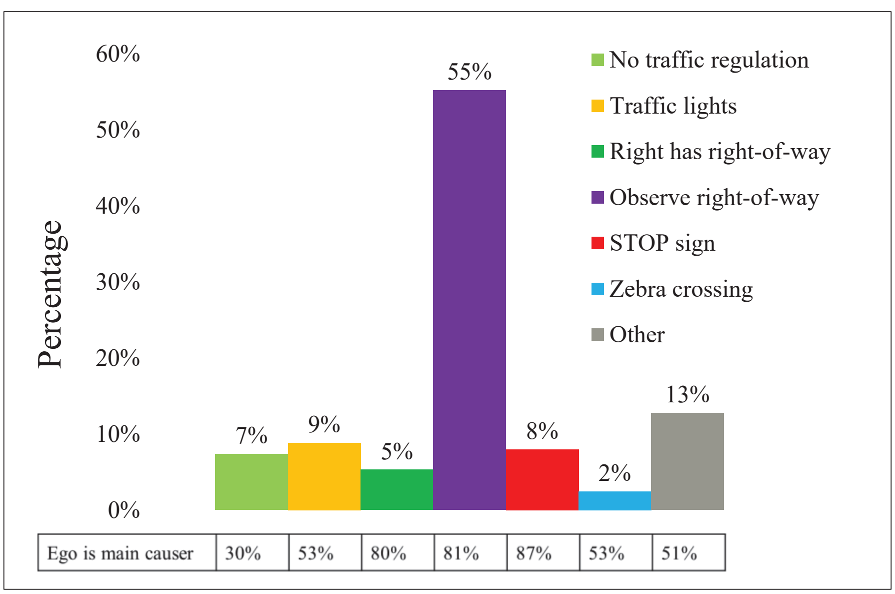


Figure 7. Kind of traffic regulation – Ego.

Table 9 shows the speed distribution. The ego vehicle initial speed is concentrated between 0 kph and 35 kph while for the opponent it is between 6 kph and 20 kph.

Table 9.
Initial speed - Ego vs. Opponent

Initial speed Ego [kph]		Initial speed Opponent [kph]											
		0	6	11	16	21	26	31	36	41	46	51	From
From	To	5	10	15	20	25	30	35	40	45	50	…	To
0	5	37	143	223	178	71	22	4	1	3			29,3%
6	10	7	96	119	55	16	5	3	1				13,0%
11	15	5	59	99	53	31	11	1	1				11,2%
16	20	3	54	74	58	17	5	1	1				9,1%
21	25	5	37	48	43	17	3	2	1				6,7%
26	30	6	35	66	45	14	1						7,2%
31	35	7	12	28	26	8	2			1			3,6%
36	40	7	31	43	28	11	1						5,2%
41	45	14	19	23	22	6	2						3,7%
46	50	19	37	51	23	11	5						6,3%
51	55	7	13	10	7	5							1,8%
56	60	6	14	5	3	1							1,2%
61	65	2	7	2									0,5%
66	70		7	7	2	1							0,7%
71	75	2	2										0,2%
76	80		3										0,1%
81	85	1	1	1									0,1%
86	90												0,0%
91	95												0,0%
96	100	1											0,0%
101	…				1								0,0%
		5,5%	24,5%	34,3%	23,4%	9,0%	2,4%	0,5%	0,2%	0,2%	0,0%	0,0%	**Total**

Less than 10 cases
10…20 cases
More than 20 cases

Complementary, [13] provide additional data on the SCP-RD BC and SCP-LD BC crash scenarios, with a focus on UTYP 341 and 342.

DISCUSSIONS & LIMITATIONS

Discussions

Research question n°1 objective was to identify the main crash scenarios leading to severely injured or killed persons described by road configuration, types of opponents, pre-crash manoeuvres and their relative frequencies. The answer is provided in the Table 5 and [1].

Research question n°2 objective was to identify the main other criteria linked to V2X that characterise each of these injury crash scenarios. Complementary the following discussions focus on the important characteristics of these injury crashes that could be addressable by V2X technology solutions in addition to conventional ADAS sensors.

Besides the positive impact, ADAS systems based on on-board sensors have on injury mitigation and accident avoidance, they are now facing their technological and physical limits. Most of all with sight obstructions and in poor environment conditions. V2X is an answer to improvements of ADAS. The referred paper [14] analyses how V2X can provide additional benefit to the road fatalities reduction with V2X-enhance-ADAS.

The scenario "*Straight Crossing Path – Right Direction (SCP-RD) Passenger Car"* is a good illustration of obstructions, as the main area identified where V2X could bring potential benefits. As described in the results, these obstructions often are structural circumstances (building) or vehicles (driving /waiting /starting /parked). In most cases, one participant fails to observe the right-of-way. V2X could reduce the danger by providing information about the opponent's presence and, therefore, improve the driver anticipation. Here, the countermeasures driver "Awareness" and "Warning" as introduced in the subsection V2X-related crash countermeasures are particularly relevant to help the driver to anticipate the hazardous situations. Conventional systems cannot provide these due to their physical limits, sensor range and line-of-sight. Furthermore, a significant number of the crashes occur in poor light conditions such as are "darkness" or "dawn/twilight". Precipitation and dense traffic are also relevant. These three last elements impact the driver's visibility, the road comprehensibility and the conventional sensors' capabilities, robustness and efficiency. As camera-based systems have limitations in difficult lighting conditions such as night and precipitation, V2X can support by confirming object detection, classification and positioning in uncertainties. Note that V2X Awareness should be taken with caution since the driver will be potentially aware of many potential hazards at the same time, and they will have to be prioritized by the system to avoid too many inputs in addition to the inputs the driver takes directly on the scene. Information from the system should not be competing but complementary and consistent.

Likewise, the "*Straight Crossing Path – Right Direction (SCP-RD) Bicyclist"* scenario, obstruction is an important field where V2X could bring potential benefits [3], [4]. The obstruction is mostly due to structural circumstances, i.e., buildings. In most of the cases, the ego vehicle caused the crash after failing to observe the right-of-way of the bicyclist. V2X could reduce the danger by providing information about the opponent's presence and, therefore, improve the driver's anticipation. Here the countermeasures driver "Awareness" and "Warning" are particularly relevant to avoid the dangerous situation. Dense traffic remains also in this scenario with the same impact on the driver and classical sensors than in SCP-RD PC. A significant part of the crashes occurs when the speed of the ego vehicle is very low (0-10 kph). In this case, the bicyclist is out of the range of conventional sensors due to the speed differential. V2X could bring potential benefits here to improve conventional sensors' detection capabilities and efficiencies to classify and detect the bicyclist. It should also be noted that bicycles cannot easily participate in V2X communication themselves, however third-party vehicles can increase the visibility of bicycles using Collective Perception V2X [14].

As for vehicle action, the characteristics of crashes relevant to V2X communication are still to be identified as a complement or substitute to traditional sensors. Particularly these actions require high performance of V2X solutions based on accurate relative positioning of participants.

From a general perspective, V2X allows safety systems to detect an object before onboard sensors themselves see it, by providing additional information such as the road user type and its dynamic parameters (speed, positioning, driving lane, heading, acceleration/braking, turning indication, airbag status, etc). These data could be used to do path prediction and to anticipate critical situation earlier. As mentioned above, V2X is almost not impacted by weaknesses of ADAS. V2X allows new services to the user through the share of specific situation information with a wide range (crash risk, danger ahead, local hazards, VRU awareness, etc.).

Limitations

This study is based on the German crash data obtained from GIDAS and DESTATIS and, therefore, does not provide a picture on crashes across the EU. To cope with this, the target population study based on CARE estimated the EU representativity. In addition to this, a study on IGLAD was conducted. The aim was to compare the main crash selection of both databases considering for IGLAD only EU cases. In contrast to the GIDAS database, the data in IGLAD are not representative for the occurrence of crashes in the countries where the data originates from. That is caused by some data providers who only record and provide fatal crashes. Therefore, the results of the analysis are only given as an additional information. While comparing the data of GIDAS and IGLAD [1], it sticks out that the results are very similar. However, in the IGLAD database, the frequency of KSI occupants in category 9 and category 21 is much higher than in GIDAS. The reason for that could be, that in IGLAD the condition that the ego vehicle must be equipped with ESC, was not used due to quality issues of this criterium in IGLAD. In category 1, category 13 and category 14, KSI occupants appear more frequently in GIDAS than in IGLAD.

This study is a target population study, crash scenarios have been identified and some characteristics of the crashes have been highlighted. However, the potential V2X safety benefits are not estimated in this paper. Target population is the first step to identifying the potential effectiveness of a countermeasure. However, previous studies highlighted the limits of conventional sensors (even ideal) and the benefits of V2X as an additional sensor to support them [3], [15], [4]. Crash parameters of these studies are not necessarily identical to those in SECUR.

To strengthen the analysis and give more insights into capabilities or limitations of V2X, a complementary study about production of failures would be interesting, to identify drivers needs and potential vehicle actions. This could provide other analysis angles to understand the needs for driver alerts, or cooperative driving, or effectiveness of warning for example.

CONCLUSION

An analysis of the main traffic crashes based on GIDAS was performed. We selected crashes for which the ego vehicle is a passenger car while the other participant could be a passenger car, a PTW, a bicyclist or a pedestrian. First, a catalog of crash "categories" has been created to cluster the different conflict situations of the crashes available in GIDAS. The aim of this categories catalog was to select the main crash situations to address with V2X. To cover all crash cases included in the GDV classification, the perspectives of both participants in the conflict situation (participant A and participant B) were considered in each case. Therefore, a safety measure will not only assist one participant but both and the crash could also potentially be addressed from both sides. Second, 15 "crash scenarios" were defined to describe the possible relevant combinations of the categories and the road user types. The crash scenarios were selected based on KSI frequencies. Third, these crash scenarios as shown in Table 5 were studied in detail. Fourthly, complementary studies based on CARE and IGLAD were done to estimate the EU target population of the selected crash scenarios.

Over the 15 crash scenarios studied deeply with GIDAS, 2 were used as illustrations in this paper: "*Straight Crossing Path – Right Direction (SCP-RD) Passenger Car*" and "Straight Crossing Path – Right Direction (SCP-RD) Bicyclist". 11 over the 16 parameters selected for the in-depth study were analysed for those two scenarios.

Important characteristics of these injury crashes that could be addressable by V2X technology solutions in addition to conventional ADAS sensors were identified based on the performed in-depth analysis.

The scenario "*Straight Crossing Path – Right Direction (SCP-RD) Passenger Car"*, is a good illustration of obstructions as the main area identified where V2X could bring potential benefits. Then, in most cases, one participant fails to observe the right-of-way. Furthermore, a significant number of the crashes occur in darkness. Precipitation and dense traffic are also present. These three elements impact the driver visibility, the road comprehensibility and the conventional sensors' capabilities, robustness and efficiency.

Likewise, in the "*Straight Crossing Path – Right Direction (SCP-RD) Bicyclist"* scenario, obstructions due to structural circumstances are also very relevant in this scenario. In most cases, the ego vehicle caused the crash after failing to observe the right-of-way of the bicyclist. Dense traffic is also relevant in this scenario with the same impact on the driver and classical onboard sensors than in SCP-RD PC. A significant part of the crashes occurs when the speed of the ego vehicle is low.

Besides the positive impact of ADAS systems based on on-board sensors on injury mitigation and accident avoidance, they are facing technological performance limitations in situations with sight obstructions and in poor environment conditions. V2X can help to improve the ADAS performance.

From a general perspective, V2X can provide additional information to safety systems such as the knowledge of the road user type and its dynamic parameters (speed, positioning, driving lane, heading, acceleration/braking, turning indication, airbag status, etc). These data could be used, under certain conditions, to do path prediction and to anticipate critical situations earlier. Additionally, it will allow new services to the user through the sharing of a wide range of specific situation information (crash risk, danger ahead, local hazards, VRU awareness, etc.).

SECUR is the first Euro NCAP-oriented project focused on V2X with the objective to outline a consistent proposal for V2X testing and assessment.

Beyond that, additional work would be required to complete and move forward on the identification, standardisation, and definition of safety V2X applications.

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APPENDIX

Table 10.
List and description of crash databases used

Database	**Country Covered**	**Database type**	**Description**
CARE	**Europe**	High level	Community database on road crashes resulting in death or injury (no statistics on damage-only crashes).
IGLAD	**Europe**	In-depth	Community database on EU road crashes. It was developed containing crash data according to a standardised data scheme that enables comparison between datasets from different countries.
DESTATIS	**Germany**	High level	National data on road traffic crashes recorded by the police. The DESTATIS data are easily used to weight the GIDAS data.
GIDAS	**Germany**	In-depth	GIDAS is the German study for in-depth traffic crash data collection and stands for German in-depth Crash Study. This database reaches up to 3,000 encoded parameters per crash.
BAAC	**France**	High level	National Road injury traffic crashes database based on police reports file (Bulletin d’Analyse des Accidents Corporels).

Table 11. Overview of the main crash scenarios selected and studied (GIDAS)

This table is only an overview of the detailed analysis conducted in SECUR WP1. Please refer to deliverable D1.2 for the full results.

			OVERVIEW OF MAIN CRASH SCENARIOS STUDIED (GIDAS 2020)											
			Weather condition	**Light condition**	**Road surface**	**Obstruction**	**Topology**	**Traffic regulation**	**Traffic density**	**Accident cause**	**Initial Speed**	**Deceleration**	**Radius of curve**	**Human failure**
	Crash Scenario **(For**	**OPPONENT**	**NP : No Precipitation** **R : Rain** **S : Snow**	**DL: Daylight** **DN: Darkness/ Dawn**	**DR: Dry** **W: Wet** **D: Damp** **S: Snow** **I: Ice**	**N: No** **Y: Yes** **SC: Structural Circumstances** **VH: Vehicle (Driving/ Starting/ Waiting/ Parking)**	**Main topology** **I: Intersection** **SL: Straight Line**	**NR: No Regulation** **ORW: Observe right of way** **TL: Traffic Light** **ST: Stop sign** **RRW: Right as right of way**	**LS: Light/Sporadic** **D: Dense** **TJ: Traffic Jam/stop and go**	**FP : Failure to observe the traffic signs regulating the priority** **FPL: Failure to observe the traffic lights/policemen regulating the priority** **MEF: Mistake Entering the flow of traffic** **IB: Improper behavior of the pedestrian** **S: Speed** **MD: Mistake made by the driver (e.g. distraction)** **ID: Insufficient Safety Distance** **TL: Turning Left Mistake** **WW: Wrong Way Driving** **AD: Ability to drive (alcohol, overfatigue)**		**BP: Breaking Percentage** **MV: Median value of breaking** **NA: No Action** **LD: Low Deceleration**	**MR: Main Radius**	**Y: Yes** **N: No**
1	**Oncoming**	**PC**	NP: 85% R: 13% S: 2%	DL: 71% DN: 29%	-	N: 91% Y: 9% (SC: 53%; VH: 37%)	I SL	-	LS: 75% D: 23%	TL: 46% WW: 11%	Ego: 26-75kph (81%) Opp: 0-56kph (81%)	-	-	Y: 75% N: 25%
2	**Straight Crossing Path – Right Direction SCP-RD**	**BC**	NP: 92% R: 7%	DL: 87% DN: 13%	-	N: 65% Y: 35% (SC: 69%; VH: 27%)	I	ORW: 55% TL: 9% ST: 8% NR: 7% RRW: 5%	LS: 80% D: 17%	FP: 58% MEF: 16%	Ego: 0-35kph (80%) Opp: 6-20kph (82%)	-	-	-
3	**Straight Crossing Path – Right Direction SCP-RD**	**PC**	NP: 86% R: 13%	DL: 74% DN: 26%	-	N: 70% Y: 30% (SC: 50% and VH: 46%)	I	ORW: 52% TL: 19% ST: 11% RRW: 11%	LS: 79% D: 18%	FP: 86% MEF: 6%	Ego: 21-70kph (81%) Opp: 0-50kph (86%)	-	-	-
4	**Straight Crossing Path – Right Direction SCP-RD**	**PD**	NP: 87% R: 11%	DL: 74% DN: 26%	-	N: 61% Y: 39% (VH: 76%; SC: 18%)	SL I	NR: 54% TL: 20% ORW: 14%	LS: 73% D: 21%	IB: 56%	Ego: 16-55kph (80%) Opp: unknown (pedestrian)	-	-	-
5	**Straight Crossing Path – Left Direction SCP-LD**	**PD**	NP: 83% R: 16%	DL: 60% DN: 40%	-	N: 60% Y: 40% (VH: 77%; SC: 9%)	SL I	NR: 51% TL: 22% ORW: 16%	LS: 75% D: 21%	IB: 54%	Ego: 16-55kph (80%) Opp: unknown (pedestrian)	-	-	-
6	**Loss of Control in Curve**	**NONE**	NP: 73% R: 21% S: 5%	-	DR: 45% W: 22% D:20% S: 7% I: 6%	-	-	-	LS: 90% D: 9%	S: 77% MD: 12%	Ego: 46 - 100kph (80%) >100kph: 10%	-	MR: 101-200m (33% of LOC-CU)	No: 85% Yes: 15%
7	**Straight Crossing Path – Left Direction SCP-LD**	**PC**	NP: 86% R: 13%	DL: 73% DN: 27%	-	N: 73% Y: 27% (SC: 60% and VH: 40%)	I	ORW: 44% TL: 25% ST: 12% RRW: 17%	LS: 80% D: 17%	FP: 91%	Ego: 11 - 60kph (80%) Opp: 16 - 60kph (78%)	-	-	-
8	**Loss Of Control in Straight Line**	**NONE**	NP: 73% R: 21% S: 5%	-	DR: 45% W: 22% D:20% S: 7% I: 6%	-	-	-	LS: 90% D: 9%	S: 45% MD: 36% AD: 8%	Ego: 46 - 100kph (64%) >100kph: 26%	-	-	No: 81% Yes: 19%
9	**Straight Crossing Path – Left Direction SCP-LD**	**BC**	NP: 88% R: 11%	DL: 80% DN: 20%	-	N: 70% Y: 30% (SC: 57% and VH: 36%)	I	ORW: 50% RRW: 15% TL: 12%	LS: 80% D: 17%	FP: 75% MEF: 11%	Ego: 0-40kph (84%) Opp: 6-25kph (92%)	-	-	-
10	**Rear End - Following vehicle RE-FV**	**PC**	NP: 87% R: 12%	DL: 78% DN: 22%	-	N: 97%	SL	-	LS: 42% D: 37% TJ: 22%	MD: 45% ID: 35% S: 14%	Ego: 26-60kph (64%) >100kph (8%) Opp: 0-50kph (87%)	Ego: BP 77%; NA 18%; MV 5,2m/s² Opp: BP 44%; LD; NA 53%; MV: 0m/s²	-	-
11	**Rear End - Previous vehicle RE-PV**	**PC**	NP: 87% R: 12%	DL: 78% DN: 22%	-	N: 100%	SL	-	LS: 42% D: 37% TJ: 22%	MD: 45% ID: 35% S: 14%	Ego: 0-50kph (87%) Opp: 26-60kph (64%) >100kph (8%)	Opp: BP 77%;NA 18%; MV 5,2m/s² Ego: BP 44%; LD; NA 53%; MV: 0m/s²	-	-
12	**Left Turn Across Path – Opposite Direction LTAP/OD**	**PC**	NP: 86% R: 13%	DL: 68% DN: 32%	-	N: 90% Y: 10% (VH: 66%; SC: 14%)	I	TL: 52% ORW: 38%	LS: 66% D: 31%	TL: 80% FPL: 11%	Ego: 0-40kph (87%) Opp: 36-75kph (80%)	-	-	-
13	**Left Turn Across Path – Opposite Direction LTAP/OD**	**PTW**	NP: 91% R: 8%	DL: 71% DN: 29%	-	N: 86% Y: 14% (VH: 65%; SC: 15%)	I	ORW: 46% TL: 29% NR: 8%	LS:73% D: 24%	TL: 88%	Ego: 0-30kph (81%) Opp: 26-60kph (78%)	-	-	-
14	**Left Turn Across Path – Left Direction LTAP/LD**	**PC**	NP: 84% R: 14%	DL: 76% DN: 24%	-	N: 67% Y: 33% (SC: 43% and VH: 54%)	I	ORW: 69% ST: 10% TL: 6%	LS: 77% D: 20%	FP: 75% MEF: 13%	Ego: 0-25kph (82%) Opp: 26-70kph (83%)	-	-	-
15	**Left Turn Across Path – Left Direction LTAP/LD**	**PTW**	NP: 93% R: 7%	DL: 79% DN: 21%	-	N: 57% Y: 43% (SC: 37% and VH: 60%)	I	ORW: 74%	LS: 71% D: 22% TJ: 6%	FP: 77% MEF: 16%	Ego: 0-20kph (87%) Opp: 26-60kph (79%)	-	-	-

ADAS IN YOUR POCKET – A REVIEW OF THE FEATURES, FUNCTIONS AND FUTURE OF SMARTPHONE-BASED ADVANCED DRIVER ASSISTANCE SYSTEMS

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ABSTRACT

Advanced Driver Assistance Systems (ADAS) are technology systems that rely on a combination of sensors that scan the road environment to detect potentially hazardous situations and assist the driver to either avoid the hazard, or to reduce the severity of outcomes if a crash is unavoidable.
Recent developments in consumer-level smartphone technology have allowed third party software applications to make ADAS functionality accessible to millions of mobile phone users. By utilising the smartphone's hardware such as cameras, positioning sensors and processors, together with software-based object recognition and tracking algorithms, these applications purport to allow users to receive real time road hazard detection and warnings. These smartphone-based ADAS applications are compatible with many popular models of smartphone and offer ADAS functionality that includes Forward Collision Warning (FCW), Lane Departure Warning (LDW) and Intelligent Speed Assist (ISA).

ADAS related applications are identified and reviewed for claimed features and functionality. Applications with the most promising functionality are acquired for more detailed evaluations.

We review the features and functionality of selected ADAS applications using several different smartphone models. We report on the results of on-road performance evaluations that examine the effectiveness and limitations of these. We also explore potential road safety benefits for drivers whose vehicle is not equipped with ADAS, but who have a smartphone available when they drive.

The results confirm that ADAS applications are capable of vehicle detection/tracking, lane marking detection, road sign detection, speed zone detection and related warning functionality, however the performance between apps varied and issues such as false alerts, non-detections and incorrect detections were recorded.

While smartphone-based ADAS can provide reliable, and potentially useful road safety benefits to drivers, these potential benefits depend on a combination of the hardware capability of the smartphone, the sophistication of the application and, to a lesser extent, the correct set up of the smartphone in the vehicle. Furthermore, while smartphone-based ADAS has the potential to improve road safety, especially where OEM-fitted ADAS is not a feasible option, there are inherent limitations posed by current technology. Finally, subject to appropriate provisions in relevant regulations, the barriers to the adoption of smartphone-based ADAS appear low and the main barrier to adoption is that smartphone users are unaware that ADAS applications exist. We foresee that continued developments in smartphone hardware and processing capability, together with software evolution in ADAS applications, will continue to improve the reliability and effectiveness of smartphone-based ADAS in the future.

INTRODUCTION

Advanced Driver Assistance Systems (ADAS) are technology systems that rely on sensors that scan the road environment and monitor vehicle systems to detect potentially hazardous situations and assist the driver to either avoid the hazard, or to reduce the severity of outcomes if a crash is unavoidable. To date ADAS has mostly only been available as a feature on new vehicles, severely limiting widespread adoption across the global vehicle fleet.

Recent developments in consumer-level smartphone technology have allowed third party software applications (apps) to make ADAS functionality accessible to billions of mobile phone users globally. By utilising the smartphone's hardware such as cameras, positioning sensors and processors, together with software-based object recognition and tracking algorithms, ADAS apps purport to allow users to receive real time road hazard detection and warnings. These smartphone-based ADAS apps are compatible with many popular models of smartphone and offer advisory ADAS functionality that includes Forward Collision Warning (FCW), Following Distance Warning (FDW), Lane Departure Warning (LDW) and Intelligent Speed Assist (ISA).

We review the features and functionality of selected, publicly available, ADAS applications using several different smartphone models and report on the results of on-road performance evaluations that examine the effectiveness and limitations of these. We also explore potential road safety benefits for drivers whose vehicle is not equipped with ADAS, but who have a smartphone available when they drive.

This research is part of a multi-stage research project by the authors to examine the performance and potential of smartphone-based ADAS applications and represents the findings from the initial stage of the project.

STATE OF SMARTPHONE ADAS IN AUSTRALIA

There are numerous applications currently available on both Android and iPhone operating systems in Australia that purport to include ADAS features. Apps range in cost from free, to several dollars, with most of the apps evaluated in this research being available for free. App developers include local and overseas developers.

The types of advisory ADAS offered by smartphone applications include ISA (camera or GPS/Map based), FCW, FDW, top speed warning, LDW, traffic sign recognition, red light camera recognition and fatigue detection. In this initial study only features related to ISA, FCW, FDW, top speed warning and LDW were evaluated. Some applications also combined two or more ADAS types (see Table 1). This is particularly common for applications that use the smartphone camera/s for visual detection (e.g., lane markings, other vehicles/pedestrians and roadside signs). Other, non-ADAS features, such as dash cam functionality, navigation or red light/speed camera warnings were also present in some applications, alongside the ADAS features.

IDENTIFICATION AND SELECTION OF ADAS APPLICATIONS FOR EVALUATION

Applications for potential inclusion in the research were identified through searching the Google Play and Apple Store app stores using various search terms (e.g., 'ADAS', 'driver assistance', 'intelligent speed assist, 'forward collision warning', 'lane departure warning' 'crash prevention', 'crash safety', etc). Some apps identified through this search were already known to the authors from previous research [1]. In total 45 apps were identified as potential candidates from the search.

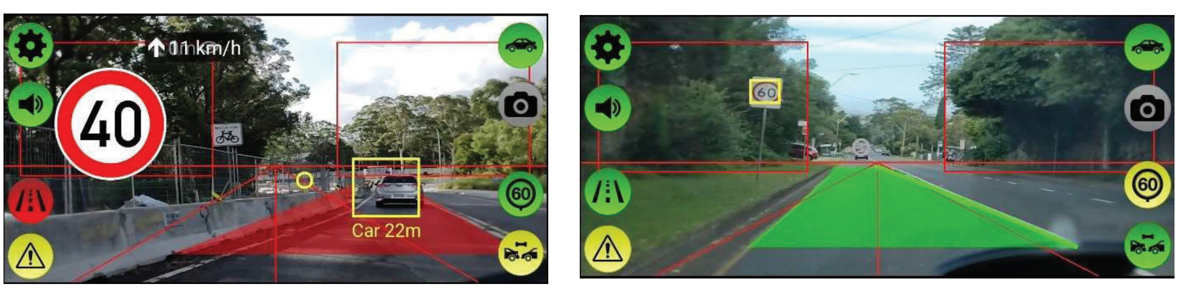
Information provided by developers about the app functionality was then reviewed and those which clearly claimed to have ADAS features/functionality were downloaded (to a compatible smartphone) and the basic functionality of the app was reviewed through limited on-road trials to confirm that the app features worked and to eliminate any apps that were not worth further testing. Some applications that purported to include ADAS functionality either did not provide ADAS features or the app was unusable (including applications that 'crashed' frequently) and these were excluded from the evaluations.

A total of 12 apps were shortlisted for the evaluations. Some apps were available for smartphones with both Android or iPhone operating systems while others were available for one operating system only. Since there is no driving automation offered by the ADAS apps (i.e., no braking or steering intervention) the apps evaluated in this research would be classified as SAE Level 0 on SAE's Levels of Driving Automation™ [2].

Table 1.
ADAS Applications Shortlisted for Evaluation

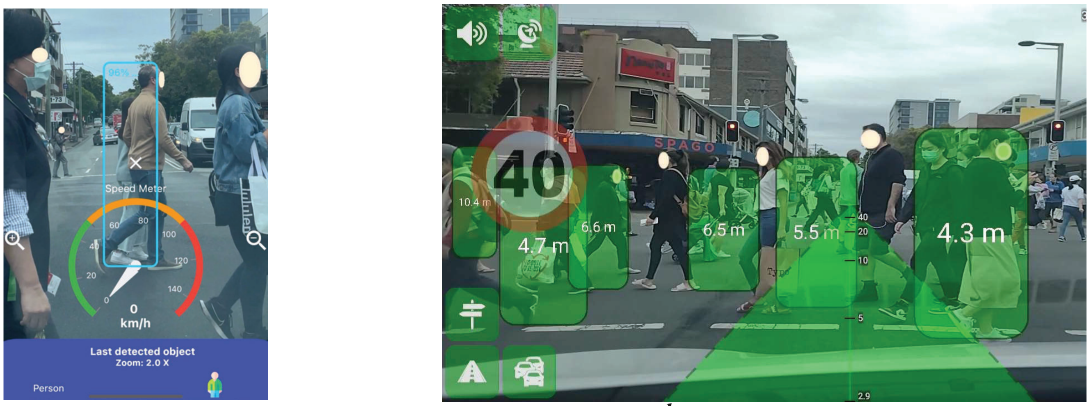
App (Developer)	ADAS features	OS platform
UGV Driver Assistant (INFOCOM LTD)	FCW, FDW, LDW, camera-based speed assist, other sign detection and warning (not evaluated)	Android and iPhone
aCoDriver (EvoTegra GmbH)	FCW, FDW, LDW, camera-based speed assist, lane departure warning	iPhone only
Roadscan AI (Samuel Souza)	FCW, LDW, red light detection (not evaluated), fatigue monitoring (not evaluated)	iPhone only
Speed Adviser (Transport for NSW)	GPS map based advisory ISA	Android and iPhone
Metroview (MetroView Systems)	GPS map based advisory ISA, manual set top speed warning	Android and iPhone
MobileSection (murbit GmbH)	Manual set top speed warning	iPhone only
Speedometer by HUDWAY (HUDWAY LLC)	Manual set top speed warning	iPhone only
Speedometer: GPS Tracker (POKET APPS, OOO)	Manual set top speed warning	iPhone only
Lane Identification Pro (Vembar LLC)	LDW	Android and iPhone
DriverAssistant (TheFrenchSoftware)	FCW, LDW	Android only
Car Assistant (FAA STUDIO)	ISA, other sign detection and warning (not evaluated)	Android only
LaneDetect+ (Hirofumi Cho)	LDW	iPhone only

Example ADAS applications
Each app provided onscreen ADAS information to the user during operation. Figures 1, 2, 4 & 5 below show actual smartphone screen captures taken while in operation during the evaluations. These images show the exact display provided to the driver during operation of the app.



a *b*

Figure 1 a & b. Screenshot from screen capture of aCoDriver App (Android). a) Speed zone reminder (40), LDW, FDW. b) Speed zone detection (60), Lane path OK, centerline detection.



a *b*

Figure 2 a & b. Pedestrian detection a) Roadscan AI (iPhone). b) UGV Driver Assistant (Android).

PERFORMANCE EVALUATIONS OF SMARTPHONE-BASED ADAS SYSTEMS AND KEY OBSERVATIONS

In-Vehicle Set Up

The smartphones were affixed to the vehicle using dashboard or windscreen-mounted cradles positioning the smartphone leftwards of the vehicle centreline (passenger side in Australia) towards the bottom edge of the windscreen. For camera-based applications the smartphone was orientated so that the leading edge of the vehicle bonnet and the LHS A pillar were at the edge of the camera field of view. Approximately the same position was used for all applications and all smartphone models, allowing for some variance due to camera field of view (for camera-based apps), smartphone size, and screen orientation (landscape or portrait) for the application.

OEM ADAS features fitted to the vehicle used for evaluation were disengaged during the evaluations to ensure that these did not conflict with the performance of the ADAS apps being evaluated.

Familiarisation with features and functions

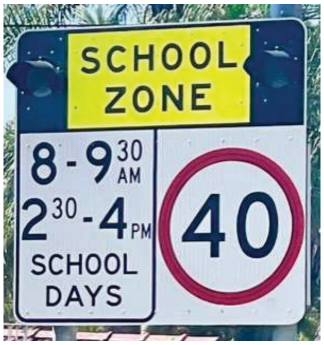
An initial ‘test drive’ was undertaken by driving on a variety of roads in various traffic conditions (with a mix of vehicles) to better understand the application functionality including setting/adjusting any relevant settings, determining the set-up position, determining the limits of the app (i.e., vehicle types/sign types that the application did/did not detect) and familiarising with the types of warnings.

Further evaluations were undertaken by driving a variety of public roads (highway, suburban, urban) at various times and in various traffic conditions.

Method of evaluation

Operations of the apps and all recordings during the evaluations were undertaken by the front seat passenger, while the driver controlled the vehicle.

Evaluations were conducted on a variety of public roads, at various times during the day in a mixture of traffic. A mixture of urban, sub-urban and highway roads at all speed limits were included, as were variable speed zones such as time variable school zones, weather dependent zones and where different speed limits apply to different vehicle types.

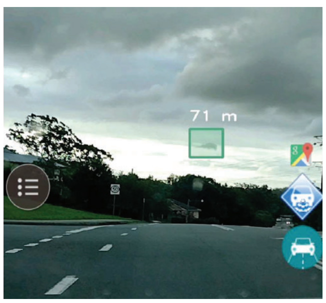


To test the warning functionality in school zones for ISA apps the smartphone clock was adjusted to be within the time period when the time variable 'school zone' was active. This allowed the zone to be driven at 'normal' (i.e., higher) speeds legally while the smartphone believed that the lower (time dependent) speed zone was in effect.

Screen recording applications were used to capture each apps' behaviour during the evaluations. These captured whatever was displayed on the screen of the smartphone, including visual warnings, and also captured any audio warnings/notifications. The captured footage was reviewed to examine reliability and consistency of app functionality including where false warnings were issued and/or where non-detection conditions occurred.

Figure 3. Australian time dependent School Zone sign. 40km/h limit applies during listed times.

PERFORMANCE OBSERVATIONS



Performance varied greatly between apps providing ADAS features of the same type. Some apps provided consistent performance, reliably reacting to trigger conditions and providing the relevant notification/warning while others either had inconsistent detections (e.g., frequently missed detection conditions), provided false alerts or detected erroneous objects (i.e., misinterpreting signs, clouds and non-road infrastructure as potential hazards).

Figure 4. Screenshot from screen capture of Driver Assistant (Android) showing detection of a 'cloud' as a potential hazard.

Apps that performed well tended to perform well consistently across multiple phone models and different operating systems, whereas apps that did not perform well did so on all models and for all operating systems. Across different phone models and operating systems, the apps generally had the same functionality however it was noted that warnings sometimes differed (e.g., the tone of warning chimes, or the voice used for verbal warnings).

Performance observations for apps that offered Speed Assist features

In general, the applications offering ISA and top speed warnings features performed well with ISA systems identifying most speed zone changes reliably and warnings deploying when the trigger conditions had been reached. Exceptions to this were time-based school zones (common in Australia), and condition dependent speed zones such as weather dependent or vehicle type dependent speed zones. Electronic variable speed signs were also not detected by any app (as is the case with many OEM ISA systems in Australia).

It should be noted, however that both GPS/map-based ISA apps ('Speed Adviser', 'Metroview') provided consistently accurate results for 'fixed' speed zones, detecting almost all speed zone changes at the point of the speed zone change. Both of these apps also correctly detected time dependent school zones but did not detect other variable or temporary speed zones (e.g., condition dependent speed zones, electronic speed signs, temporary roadworks speed zones).

For camera-based ISA apps the 'UGV Driver Assistant' and 'aCoDriver' apps had good performance at detecting most speed signs, although in some cases signs behind other objects (trees, other large vehicles) were not detected. Both these apps detected temporary speed zones that the map-based ISA apps did not, however these also detected speed signs on the back of vehicles (see Figure 6 below) and could not correctly determine the applicable speed limit for school zones, weather dependant speed zones or vehicle dependant speed zones. However, for the 'Car Assistant' app the camera-based speed sign detection performed poorly with very inconsistent results in detection; signs were often missed, and where a speed sign was detected the value detected was often incorrect.

For apps with a top speed warning ('Metroview', 'Mobile Section', 'Speedometer by HUDWAY', 'Speedometer: GPS Tracker') these worked accurately and provided warnings when the set top speed warning threshold was reached, however it was noted that adjusting the top speed setting (where adjustable) for these was impractical for the driver to achieve while driving. It was further noted that several of these apps only allowed a few (or a single) top speed setting options.

Performance observations for apps that offered FCW and/or FDW features

Most apps with FCW and/or FDW consistently and reliably identified other vehicles in the camera's field of vision, however not all apps detected vulnerable roads users such as pedestrians, cyclists or motorcyclists suggesting that some apps are not keeping pace with the detection capabilities of OEM FCW/FDW systems in Australia.

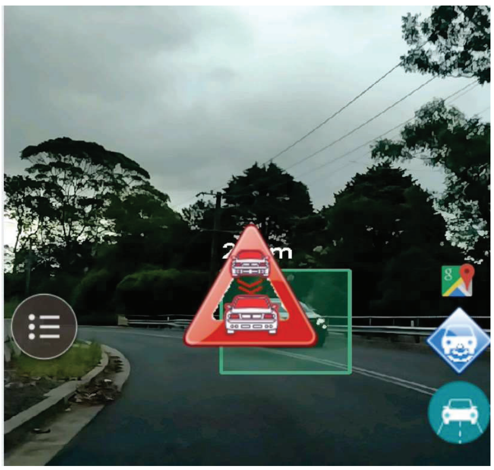


Figure 5. Screenshot from screen capture of Driver Assistant (Android) showing false FCW alert.

For the FCW/FDW apps 'Roadscan AI', 'aCoDriver' and 'UGV Driver Assistant' reliably detected other light vehicles (e.g., cars) and large vehicles (buses and trucks) and also pedestrians but only UGV appeared to identify motorcycles and bicycles as potential hazards.

FDW features showed distance estimates to surrounding vehicles and provided audio/visual warnings when the vehicle in front became too close (approx. 1 second gap). The distance estimates for surrounding vehicles were updated in real time and generally seemed to be accurate (comparative measurement was used to estimate accuracy) however both 'Roadscan AI' and 'UGV Driver Assistant' tended to struggle with long vehicles (e.g., truck trailer combinations) where the distance measurement would fluctuate along the length of the vehicle.

All FCW/FDW apps had instances of false warnings, either warning of impending collisions with a vehicle/pedestrian that was either too far away, or for oncoming traffic that was not on a collision trajectory. Similarly, some false warnings were provided for objects that were not vehicles/pedestrians and that did not pose a hazard. In particular the frequency of false alerts provided by the 'Driver Assistance' app made it impossible to assess its performance and evaluations were discontinued for this app.

Performance observations for apps that offered LDW features

None of the apps offering LDW provided consistent performance. While some apps provided warnings for lane change manoeuvres all apps offering LDW suffered from false alerts and path matching issues where the predicted road path did not match the actual road path. The severity of these issues varied however for some applications these were so frequent that further testing was abandoned. The performance offered by the LDW features were significantly inferior to the performance of modern OEM LDW systems in Australia.

Some apps had adjustable settings for LDW (e.g., lane width, horizon level, etc) and may have been sensitive to set up location and orientation. These will be investigated in further research, however if this is the case then additional guidance would need to be provided to the user to ensure that the systems are correctly set up (including positioning).

Comments about warnings and notifications

A variety of warnings were used including visual and audible. Audible warnings varied from chimes/beeps to spoken warnings. Visual warnings included the appearance of onscreen icons, colour changes for on screen icons or the screen background, flashing of onscreen icons or a combination of these. There was little consistency in warning types (either audible or visual) between the apps. Although performance of the warning type/s was not evaluated it was noted that in many apps the warnings were subtle with warning volumes quite low and/or visual warnings being so small they could be overlooked, or the user might experience difficulty interpreting the nature of the warning. Furthermore, for some applications with multiple ADAS functions, distinguishing between different warning types could be difficult since the same warning types were used for different ADAS functions, or the warning types were only subtly different.

Several apps were capable of muting/pausing other audio (radio, music streaming app) when connected to the vehicle (wirelessly or via USB connection) to eliminate some in-car noise that could obscure safety alerts and to emphasise warnings provided by the app.

Comments about adjusting app settings
Some apps required either or both detection types or warning types to be enabled since the default setting was 'off'. Where apps had variable settings (e.g., FCW distance, lane width, horizon line, top speed, etc), changing these often involved several steps to access a settings screen and it was often not clear which setting was relevant or which value/setting was suitable. In general, the apps also did not provide useful guidance for troubleshooting these types of issues or for selecting the appropriate settings. However, several apps required little, or no, settings adjustment and provided useful functionality with the default settings.

General limitations and issues of evaluated apps
Where electronic variable speed signs were present, or where variable speed zones existed (e.g., school zones, weather dependent speed zones, or speed zones that apply to certain vehicle types only) most apps with ISA functionality struggled. The exceptions were school zone performance for Speed Advisor and Metroview which both performed well in detecting the applicable speed limit at all times.

Map-based ISA systems are unable to adapt to temporary changes to physical signs such as where signage is temporarily changed, such as for road work speed zones. Although map-based ISA systems can become inaccurate if changes to speed zones are not updated in the digital map, leading to the system communicating out-of-date speed limits to the driver, this was not an issue that was observed in any of the apps evaluated as part of this research.

It was noted that for apps which relied on the smartphone camera that partial obstruction (e.g., by trees, vehicles or other roadside infrastructure) affected detection of roadside signs, particular speed signs at changes of speed zone. This is a known issue for systems that rely upon cameras for detection [3].

Camera-based apps also incorrectly identified signage on some vehicles that relate to the maximum speed of the vehicle or conditional speed limits that are intermittently active. In Australia, some buses that are operated as route service buses for school children are equipped with a speed indication sign (40km/h) and flashing lights. The 40km/h speed limit is only in effect when the flashing lights are in operation (e.g., when setting down/picking up schoolchildren) however the sign is always visible.

Figure 6. Screenshot from screen capture of UGV Driver Assistant (Android) detection of 40km/h sign on rear of bus (40km/h zone not active).

Buses are not the only vehicle type that may display a speed indication sign in Australia, with other examples including trucks that are top speed limited (e.g., to 100km/h) and some delivery vehicles that have an effective top speed (e.g., postal service delivery 'trikes') and it is likely that camera-based ISA apps would also incorrectly identify these speed indication signs as roadside speed limit signs.

Figure 7. Speed indication sign on a vehicle. Postal service delivery trike (top speed 45km/h).

DISCUSSION OF RESULTS OF EVALUATIONS AND KEY OBSERVATIONS

Our analysis of the evaluations confirms that smartphone-based ADAS applications are capable of vehicle detection/tracking, lane marking detection, speed sign detection/speed zone detection and related warning functionality to provide advisory ISA, FCW, FDW, LDW and top speed warning functions. We found that performance varied between different apps offering the same types of ADAS and even between the same apps on different operating systems.

Importantly, from our observations we conclude that the ADAS offered in the apps evaluated includes examples that offer reliable detection of relevant trigger conditions and deployment of an associated warning for ISA, FCW, FDW and top speed warning functions.

LDW functions were not as reliable and although our observations confirmed that the applications offering LDW features were often able to determine the lane boundaries, they also often detected erroneous lane boundaries and provided incorrect feedback to the user.

Potential benefits of smartphone based ADAS systems

While estimates of advisory ADAS effectiveness vary (depending on prevailing environmental conditions, road infrastructure design, or driver behaviour [3] [4]), what has been demonstrated in multiple studies is that advisory ADAS can provide an overall road safety benefit when they are used [1] [3] [5] [6]. Aside of crash risk reductions for the driver, there are also benefits to other road users (those who may also be involved in a crash) and economic benefits to the driver (reduction in speeding fines, reduced fuel costs) [6] [7] [8].

Table 2.

Estimated effectiveness for selected ADAS

Type of ADAS	**% Reduction in relevant crashes**
Camera-based Forward Collision Alert[1]	21% of rear-end crashes
Following Distance Warning[2]	10% of rear-end crashes
Lane Departure Warning[1]	10% of lane-departure crashes
Intelligent Speed Assist (Advisory ISA)[3]	20% of all serious crashes in Australia

Notes:

1. Based on 127,377 GM cars involved in Police-reported crashes in the USA. [9]

2. Based on estimates for Australia. [10]

3. Based on ISA trials in Australia. [1]

While OEM-fitted ADAS systems (AEB, LKA, speed-limiting ISA, ACC) that are optimised for specific vehicles are undoubtedly more effective than aftermarket advisory ADAS (i.e., of the kind provided by smartphone based ADAS apps) there are many vehicles worldwide that are not fitted with ADAS of any kind. Drivers of these vehicles are likely to benefit from using an advisory ADAS system. As we have described above, smartphone ADAS apps could realise this potential by providing advisory ADAS including ISA, FCW/FDW, LDW and top speed warning, and could deliver these features in a single application - although from this study we found that LDW functionality may require further development.

Smartphone ADAS apps avoid the component and installation cost barrier that has constrained uptake of some aftermarket ADAS systems using proprietary hardware (for example the Mobileye and IRoad systems), with the additional bonus that smartphone ADAS apps are easily moved between different vehicles as they are not hardwired into the vehicle.

The low cost and straightforward, non-specialised, non-permanent set up of a windscreen or dash mounted smartphone cradle means that smartphone-based ADAS apps are more accessible to drivers who cannot otherwise afford access to ADAS systems that require more specialised installation, or who use car sharing for access to a vehicle that they do not own (and are unable to modify).

Another advantage of ADAS apps is that they can utilise established distribution methods (i.e., app stores) to quickly, easily and cheaply deploy ADAS apps to end users, reducing constraints on uptake and making for efficient implementation of any local, regional or global initiatives to increase the use of ADAS apps.

Of the approximately 1 billion cars in use worldwide it is estimated that only 10% of these (100 million) are fitted with some form of ADAS [11]. While this is an excellent achievement in terms of road safety progress, it still remains that the other 90% of the global car fleet (900 million vehicles) lack any form of ADAS.

Smartphone ownership rates vary globally between advanced and developing economies, and between different socioeconomic groups within these economies. While not every smartphone user is guaranteed to be the driver of a vehicle lacking ADAS, we speculate that many millions across the globe are.

Given the estimated 900 million cars in use which are not fitted with ADAS, and the number of smartphone owners who are likely to be driving these vehicles, smartphone-based ADAS apps can provide a cost-effective, accessible means of improving equitable access to ADAS for potentially millions of road users globally.

Barriers to the uptake of ADAS apps

Barriers to adoption of ADAS apps by users Despite generally positive user ratings (based on app store ratings) the download volumes for ADAS apps have been fairly low. For example, despite being launched in 2014 the 'Speed Adviser' app, developed by Transport for NSW (an Australian state government body) has only been downloaded 77,000 times (as of December 2022) across both Android and iPhone platforms [12]. Similarly, the aCoDriver app on Android has only had around 50,000 downloads since its launch in 2013. User acceptance is probably not a significant barrier since ADAS systems have become commonplace in new vehicles and are largely accepted by drivers. Cost is also unlikely a barrier since most of these apps are available for free, or only cost a few dollars. Equipment compatibility is probably not a factor as we demonstrated that the applications work across different models of phones and operating systems. Access to equipment is also less of a barrier for many potential users as smartphone ownership is considerable (and growing) globally, in both advanced and emerging economies and furthermore (as noted above) apps are available through established online distribution mechanisms (i.e., app stores) that provide users with quick, easy and low-cost access. Therefore, a key reason for drivers not up taking these free road safety tools is likely a lack of awareness, as ADAS apps have received little media attention and are not marketed widely.

Regulatory Barriers An additional barrier to the uptake of ADAS apps in some regions are restrictions placed on the use of mobile phones for some drivers (e.g., novice drivers). Some Australian States ban drivers from touching a smartphone screen for any purpose, while driving. While these restrictions are more aimed at preventing distraction due to phone use for texting, social media use or website browsing, etc., it also may prevent some drivers from being able to use smartphone-based ADAS apps while driving. For example, the Speed Adviser app, developed by Transport for NSW (a department of the regional government) may not be used by novice drivers (those on Learner or Provisional licences). Regional authorities should consider strategies to support the legitimate use of smartphone-based ADAS to improve road safety while maintaining restrictions intended to prevent distractions to the driver from phone use while driving.

Infrastructure Barriers To function properly some ADAS systems require that the road infrastructure is designed (and maintained) to support the system. For example, LDW systems require clear lane markings, camera-based ISA systems require unobstructed roadside speed signs, and map-based ISA systems require up-to-date digital maps of speed zones. In some cases, ADAS systems may benefit from optimisation of road infrastructure (e.g., standardisation of sign types, or lane marking dimensions). Good design and maintenance of road infrastructure also benefits other road users (not just users of ADAS). Although there are potentially significant costs associated with this, these should already be budgeted for by responsible road authorities. Where speed zone map data is required this can be outsourced to third parties, as has been done in OEM ISA systems built into the vehicle navigations systems.

Comments on overcoming common limitations/issues observed during evaluations

One notable observation during our evaluations is that while the map-based and camera-based ISA apps each performed reasonably well, there are areas of performance where each has inherent advantages and disadvantages – and those areas of disadvantage for one type of app are generally covered by the performance strengths of the other. For example, where camera-based ISA systems missed signs that were behind objects, or that were faded, map-based ISA apps detected these zones well. Conversely, map-based ISA systems failed to recognise temporary speed zones (e.g., roadworks zones) whereas camera-based apps detected these. One way to enhance ADAS apps with ISA features could be to develop applications that utilise both camera detection and map-based speed zones to detect speed zones even more comprehensively.

We observed that FCW and FDW features in particular seemed susceptible to false positives. Anderson et al (2012) [3] found that FCW systems with wider fields of view may be more susceptible to false positives. A review of the applications evaluated that displayed an onscreen overlay of the camera view showed that all of these had very wide fields of view, often extending well beyond the road to include road adjacent areas and portions of sky. Anderson et al (2012) [3] proposed narrowing the field of view as a potential solution to this issue and the apps evaluated in this study may benefit from this.

One likely barrier to the uptake of smartphone ADAS apps is a lack of awareness and we postulate that these potentially beneficial road safety tools require more promotion to reach their intended end users, however it's important that only apps that demonstrate consistent, beneficial performance are promoted. As such a method of evaluating, and perhaps rating ADAS apps could be worthwhile to ensure that end users can make informed choices in the selection of an ADAS app based on its comparative performance. Consumer rating programs such as the various NCAP programs (new vehicles), CREP (child car seats) and SHARP (motorcycle helmets) have proved to be effective in increasing consumer awareness of varying performance in road safety technology and also for driving improvements in design. It seems likely that a rating program for smartphone ADAS would assist consumers in selecting the best performing applications and may also help drive further improvements in ADAS app design.

While there are some issues with the systems evaluated there appear to be obvious avenues to address these through improved app design, by combining technology types and through future advancements in technology - for example ADAS apps will benefit from further improvements in processor speed, camera optics and GPS chipset accuracy. Clear, reliable warnings are an essential component of an advisory ADAS system and improvements in this area are likely to increase the benefits of ADAS apps. Improvements in HMI design for warnings such as increasing the visibility, contrast and persistence of warnings would also address some of the issues we noted with inadequate warnings, however more research is needed in this area. The latest research into HMI design may inform apps developers on the most effective warning types, which will further improve the effectiveness of ADAS apps and ensure these apps are a benefit rather than a distraction.

LIMITATIONS OF THIS STUDY

The evaluations do not cover the full range of potential scenarios possible (future research will investigate more scenarios and the results of this research will be published separately).

Due to geographical constraints only ADAS apps available in Australia could be evaluated so ADAS apps available in other regions have not been evaluated. Similarly, the smartphone models used for the performance evaluations were models available on the Australian market, however these were popular models widely available globally and this is not considered to impact the outcomes of the performance evaluation.

The evaluated device/application combinations were limited to several selected examples and do not cover the full range of potential device/app combinations. Similarly, only limited app/operating system version combinations were evaluated and these do not cover the full range of potential app/operating system version combinations. While the models of smartphone used for the evaluations varied somewhat in technical characteristics (e.g., operating system, processor speed, lens type, etc.) they are not representative of the most basic or the most advanced smartphones that exist in the market.

The performance evaluations were conducted on public roads in Australia in regional and metropolitan areas in the States/Territories of New South Wales, Victoria and the Australian Capital territory (ACT). As such the ADAS apps were evaluated against Australian road infrastructure such as speed limit signs and lane markings.

Some applications may have been optimised for overseas road infrastructure (despite being available in Australia).

Only scenarios that arose during normal driving conditions were included. No scenarios where potential collision could have occurred were considered. Pedestrian detection was only undertaken during a stationary position at traffic lights with a pedestrian crossing, with pedestrians passing across the field of new (perpendicular to direction of travel).

No evaluations of differences in effectiveness of warning type, loudness or effect on driver behaviour were undertaken (although warning types were recorded).

For some applications, especially those utilising cameras, a more optimum position may have been possible which may have improved performance of the app - however in early trials the apps did not appear overly sensitive to positioning, provided the camera was centred with respect to the lane ahead of the vehicle and its view was not obstructed.

Lane departure warning manoeuvres were only undertaken where dashed line separation markings were present so other types of lane markings, or unmarked road edge detection, were not evaluated.

It is stressed that these were preliminary evaluations under the limitations described above and that the results for particular apps are not necessarily representative of their performance under more detailed evaluation. The outcomes should be regarded as indicative only.

CONCLUSIONS

Smartphone-based ADAS apps are an extremely low-cost road safety tool that have been mostly overlooked by drivers and the road safety community for many years.

While smartphone-based ADAS can provide reliable, and potentially useful road safety benefits to drivers, the potential benefits depend on a combination of the hardware capability of the smartphone, the sophistication of the application and to a lesser extent the correct set up of the smartphone in the vehicle. We found examples of apps that provided seemingly effective FCW/FDW and speed assist functionality in particular, but also found that LDW performance was uniformly poor in the apps evaluated.

Although the ADAS functionality offered by smartphone apps lags behind that offered by in-vehicle, OEM-fitted ADAS systems, there appear to be potentially significant benefits for drivers of vehicles that lack OEM-fitted ADAS, or where their vehicle lacks either ISA, FCW/FDW or a manual set, top speed warning. Our research identifies that while some ADAS apps appear to provide useful features, some do not, so more work is required to develop and promote worthwhile ADAS apps to end users.

Developers of ADAS apps need to ensure that their apps function well and provide beneficial, relevant features to drivers by taking advantage not only of the latest developments in smartphone technology, but also by applying existing road safety research findings. App developers would benefit from examining previous research into advisory ADAS, and the latest research into HMI design to ensure that the lessons learned through decades of ADAS development for new vehicles are applied to smartphone ADAS apps. It is also likely that subsequent improvements in warnings to drivers would enhance the effectiveness of ADAS apps to ensure that the warnings are more easily and correctly interpreted by drivers and that driver distraction is minimised.

Furthermore, while smartphone-based ADAS has the potential to improve road safety, especially where OEM-fitted ADAS is not a feasible option, there are inherent limitations posed by current technology. These may be overcome through future improvements in technology (smartphone processor or camera capabilities), through improvements in HMI design, or by combining different types of technology (for example by combining map based and optical recognition for ISA applications to improve the detection of all speed zones). We foresee that continued developments in smartphone hardware and processing capability, together with software evolution in ADAS applications, will continue to improve the reliability and effectiveness of smartphone-based ADAS in the future.

Road authorities should ensure that the road infrastructure supports ADAS functionality through good infrastructure design and maintenance. They should also ensure that other road safety initiatives, especially those aimed at reducing driver distraction through phone use, do not impose onerous conditions on drivers who legitimately wish to use ADAS apps for their safety benefits.

Subject to appropriate provisions in relevant regulations, the barriers to the adoption of smartphone-based ADAS appear low and the main barrier to adoption is that smartphone users are unaware that ADAS applications exist. These apps could be better promoted by road safety advocates/champions, to bring them to the attention and (hopefully) use of millions of drivers worldwide whose vehicles are not currently ADAS-equipped. However, advocates must be careful only to promote those apps that provide real benefits and that function well. In order to ensure this, a method of evaluating and rating the available apps may assist in identifying the most beneficial apps to promote. Consumer rating programs may be an effective way to promote and encourage the best performing ADAS apps and may also help drive further improvements in ADAS app design.

As we look for road safety strategies that provide more equitable access to road safety technology across the world, it appears that there may be a low cost, swiftly deployable option for the millions of drivers globally who do not have access to an ADAS equipped vehicle, but who do have access to a smartphone when they drive.

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Active Safety of Self-Propelled Trailers: Proposal for Safety Requirements

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Paper Number 23-0269

ABSTRACT

Trailers are by definition non-propelled, towed vehicles. They pose resistance forces to the towing vehicle, resulting from e.g. rolling resistance, friction, air resistance. New concepts are proposed where trailers would be able to support the towing vehicle by reduction of the toeball forces, sometimes even pushing the towing vehicle. This would allow for higher traction of the vehicle combination, possibly even a higher overall energy efficiency when the required energy storage system would be distributed to both vehicles.

A study conducted by BASt did investigate the possible influence of driven trailers on the driving dynamic properties of the vehicle combinations.

Driving experiments with two prototype trailers (caravans) had been carried out in direct comparisons with active and inactive trailer motors. The experiments focused on possible effects on the handling (double lane change test) and lateral stability (yaw damping test). Additionally, calculations had been carried out to investigate the transferability of the results.

Based on the available data, it was shown that there is no negative impact of the propelled trailer to the stability of the towing vehicle and vehicle combination, provided that there is always a remaining towing force in the towball, and no torque vectoring between the trailer wheels. It was also found that handling benefits from a driven trailer. Theoretical calculations show that when these two conditions are met (=no torque vectoring, no pushing), propelled trailers are safe with regards to driving dynamics.

Theoretical calculations also show that torque vectoring has a potential to even further improve handling and stability, however possible faults of the drive system and control strategy could negatively influence handling and stability.

The study had been carried out with only two prototype vehicles. Calculations checked that the results can be transferred to almost all kinds of trailers. Articulated trailers that have a steering of their own, however, need to be excluded from the conclusions without further research. Trailers for single-track vehicles (motorcycles, bicycles) are still under investigation.

As a conclusion, it has been identified that propelled trailers where a towing force in the coupling remains (=the trailers compensate their driving resistance only partially, they do not push the towing vehicle) and without torque vectoring do not have negative effects on the stability of the combination and can have possible effects on the handling. This is true for non-articulated trailers, including semi-trailers and central-axle trailers. Regulations could as a next step be adapted, so that the positive effects towards traction and energy efficiency could be demonstrated. Also as a next step, the benefits and possible issues with torque vectoring should be identified.

INTRODUCTION

Motivation

Trailers are by definition non-driven vehicles designed to be attached to driven vehicles. This means that the traction required for a combination to overcome the driving resistance can only be provided by the foremost, the towing vehicle.

The question therefore arises whether, from a scientific point of view (= technical point of view and from the point of view of driving dynamics), powered trailers could make sense. This is possible in principle in that

- each trailer only drives itself (partially compensates for its driving resistance, for example air resistance, or at best fully compensates for it, so that the trailer is still towed), or
- individual trailers apply more power than is required to overcome the driving resistance (then connecting devices are also loaded in compression, individual trailers push).

The benefits of powered trailers in both cases would be an increase in the traction of the combination and thus the ability to overcome slopes even under adverse friction conditions, the ability to distribute and use energy storage more efficiently since each trailer could store its own required energy, and the ability to recuperate energy more efficiently, i.e. to make better use of braking energy. This can improve traffic flow (for example, disruptions caused by broken-down combinations on motorway gradients in winter) and energy efficiency (through higher energy recovery and through more reasonable dimensions of the towing vehicle energy storage).

To be more specific, the slope $q_{\max}$ (typically dimensionless, equal to the sinus of the slope angle) a vehicle-trailer-combination can climb is the product of the friction coefficient μ (between horizontal tire force and tire load, $F_{horizontal,max}/F_z$) and the traction coefficient τ (between the axle load of all driven axles and the weight of the full vehicle combination, $F_{z,driven\ axle}/(m \cdot g)$):

$$q_{max} = \tau \cdot \mu.$$

The traction typically becomes a problem on snowy roads (e.g. μ <0.3) with vehicle combinations with a low traction coefficient (e.g. 1 out of 5 axles driven, τ = 0.2) on highways with a slope of 6% and higher.

However, an essential prerequisite for this would be precisely controllable (typically electric) motors in the trailer.

Regulatory Background

UN ECE's special resolution R.E.3 (ECE/TRANS/WP.29/78/RE3), which defines amongst other items the vehicle categories, has a definition for trailers: "'Trailer' means any non-self propelled vehicle, which is designed and constructed to be towed by a power driven vehicle and includes semi–trailers."

The defition in the European Type Approval Framework in Regulation (EC) No. 858/2018 is similar but more specific:

"'Trailer' means any non-self-propelled vehicle on wheels designed and constructed to be towed by a motor vehicle, that can articulate at least around a horizontal axis perpendicular to the longitudinal median plane and around a vertical axis parallel to the longitudinal median plane of the towing motor vehicle;"

Both these definitions exclude the posibility for the trailer to be self-propelled.

State of the Art

Since the relevant regulations at least in Europe prohibit driven trailer axles, no series production vehicles are known. There are, however, a number of prototype vehicles or prototype components are known in the vehicles categories O_2 [1], $O_{3/4}$ [2] and for bicycles [3]. In all of these examples, trailers are not pushing the vehicle combination, sometimes with the exception of low speeds.

Aims of the research

While there are advantages for traffic flow and energy efficienty, there could be new risks introduced through driven trailes. The aim of this research was to identify possible negative implications for driving dynamics, both with calculations and experiments with prototype vehicles, in order to propose requirements for driven trailers.

METHODOLOGY

The aim of the research, as discussed above, is to identify hazards to road safety from driven axles of trailers (for two-track vehicles) and, if necessary, to determine what requirements should be placed on trailers to avoid these hazards.

To do this, it is necessary to analyse the driving dynamics of trailers, describe the dependencies of the relevant physical variables and derive road safety criteria from them. These descriptions can then be verified and supplemented by driving tests.

Self-propelled Trailer Driving Dynamics

A challenge in trailer driving dynamics is the possible destabilisation of the towing vehicle about the yaw axis due to lateral forces introduced at the trailer coupling device and longitudinal forces pushing the towing vehicle (both forces increase the yaw angle of the towing vehicle). Pulling longitudinal forces around the yaw axis stabilise the yaw movement (they reduce the yaw angle of the towing vehicle).

Thus, first of all, it is assumed that trailers in normal operation should not transmit any compressive forces to the towing vehicle; this could be ensured by the requirement to always remain in towing operation despite a driven trailer, and by appropriate safeguarding of functional safety.

In this case, it can be assumed that additional lateral forces at the coupling device are generated by the trailer drive in the following cases:

- during stationary circular travel (in this case it can be expected that the lateral force at the coupling device F_y is lower since $F_{longitudinal}$ is lower),
- during corner braking (in this case there should be no driving force on the trailer axle, so that no influence of the drive is expected here either), as well as
- dynamically due to weave mode at higher speeds.

Model for weave motion

It is assumed that weave movements at high speed are the case in which influences by driven trailers are most likely to show: In the cases of corner braking, cornering, corner acceleration, lateral forces will occur, but not more strongly than in the case of the non-driven trailer (assuming correct system function without a pushing trailer, which is then a problem of functional safety).

Due to the large number of different trailer designs, the initial aim is to describe the influence of the driving force of non-driven trailers (rigid drawbar trailers, and due to the fundamentally different driving dynamics, singletrack vehicles are excluded) on the coupling forces, with the assumption that driving safety is not impaired if the lateral force introduced with drive is lower in the respective direct comparison (with/without drive) at all times.

For the theoretical derivations, the single-wheel model is used, in which the contact patch forces at all wheels are projected onto a single wheel (Figure 1). Furthermore, the angles should be small so that the cosine of the articulation angle becomes 1, the sine of the articulation angle then is the angle itself (in radians).

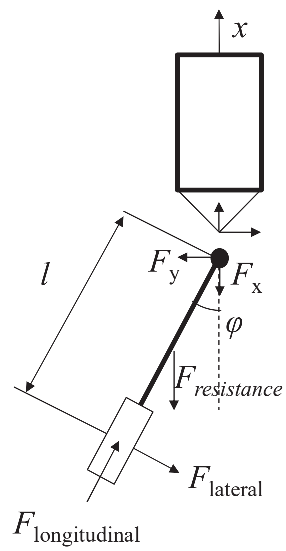

Figure 1: single-wheel model for trailer in weave motion

The lateral trailer forces for symmetric wheel torques depend only on the tire slip angle and its derivate, so no lateral force F_y is introduced specifically by the propelled trailer:

$$F_{lateral} = k_\alpha \cdot m \cdot g \cdot \left(\varphi + \frac{l}{\dot{x}} \cdot \dot{\varphi}\right)$$

with the lateral tire stiffness k_α, the sideslip angle φ (in this case of pure weave motion approximately equal to the articulation angle, speed $\dot{x}$ and distance of wheel centers to towball l).

The longitudinal force $F_{longitudinal}$ points – for symmetric trailer design – to the towball of the towing vehicle. It does not introduce additional side forces into the towing vehicle either, and will not destailibize the towing vehicle as long as $F_{longitudnal}$ is smaller than the resistance force $F_{resistance}$.

Non-symmetric torques on both sides of the trailer have the advantange that active stabilization of the trailer becomes possible, analog to what electronic stability control can do for towing vehicles, however lateral destabilization of the towing vehicle can occur as well.

Controllability

A propelled trailer will change the driving performance of the combination. An assessment of the effect of these changes for the drivers is possible in the closed-loop test. A good test for controllability

Figure 2: Non-valid test run in double lane change test

problems for example is the closed-loop double lane change test.

Experiments

The standard test for high speed stability defined in ISO 9815:2010 "Road vehicles – Passenger-car and trailer combinations – lateral stability test" [4]. The test contains an excitation on the steering wheel with a specific speed and amplitude, after which the trailer weaves in its natural frequency. The excitation has been conducted using a driving robot, so the steering actuation has been consistant between experiments with self-propelled trailer and non-self-propelled trailer. Key performance indicator is the natural frequency and damping for the trailer around the yaw axis. As long as these characteristics are similar for self-propelled and non-self-propelled trailers, no negative influence is assumed.

The test for the controllability is the double lane change according to ISO 3888-1:2018 [5] with the parameters as shown in Figure 3. Key performance indicator is the maximum speed for which the driver was able to drive through the corridor without touching one of the cones. To be more robust, three trials were available for a given test speed, and one valid trial was sufficient to qualify for the next higher speed. Speeds were selected with a spacing of 5 km/h. The test was driven with constant speed (maintained by the speed limiter device of the towing vehicle).

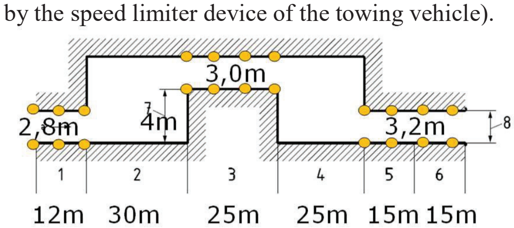

Figure 3: Characteristics of double lane change test: cones and spacing

An impression of a non-valid experiment is shown in Figure 2.

Tools

Experiments were conducted with two prototype trailers (A: mass approx. 2.1 tons, single axle, *l* approx. 4 m, motors fully active up to 100 km/h, symmetric torques, and B: 1.8 tons, tandem axle, *l* approx. 9 m, motors active up to 85 km/h, symmetric torques), towed by a large SUV (mass approx. 2.2 tons in test configuraiton). The towing vehicle was equipped with precise position measurements equipment and a steering robot. The trailers were equipped with precise position measurement equipment as well, trailer A was equipped to measure towball forces, allowing the verification of the single wheel model for high speed stability with regard to the forces. The test configuration can be seen in Figure 4.

Figure 4: Towing vehicle and one of the trailers on test track.

RESULTS

High-speed stability (weave mode)

A representative example of the towball forces and the articulation angle is given in Figure 5 below. Plots for experiments with self-propelled trailer are red, plots for experiments with non-self-propelled trailer black.
It can be seen that the articulation angle is consistant between test runs. Differences between configurations (self-propelled – non-self-propelled) in this case are hardly noticable. This is not the case for all test runs; however, the characeritic velocity for trailer A – the speed, for which the damping ratio is calculated to become zero – is 5% lower for the self-propelled trailer (101.4 to 105.1 km/h). For trailer B, the difference for characteristic velocity is neglectable (93.4 to 93.6 km/h).
As a consequence, there is no reason to assume that propelling a trailer will negatively influence the weave mode of the vehicle combination.

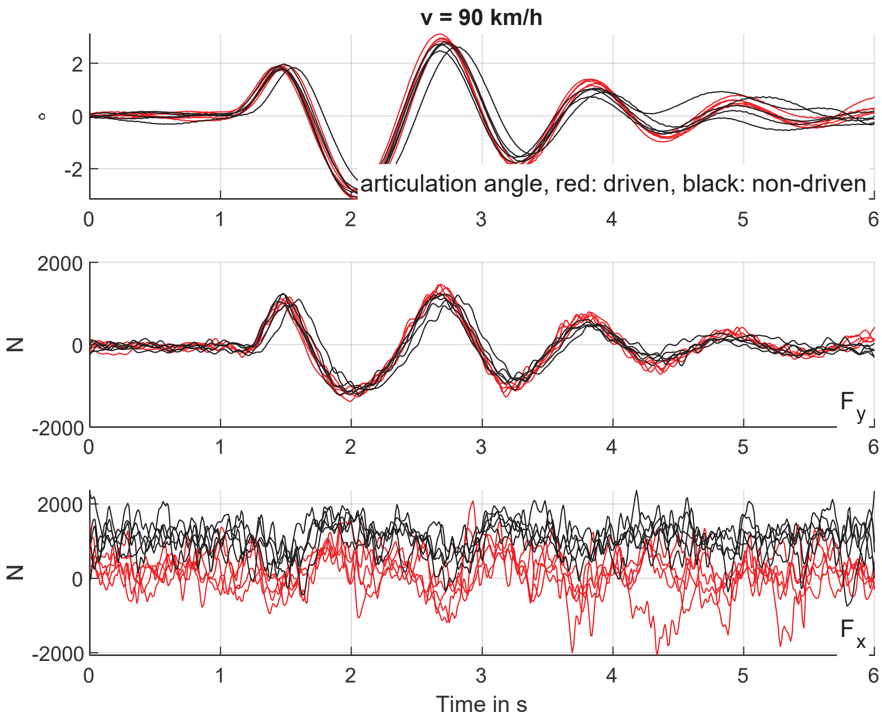

Figure 5: Example test run for trailer A

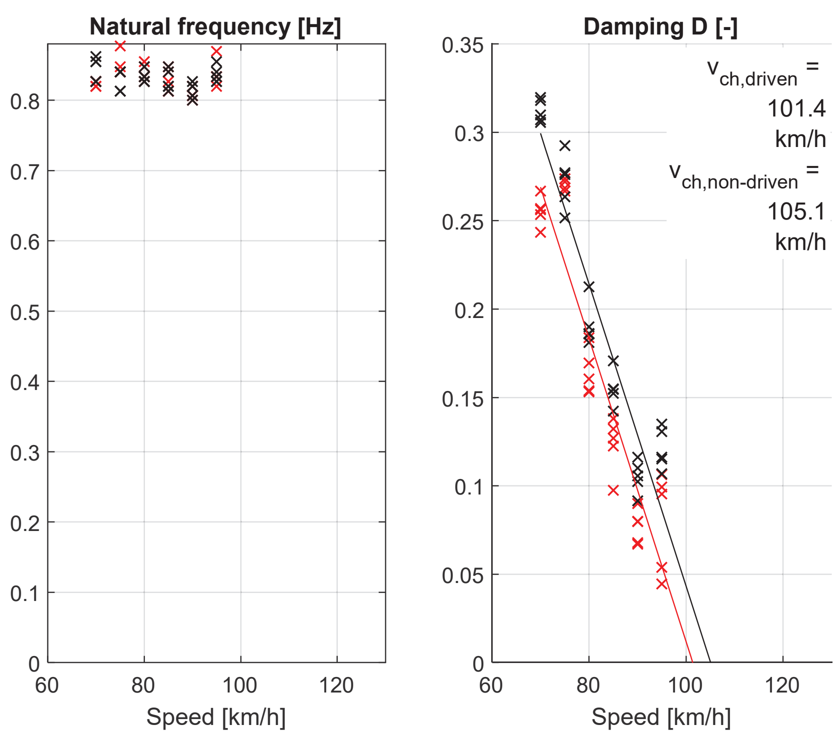

Figure 6: Natural frequency and characteristic velocity for trailer A

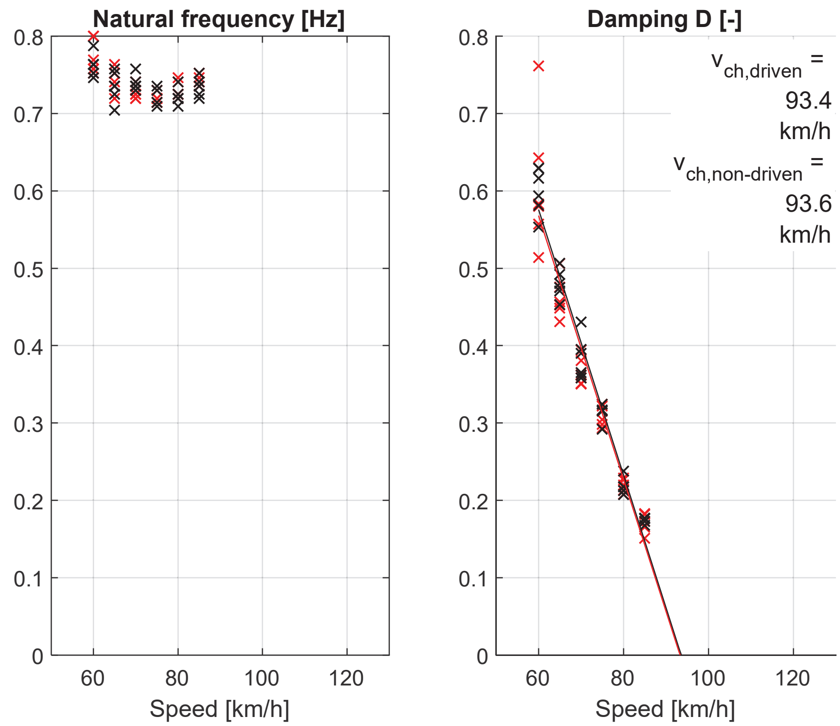

Figure 7: Natural frequency and characteristic velocity for trailer B

Double Lane Change

The double lane change results are given as number of required runs for one valid test run in the following Table 1. While the performance of the driver with trailer A is quite comparable and the final maximum speed is the same, 95 km/h (above which the test runs were stopped due to safety considerations), the performance of the driver with the much longer trailer B shows advantages for the self-propelled configuration (80 km/h with only one test run required for a valid test run, while at 70 km/h for the non-self-propelled configuration, three test runs were required for one valid test run). This means that trailer handling was obviously better with self-propelled configuration.

One remark here: it could very well be the case that trailer A also has a better handling when self-propelled, however since it is much shorter, this might not have influenced the driver's double lane change performance.

Table 1: Required test runs for one valid test run, self-propelled (sp) and non-self-propelled (nsp)

v [km/h]	A (sp)	A (nsp)	B (sp)	B (nsp)
50	1			
60	1			3
65	1			
70	2		1	**3**
75	1		1	No valid run
80	1	1	**1**	
85	3	1	No valid run	
90	2	1		
95	**3**	**3**		

The results for the double lane change test are consistent with the weave results above in that there is no reason to assume that self-propelled trailers influence the handling negatively.

Transferability of Results

For checking the validity of the equations for the single-track weave model, in particular also for estimating the lateral force based on the articulation angle of the combination, the measured values (forces and articulation angle) for trailer A can be used.

The following additional assumptions are required:

- Sideslip stiffness of the tires $k_\alpha = 0.75$ 1/rad,
- Time delay between angle measurement and force measurement constant 0.2 s (this indicates a 5 Hz low-pass filter in the inaccessible hardware and software of the force measurement).

With these assumptions, there is apparently good agreement between measurement and calculation (Figure 8), although the calculation tends to overestimate the lateral forces at higher driving speeds (Figure 9).

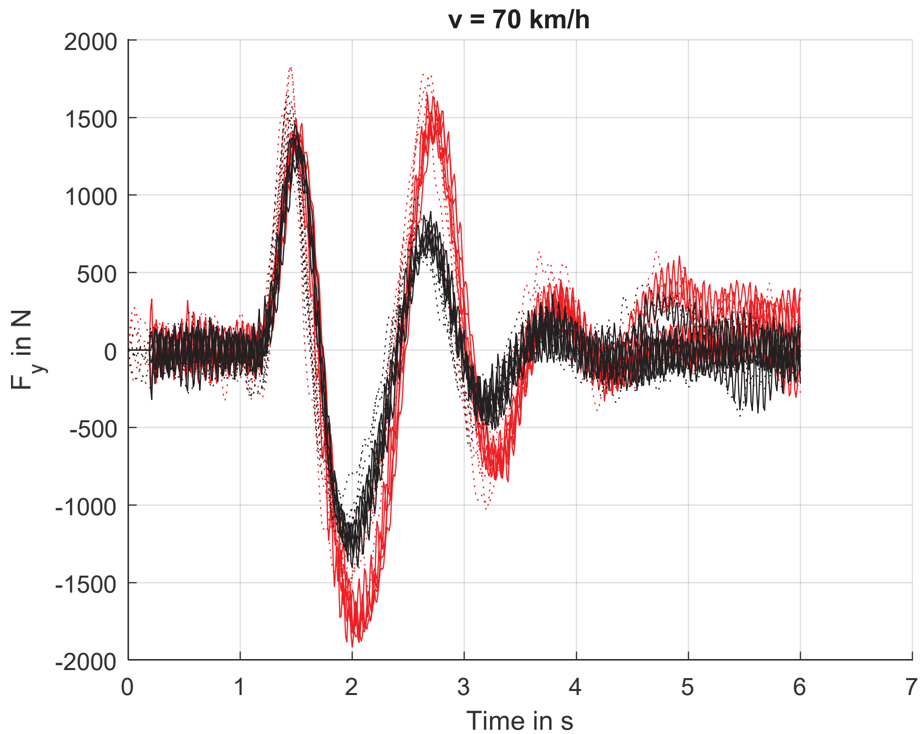

Figure 8: Comparison between measured (solid line) and calculated (dashed line) lateral forces, trailer A, 70 km/h

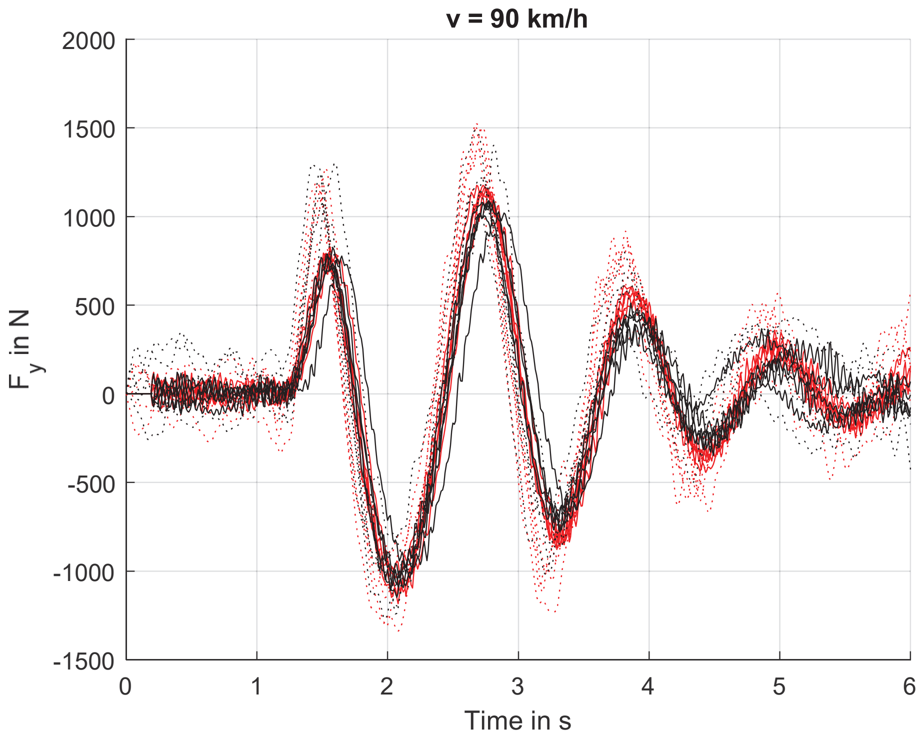

Figure 9: same as above, but for 90 km/h

Based on the fact that the driving dynamic calculations do not seem to show any fundamental differences to the measured lateral force, it is assumed that the findings are transferable at least to other trailer types that can be simplified as a single-wheel model. Trailer types for which this is not possible are those with several degrees of articulation freedom, such as turntable drawbar trailers.

CONCLUSIONS

Theoretical considerations show that trailers with symmetrical drive force which is less than the driving resistance force of the trailer are not critical with regard to the impairment of the driving dynamics of the vehicle combination. The theoretical considerations have been verified with data from high speed stability tests, and the test results show that the characteristic velocity – the velocity at which the damping could beome zero – is not substantially influenced.

Driven trailers should have a positive influence on the driveability of the vehicle combination due to lower towing forces to be applied by the towing vehicle, which has been verified with double lane change tests. Based on these results, it is not assumed that there are implications to vehicle safety if self-propelled trailers are designed so that the drive forces are distributed equally over both sides of the trailer and that the trailers do not push the towing vehicle.

Proposal for requirements

Based on the conclusions above, the following requirements for self-propelled trailers can be proposed:

- The driving force should not exceed the driving resistances so that the trailer is always towed. Then no greater – destabilising - lateral forces are expected at the trailer coupling than in the non-propelled case.

- The driving force should be applied to wheels on both sides equally in terms of magnitude and phase. This should be demonstrable by considering the functional safety of the system.

Trailers designed according to those requirements will have no negative effect on traffic safety, but might have a positive effect on traffic flow (traction on slippery highway slopes) and energy efficiency (e.g. longer ranges for electric vehicles, better brake energy recuperation). To be able to bring self-propelled trailers to the market, the type approval framework on

European level (Regulation (EC) No. 858/2018) and at UN level (R.E. 3) needs to be amended.

In a next step, trailers with non-symmetric forces on both sides could possibly assist in stabilizing the vehicle combination. Requirements for these trailers have to be defined at a later stage.

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ADAS Reliability against Weather Conditions: Quantification of Performance Robustness

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ABSTRACT

Advanced Driving Assistance System (ADAS) technologies provide an additional safety layer besides human drivers. Continual evaluation of the safety of the dynamic driving task enables ADAS to initiate a corrective (e.g., automated braking) and/or a preventative (e.g., audio-visual alerts) action if and when an unsafe roadway event is detected. To provide situational awareness, these safety systems principally rely on the vehicle mounted sensors whose performance can be greatly affected by weather events such as strong sunlight, atmospheric precipitation (rain, snowfall, fog), etc. Correspondingly, this study was conducted to characterize the performance of ADAS features in different weather conditions. Automated emergency braking (AEB) was selected as a representative ADAS feature. Two vehicles under test (VUT) were equipped with perception sensors such as LiDAR, RGB camera, infrared camera, radar, inertial measurement unit, GNSS, etc. Relevance and prominent use of these sensors in pre-production and developmental driving automation systems are widely reported in the literature. In addition, the data available through the OBD-II port of the VUTs was also recorded with temporal correspondence with the external sensors. Although weather related tests involving automotive systems have been traditionally performed in weather chambers, adoption of these test protocols for ADAS testing can be challenging. Because testing of ADAS must be performed dynamically, a runway of several hundred meters is necessary, and typical weather chambers cannot accommodate this requirement. Alternatively, this study utilized naturally occurring weather events to record AEB performance. For the purpose of this study, AEB tests performed under optimal weather conditions (sunny and bright) constituted the baseline performance. The same tests were performed in a number of different weather and roadway conditions; e.g., day/night, snow covered asphalt, persistent snowfall, overcast, rainfall etc. A number of metrics resulting from the test data analysis were used to quantify AEB performance in adverse weather conditions. These include distance of the test target when AEB system detected an imminent collision in different weather conditions, distance of the test target when AEB initiated an automated braking action in different road surface conditions (dry/wet asphalt vs snow covered asphalt), and whether AEB was successful in stopping a collision from happening in the test scenarios. These metrics helped to identify the failure modes of AEB in adverse weather conditions. It should be noted that quantification of ADAS performance robustness against adverse weather conditions is closely related to quantification of operational design domain (ODD), which is an emerging topic in driving automation systems literature. Nonetheless, observations and inferences made from this study will be used to design more comprehensive and elaborate test protocols for ADAS that are expected to improve in system capacity and ODD in near future.

INTRODUCTION

Although not formally recognized in SAE standard J3016 [1], the term ADAS (advanced driver assistance systems) commonly refers to SAE L0-L2 features/systems that assist human drivers in performing some aspect of the dynamic driving task (DDT). Implementation of these systems may take many forms. Examples include executing momentary interventional actions (e.g., automatic emergency braking - AEB), exerting sustained control over vehicle operation in limited scope (e.g., adaptive cruise control - ACC, lane support system - LSS), or simply alerting the driver when a potentially unsafe event is detected (e.g., forward collision warning - FCW). Improving safety and reducing the cognitive load of the DDT for human drivers are the two main value propositions of ADAS. Sensors and perception algorithms work together to enable ADAS to monitor the dynamic driving environment in real-time by detecting, recognizing and classifying relevant objects and events so that appropriate responses can be prepared and executed. Correspondingly, ADAS can be broadly decomposed into two functionally distinct, yet closely related building blocks: detection & control. Due to sub-optimal visibility and challenging road traction characteristics, weather events (e.g., snowfall, rain, fog, etc.) may have adverse effects on both the detection and the control functions of ADAS. This paper studied the combined performance of both functions against varying weather conditions. To this end, two ADAS-equipped vehicles (2021 Volkswagon Jetta and 2021 Toyota RAV4) were instrumented with external perception sensors so that the vehicles' responses in different test scenarios can be recorded and analyzed. It should be noted that the deployed instrumentation did not significantly interfere with the ADAS functions because interference contributed by the active elements (LiDAR & radar) was considered minimal. Studying weather effects on ADAS features can be a challenging endeavor. Although weather testing for automotive has been traditionally performed in weather chambers, performance evaluation of ADAS features, especially in dynamic test scenarios, would generally require several hundred meters of testing roadway with simulated weather events. Developing such a test facility can be resource intensive. As an alternative, this study employed opportunistic data acquisition in different naturally occurring weather events. Tests were performed in sunny , rainfall, and snowfall conditions with the AEB system as a representative ADAS feature.

A brief literature review provided below indicates that performance quantification of ADAS in adverse weather condition is an emerging topic in the literature. Heuristic knowledge of how weather events affect sensor performance, and how degraded sensor data affect perception algorithms is still developing. As a result, this study was designed as an exploratory endeavor in response to the scarcity of prior instances of studies on ADAS performance degradation due to weather events. Correspondingly, a data acquisition system that can collect multi-modal sensor data with sufficiently accurate spatio-temporal correspondence was constructed, and data provided by the system was analyzed with a view to discover AEB failure modes related to weather events.

RELATED WORK & RATIONALE FOR PRESENTED STUDY

How adverse weather conditions affect performance of automotive perception sensors has generated strong interest from the research community in recent years. For example, Lambert *et. al.* in [2, 3] recorded static and dynamic performance of 10 different automotive LiDAR models in different controlled weather conditions (rain, fog and strong light) in a 200 meters long weather chamber to create the LIBRE dataset. In another weather chamber study, Judd *et. al.* experimentally evaluated imaging performance of multi-spectral sensors in foggy conditions in a 55 meters long weather chamber [4]. Infrared camera operating in different wavebands (LWIR: 7-14 μm, MWIR: 3-5 μm, SWIR: 0.95-1.7 μm), a regular RGB camera, and a Velodyne VLP-16 LiDAR were the sensors used in this study. Since the environmental enclosure constructed to protect the sensors from the simulated fog particles hindered the operation of the LiDAR, its imaging performance was excluded from the analysis. This study showed that, even in thick foggy condition that is completely opaque to the human eye, the LWIR sensor is the most capable sensor in terms of detecting pedestrians and cyclists (i.e., vulnerable road users - VRU). Unlike the aforementioned studies that employed weather chambers for simulating adverse weather conditions, the study in [5] utilized naturally occurring weather events (rain, heavy snow and fog) to study the performance of two LiDAR sensors (Velodyne VLP-32C and Ouster OS1-32). Their experimental data showed that while rain and snow had little effect, foggy conditions severely affected sensing performance. It is not surprising that radar sensors are not well represented in these studies. The underlying sensing modality of radar sensors render them the most resilient in adverse weather conditions [6]. The experimental data presented in [7] indicate that the minimum detection range for radar sensors in heavy fog is 260 meters i.e., (evaluated with signal to noise - SNR ratio threshold of 20 dB). A detection range of 260 meters can be characterized as sufficient for most contemporary ADAS applications. Correspondingly, radar and GNSS have been identified as the two sensing modalities that are relatively more robust against weather induced performance degradation in a qualitative evaluation presented in [6]. See Table 1 for a summary.

The aforementioned studies primarily focus on raw sensor performance. Consideration of other functional sub-systems of ADAS such as perception algorithms that enable detection, recognition and classification of relevant objects and events, and the control functions performing corrective driving maneuvers were found to be scarce. Nonetheless, aggregate performances of an *a priori* map-based place recognition system utilizing data from two sensing modalities under adverse weather conditions were evaluated in [8]. The same processing pipeline was used for both sensors for a

Table 1. Influence of weather on different sensing modalities as qualitatively evaluated in [6].

Modality	Light/Heavy rain		Dense smoke/Mist, Fog, Haze/Smog			Snow	Strong Light
	<4mm/hr	>25mm/hr	vis. <0.1km	vis.<0.5km	vis. >2km		
LiDAR	2	3	5	4	1	5	2
Radar	0	1	2	0	0	2	-
Camera	3	4	5	4	3	2 (dynamic) 3 (static)	5
Stereo Camera	almost same as monocular camera						
Gated NIR Camera[1]	2	3	2	1	0	2	4
FIR Camera[2]	2	3	3	1	0	2	4
GNSS	0	2	0	0	0	0	0

[1]NIR λ: 0.8-0.95μm [2]FIR λ: 15-1000μm
[3]Qualitative performance rubric:
0 - negligible: weather effects can almost be ignored.
1 - minor: weather effects barely cause detection error.
2 - slight: weather effects cause small errors in edge cases.
3 - moderate: weather effects cause perception error up to 30% of the time.
4 - serious: weather effects cause perception error 30-50% of the time.
5 - severe: weather effects can cause false positives or negatives.

fair comparison. This study found the LiDAR-based system to be more robust than the camera-based system. Since observations of this study is limited to the dataset used, more elaborate experiments must be performed before one can draw general conclusions.

Regardless of whether an ADAS performance study focuses on overall system performance or individual component performance, the body of literature dealing with pre-production/developmental ADAS is relatively richer than that involving production ADAS found in consumer road vehicles. Some examples of the latter include [9] and [10]. The elaborate experiment-based study [9] involving 36 ADAS equipped vehicles (model years including 2012-2018) from 15 different automakers exposed gaps in terms of performance variability. Even in some cases complete failure of the intended function was recorded (e.g., AEB systems designed to avoid collisions with pedestrians failing to do so in test scenarios). This study represents a total of ~100,000kms of on-road and test-track driving, and overall system performance of ADAS features was the main focus. It should be mentioned that commercial ADAS are proprietary in nature, and evaluating overall system performance is considered the only way to study their effectiveness because knowledge of their internal architecture is not readily available. The multi-year study [9] underscored the necessity of approaching ADAS as a stochastic system whose performance must be evaluated accordingly; i.e., by analyzing statistically significant datasets created from real-world tests and/or simulation models that represent real-world objects, events and their interactions with sufficient accuracy. The study presented in this paper can be considered a continuation of the study in [9] that attempted to expand the testing scope by integrating a data acquisition system composed laboratory grade automotive perception sensors so that: (a) the perception potential of a test scenario in adverse weather conditions using state-of-the-art sensing technologies can be independently assessed, and (b) greater insight into the failure modes of commercial ADAS can be obtained.

DATA ACQUISITION SYSTEM

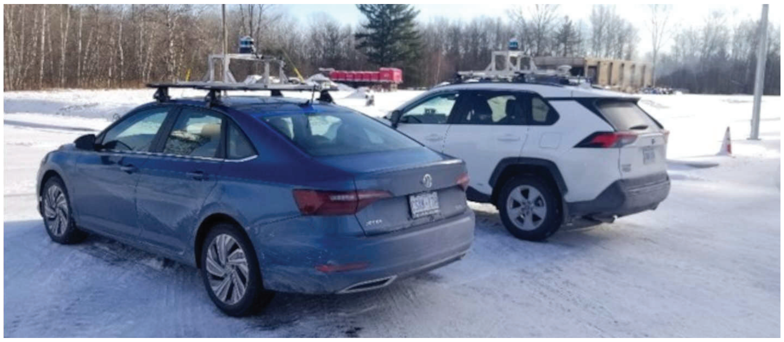
The two vehicles under test (VUT) were designated as VUT-1: 2021 RAV4 and VUT-2: 2021 Jetta. Each of the VUT was outfitted with a data acquisition system (DAQ). Except for the LiDAR sensor, the two data acquisition systems were identical. See Figure 1(a) for a pictorial of the two instrumented VUTs. The DAQ system was designed specifically for supporting driving automation research in a cost-effective manner by taking advantage of internal resources (e.g., electro-mechanical & electronics design & fabrication, and in-house software development) and open-source software. This approach resulted in a DAQ system that is scalable, guarded against near-future obsolescence, and capable of any customization required to address project-specific needs.

Table 2. Sensor stack specifications.

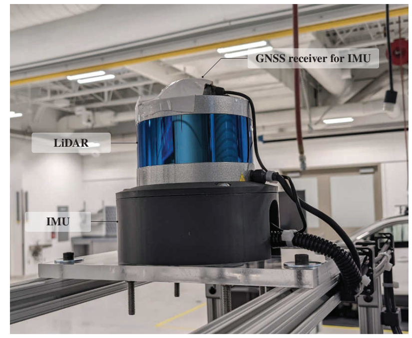
Sensors (# per VUT)	**Specifications**	
	VUT-1: 2021 RAV4	**VUT-2: 2021 Jetta**
LiDAR (1)	**Velodyne VLP-32C** 360° horizontal FOV, 40° vertical FOV 200m max range, 32 channels	**Velodyne VLP-16** 360° horizontal FOV, 30° vertical FOV 100m max range, 16 channels
Infrared camera (1)	**Intel RealSense D415** 850nm NIR, 1920 × 1080 active pixels 69.4° horizontal FOV, 42.5° vertical FOV	Same as VUT-1
RGB camera (1)	**Intel RealSense D415** 1920 × 1080 active pixels 69.4° horizontal FOV, 42.5° vertical FOV	Same as VUT-1
GNSS-RTK (1)	**SwiftNAV Piksi Multi** GPS, GLONASS, Galileio, BeiDou constellations, RTK relative accuracy: ~1cm horizontal, ~1.5cm vertical	Same as VUT-1
Radar array (3)	**Texas Instruments mmWave** 76-81GHz Single plane sensing w/±60° horizontal FOV	Same as VUT-1
IMU (1)	**Xsens 680G INS** Sensor fusion performance: Roll/pitch: 0.2° RMS Yaw/heading: 0.5° RMS Position: 1cm CEP, velocity: 0.05m/s RMS	Same as VUT-1
Instrument Cluster Camera (1)	720p consumer webcam	Same as VUT-1
CAN-bus monitor (1)	OBD-II CAN-bus monitor w/ SocketCan support	Same as VUT-1
In-vehicle power (1)	1000Wh rechargeable power station	Same as VUT-1

Hardware Stack

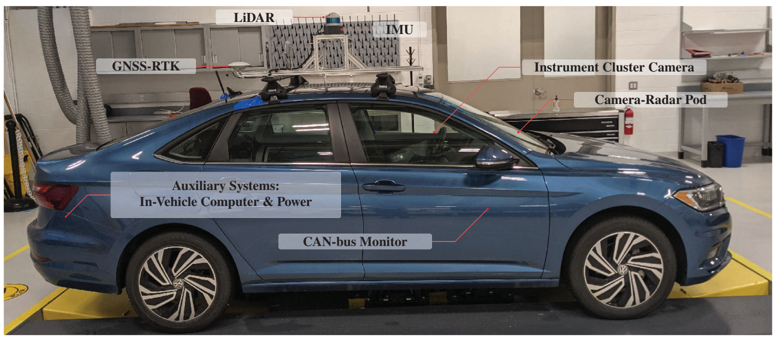
The hardware stack of the DAQ system can be categorized into three groups: (a) sensors, (b) computing platform to host the DAQ software stack, and (c) auxiliary components. The auxiliary components include a mobile power source and the cabling required for power and data transport. The computing platform and the mobile power source were installed inside the VUT trunk for convenience [see Figure 1(e)]. Specifications of the sensors in the DAQ system are provided in Table 2. LiDAR, IMU, GNSS-RTK sensors were installed on a rigid mechanical railing system on the roof of the VUT [see Figures 1(a) and 1(c)]. In addition, sensors installed inside the cabin include the camera-radar pod [see Figures 1(d) and 1(f)], a camera looking at the instrument cluster to record VUT ADAS responses, and a CAN-bus monitor plugged into the OBD-II port of the VUT. The IMU and the LiDAR sensors were assembled in a pod to ensure geometric alignment of sensors' z-axes to facilitate environmental characterization through the applicationof SLAM (simultaneous localization and mapping) techniques. Furthermore, the camera-radar pod [see Figure 1(d)] was built to facilitate multi-modal sensor fusion. The LiDAR-IMU and the camera-radar pods were centered on the vertical plane that bisects the lateral profile of the VUT.



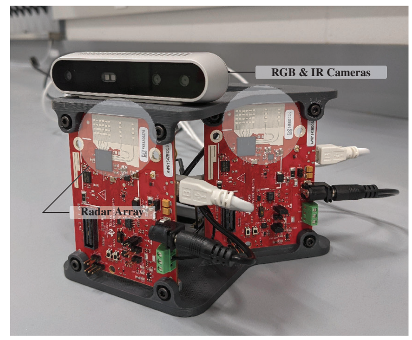
(a) Two instrumented VUTs.



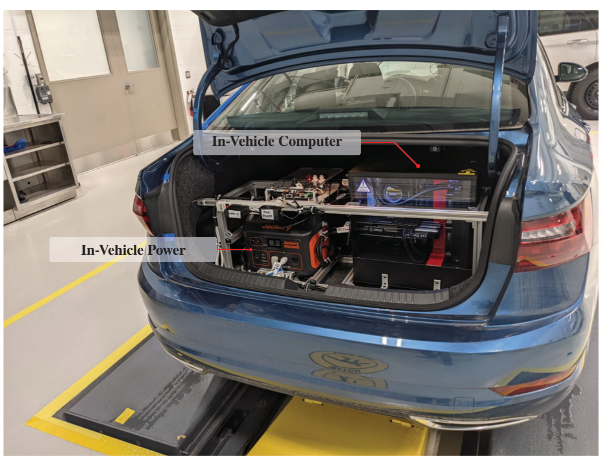
(b) LiDAR-IMU pod.



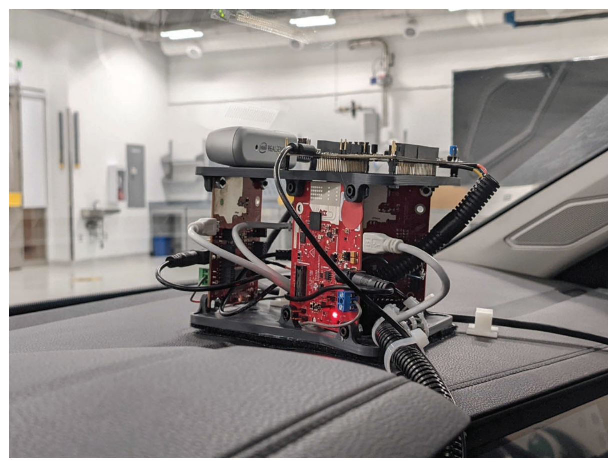
(c) Instrumentation of VUT.



(d) Camera-radar pod.



(e) Auxiliary systems of DAQ.



(f) Camera-radar pod mounted on the VUT dashboard.

Figure 1. Data acquisition system for ADAS performance evaluation.

Software Stack

The software stack of the DAQ is based on Robot Operating System (ROS) [11] hosted on a Linux (Ubuntu 18.04) computer. ROS is an open-source, meta-operating system originally developed for robotics reseach, and has been continually supported by a large, thriving community of developers. Industrial support for ROS has also been ubiquitous. OEMs of sensors and robotics platforms often provide open-source ROS drivers for their products that interface either directly with the target hardware or with a closed-source OEM-supplied driver package. ROS was chosen as the foundation of the DAQ software stack for a number of reasons. First of all, it provides a convenient way to interface with the sensor hardware utilizing OEM supplied drivers under a common framework. In addition, it is built for scalability that renders integration of new sensors into the DAQ a relatively easy task. ROS also ensures temporal

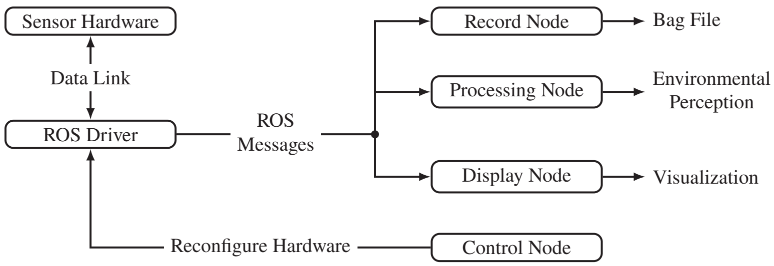


Figure 2. Typical ROS pipeline.

consistency among heterogeneous, multi-modal sensor data by enabling data acquisition under a common timestamp. In order to illustrate how ROS operates, a typical data pipeline in a ROS system is shown in Figure 2 where the sensor hardware is connected to the ROS driver *node* (i.e., a functional block in a ROS system) through a physical data link that transports binary data. The ROS driver node is programmed to parse the binary data and subsequently *publish* this parsed data under a *topic* as *messages*. Other nodes may *subscribe* to this topic and receive these messages concurrently to perform their individual functions. For example, the record node in Figure 2 subscribes to the topic advertised by the driver node, and can record the published messages in a *bag* file. Through this publish-subscribe paradigm of data exchange, two other nodes in Figure 2 also receive the same messages to deliver their intended functions (e.g., the processing node applies perception algorithms to characterize the environment, and the display node enables viewing of the data in real-time). In addition, the control node in Figure 2 can interact with the ROS driver node through a *separate* topic in order to reconfigure the sensor hardware on the fly.

As part of the software stack a GUI (graphical user front-end) was developed to enable operators to interact, monitor and record sensor data in bag files during tests. It should be mentioned that a bag file is a binary file that stores all or a subset of the messages available in a ROS system with appropriate timestamps. A bag file can later be played back so that recorded messages appear chronologically with accurate time deltas. The replay feature allows to review the test data on demand, and to perform analysis of the recorded data.

Table 3. AEB testing protocols.

#	Ref.	Objective	Description	Expected Outcome
A	[12, 13]	Evaluate performance of forward collision avoidance involving a stationary target.	VUT travels at speeds of 20kph to 60kph towards a stationary target vehicle (see Figure 3-A) or a stationary VRU target (see Figure 3-C&D) positioned at x% of the lateral length of the front bumper ($x = 10, 25$). EuroNCAP Pedestrian Target Child - EPTc & EuroNCAP Pedestrian Target Adult - EPTa are used as VRU targets. The VRU tests are not *stricto sensu* part of EuroNCAP test protocols.	AEB is expected to detect the potential forward collision event, and activate the brakes accordingly to avoid collision.
B	[12]	Evaluate performance of forward collision avoidance involving a moving target.	VUT travels at speeds of 30kph to 60kph towards a target vehicle moving at 20kph (see Figure 3-B).	AEB is expected to detect the potential forward collision event, and activate the brakes accordingly to avoid collision.

TEST DATA ACQUISITION & ANALYSIS

Test Execution & Data Recording

Test procedures used in this study were developed from the UNECE R152 [12] and the EuroNCAP VRU [13] test

Figure 3. Test protocols used in this study.

Table 4. Tests performed for VUT-1 & 2 in different weather conditions.

Test Conditions	**Test Target**					
	Vehicle		**EPTa**		**EPTc**	
	VUT-1	**VUT-2**	**VUT-1**	**VUT-2**	**VUT-1**	**VUT-2**
Clear	20	17	0	0	16	0
Precipitation	7	0	15	20	18	18

protocols. A total of 2 types of tests were designed to provide coverage for various AEB scenarios. See Table 3 for details of these two test protocols. A total of 131 AEB tests involving both VUTs were conducted at different speeds in different combinations of these ambient conditions: day/night, clear sky/overcast, and dry/precipitation (snowfall & rain). Out of these 131 tests, 76 were performed on the VUT-1 vehicle and 55 were performed on VUT-2. In addition, 78 (~60%) of these tests were opportunistically performed in natural precipitation conditions. It should be noted that the naturally occurring precipitation conditions could not be kept uniform for all the test samples. Regardless, data points from these tests can be considered very valuable because of their potential to provide deep insight into AEB performance degradation in adverse weather.

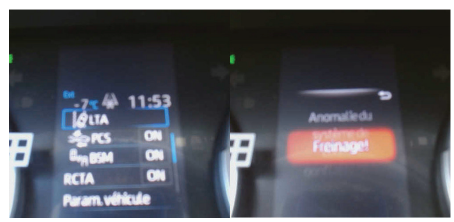
Data Analysis

The 131 AEB tests produced ~1 TB of binary data, and presenting an analysis of the entire dataset was considered to be beyond the scope of this paper. The data was recorded in the bag binary format, which has been developed for ROS systems. The bag format enabled "play-back" of the timeline of each test in real-time for analysis. When closer scrutiny of the data was necessary, play-back was performed at slower speeds. In the planning phase of the data analysis, several automated data processing methods involving image and pointcloud processing were prototyped and evaluated. Because of the diversity of the ambient test conditions, the multi-modal data showed a lot of variability, and the robustness of the prototyped data processing algorithms were considered insufficient for the data analysis activity. However, the ability to review the data visually at a slower frame rate was proved to be an effective method for evaluation. For example, the image frame where the VUT collided with a vehicle target in test sceneario "A" was isolated for the purpose of determining the exact time of collision (see Figure 4). It should be mentioned that the inertial force signature of collision with a soft target was too small for the IMU to register the event reliably.

Figure 4. Moment of collision with vehicle target in test scenario "A" (depression in the inflated target is the only indication of collision).

Since it was observed the AEBs of both VUTs failed in tests performed at speeds of 50-60kph, these tests were selected for analyzing AEB failure . Although radar sensors are more robust to weather effects, the units installed on the VUTs have limited range. Therefore, their performance was considered to be inadequate for the AEB experiments, and LiDAR was selected as the primary ranging sensor. An intermittent malfunction of the LiDAR unit installed on VUT-2 was discovered during data analysis. This rendered analysis of the VUT-2 AEB tests using LiDAR ranging untenable. Nonetheless, a total of 21 data points involving testing speeds of 60kph for the VUT-1 were analyzed and presented in this paper.

(a) YOLOv3 DNN model detecting and classifying target objects (left:input, right: output).



(b) Instrument cluster transitioning from normal state to AEB warning state.

Figure 5. Detection of events E1 and E2.

For the purpose of performance evaluation of AEB systems, each individual test timeline was broken into three separate events: (a) E1: when the test target is close enough for a typical perception algorithm to detect it, (b) E2: when the AEB system provides a warning to the instrument cluster of the VUT, and (c) E3: when an automated braking action (if any) is initiated by the AEB. The seminal deep neural network (DNN) model developed for object detection & classification in images [14] was selected as a typical perception algorithm for determining the occurrence of event E1. Specifically, event E1 was considered to have taken place when the DNN model (YOLOv3) first accurately detected & classified the test target in the images from the camera installed on the VUT dash. Continuity of the detection performance in subsequent frames was not considered for the sake of simplicity. The YOLOv3 DNN model was configured to detect and classify vehicle and people with an arbitrarily chosen prediction confidence score of 0.3 or higher [see Figure 5(a)]. In order to detect the occurrence of E2, a simple image processing algorithm was developed that determine the exact moment when the instrument cluster start showing an AEB warning message. To this end, images from the instrument cluster camera were segmented based on HSV (hue, saturation, value) representation of the distinctive color of the warning message shown on the instrument cluster [see Figure 5(b)]. Finally, event E3 was detected from the VUT's motion states (see Figure 6). For this purpose, the IMU reported velocity was fitted to a spline curve, and its first derivative provided acceleration values, and the second derivative provided jerk values. It should be mentioned that

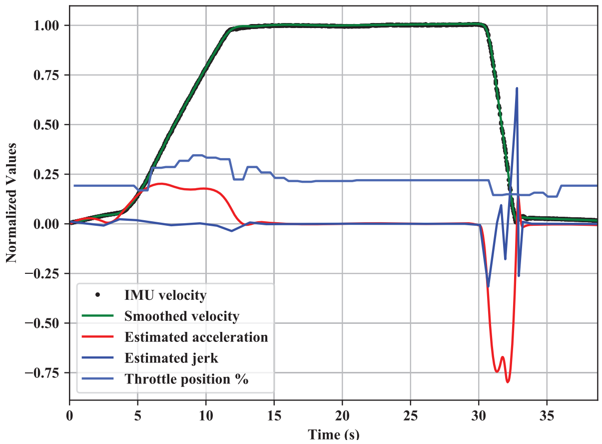


Figure 6. Detection of event E3 based on motion state of the VUT.

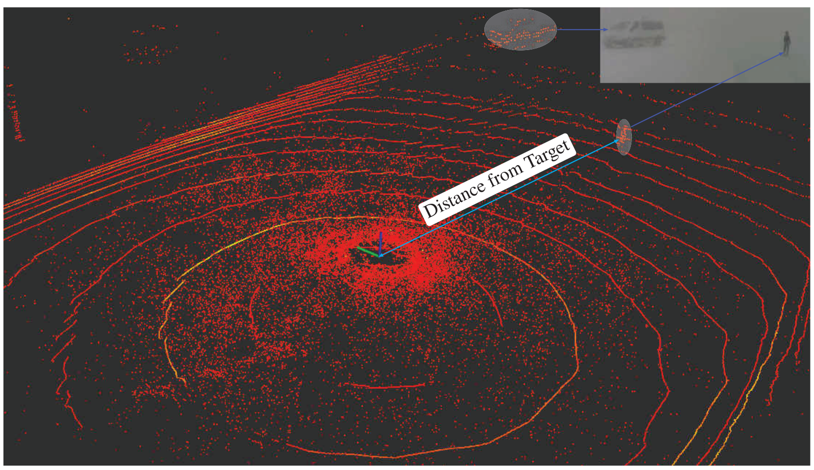


Figure 7. Determination of distance from target in the LiDAR data in snowfall conditions (false-positive noise generated by light pulses reflected from falling snow particles can be seen).

Figure 8. DNN-based object recognition and classification demonstrated irregular performance (left: input image from test conducted at night, middle: relevant objects detected and classified in the left image, right: detection failed even in sunny conditions).

except for the throttle position % parameter, other signals shown in Figure 6 were normalized over a range provided by the respective minimum and maximum values to facilitate easy visualization of the data. Furthermore, the OBD-II port of the VUT was queried with the appropriate CAN messages from the DAQ computer to obtain three vehicle states: engine RPM, vehicle speed, and throttle position %. Although the throttle position can be used as an indication of an automated braking event, it is generally not considered a reliable one because other sub-systems/features may cause it to change. In addition, the IMU reported speed was considered to be more accurate than the speed reported through the OBD-II port. In order to determine the exact braking time, the steady-state speed prior to a braking event was considered. A braking event was considered to have happened when the instantaneous vehicle speed went below 2% of the steady-state speed. The 2% margin enabled the algorithm to remain insensitive to the measurement errors. The distance from the test target at these three events was determined from the LiDAR data (see Figure 7).

Test Results

In order to characterize the performance of OEM AEB systems, data collected from the external sensors was analyzed and compiled in Tables 5 and 6. The performance of the YOLOv3 DNN model was found to be irregular in all test scenarios. Correspondingly, detection of event E1 showed a lot of variability, which underscores the distinction between two relevant terms: *sensing* and *perception* (i.e., being able to sense is not analogous to being able to perceive). Nonetheless, application of the DNN model provided this study with an independent way of evaluating the "perception potential" of a test scene.

Table 5. Distance between VUT-1 and target in different "A" test scenarios.

#	Target	Speed	Test Conditions	Distance (m) from Target at Events			Collision?
				E1	E2	E3	
1	Vehicle	60kph	Day, overcast, high visibility & slightly wet road surface.	110.57	×	20.27	Yes
2	Vehicle	60kph	Day, overcast, high visibility & slightly wet road surface.	116.91	×	19.92	Yes
3	EPTc 10%	60kph	Day, heavy snowfall, limited visibility & snow covered road surface.	32.46	19.84	×	Yes
4	EPTc 10%	60kph	Day, slight snowfall, moderate visibility & snow covered road surface.	42.57	17.53	×	Yes
5	EPTc 10%	60kph	Day, slight snowfall, moderate visibility & snow covered road surface.	37.95	F	×	Yes
6	EPTc 25%	60kph	Day, moderate snowfall, limited visibility & snow covered road surface.	46.55	23.06	×	Yes
7	EPTc 10%	60kph	Day, moderate snowfall, limited visibility & snow covered road surface.	42.84	F	×	Yes
8	EPTc 10%	60kph	Day, heavy snowfall, limited visibility & snow covered road surface.	38.02	26.60	×	Yes
9	EPTc 25%	60kph	Day, heavy snowfall, limited visibility & snow covered road surface.	48.10	28.70	×	Yes
10	EPTc 25%	60kph	Day, heavy snowfall, limited visibility & snow covered road surface.	50.20	27.46	×	Yes
11	EPTc 10%	60kph	Day, heavy snowfall, limited visibility & snow covered road surface.	44.14	27.75	×	Yes
12	EPTc 25%	60kph	Night, no precipitation, limited visibility & snow covered road surface.	23.23	×	×	Yes
13	EPTc 10%	60kph	Night, no precipitation, limited visibility & snow covered road surface.	32.91	×	×	Yes
14	EPTa 25%	60kph	Night, moderate rainfall, poor visibility & snow covered road surface.	58.59	×	×	Yes

× = Data not available F = System failed E1 = Target detected by YOLO
E2 = Warning shown on instrument cluster E3 = Automated braking initiated

In Table 5 results from test scenario“A” are presented. Images from the camera pointed at the instrument cluster were absent from some of the tests, and these cases were appropriately indicated in Table 5. For some tests, the AEB system did not provide any warning, and such an occurrence was considered a failure (tests 5 & 7). In some cases, the VUT was manually steered away from the target for safety reasons (tests 3-11), correspondingly event E3 did not have a chance to happen. In tests 12-14, images from the instrument cluster were absent, and the VUT was manually steered away from the target. In all of the tests in Table 5 with images of the instrument cluster available (except tests 5 & 7), the AEB provided a warning to the driver when the target was at a distance range of 17.53 meters to 27.75 meters, even when visibility was challenged by precipitation conditions. In tests 1 & 2, there was clear indication of collision with the target. In other tests collision did not take place because of the safety action involving steering away from the target. Nonetheless, it was determined that a collision would have happened if the safety action was not taken.

Results from test scenario “B” are presented in Table 6. All tests were performed in sunny conditions with excellent visibility. The poor performance of the DNN model, as shown by the variability in the E1 column of Table 6, can be attributed to the sunny ambient condition. In some cases the direction of the sunlight created artefacts in the image which potentially caused irregular detection performance. Nonetheless, the AEB performance indicated by events E2 and E3 was fairly consistent. Warnings were provided to the instrument cluster when the vehicle target was 27.91-31.70 meters away from the VUT. Automated braking was initiated when the vehicle target was 13.18-14.91 meters away. Collision only occurred when the road surface was covered in snow (test 7), and failure of the AEB control functions, instead of the perception functions, can be attributed as the principal cause for collision. Later than average initiation of braking along with challenging road conditions rendered it difficult for the VUT to come to a stop safely.

Table 6. Distance between VUT-1 and target in different “B” test scenarios.

#	Target	Speed	Test Conditions	Distance (m) from Target at Events			Collision?
				E1	E2	E3	
1	Vehicle	60kph	Sunny, excellent visibility & dry road surface.	122.46	31.02	13.68	No
2	Vehicle	60kph	Sunny, excellent visibility & dry road surface.	150.56	31.70	14.25	No
3	Vehicle	60kph	Sunny, excellent visibility & dry road surface.	157.86	29.16	13.98	No
4	Vehicle	60kph	Sunny, excellent visibility & dry road surface.	119.58	31.18	14.91	No
5	Vehicle	60kph	Sunny, excellent visibility & dry road surface.	53.88	31.4	13.9	No
6	Vehicle	60kph	Sunny, excellent visibility & dry road surface.	121.02	27.91	13.77	No
7	Vehicle	60kph	Sunny, excellent visibility & snow covered road surface.	33.91	×	13.18	Yes

× = Data not available E1 = Target detected by YOLO E2 = Warning shown on instrument cluster
E3 = Automated braking initiated

DISCUSSION, LIMITATIONS

Market penetration of ADAS features are expected to widen exponentially in near future. As system capabilities increase and drivers become more reliant on these systems, they will continue to be exposed to sub-optimal driving conditions including weather events that can degrade their performance. System availability in adverse weather conditions is one of the avenues where operational design domains (ODD) of ADAS can potentially see rapid advancements. Correspondingly, quantifying the effects of weather on ADAS performance has become increasingly important so that drivers can operate these systems safely within their safety limits. To this end, more complex and elaborate test procedures and protocols must be developed to evaluate these systems more extensively. Specifically, the safety and the functionalities of these systems in different weather conditions must be experimentally evaluated to substantiate claims of robust performance. This study attempted to innovate ADAS testing by using external perception sensors so that the test environment could be characterized with more definition than what was possible with test procedures implemented before. This facilitated analysis of the failure modes of ADAS with deeper insight. The demonstrated ability to acquire rich spatio-temporal data of the test environment open up numerous possibilities for the next evolution of ADAS testing, which may range from formulating more complex tests involving multiple dynamic roadway elements to conducting tests without having to install extensive support infrastructure. As a first step toward this direction, the AEB system was focused as a representative ADAS feature.

Acquiring multi-modal sensor data in a temporally consistent manner, and subsequently making inferences from them are challenging tasks. This study achieved both by constructing a DAQ system that was robust enough to operate in adverse weather conditions, and also could withstand the rigors of test protocols involving collisions with soft/inflatable targets at high speeds. By leveraging open-source software and by exploiting internally developed intellectual properties involving software & hardware components, the DAQ system was constructed to be easily scalable and rapidly reconfigured or upgraded to address the demands of the application-specific needs.

The tests presented in this paper involved recording AEB performance in different naturally occurring weather conditions in a controlled test environment (i.e., a test-track). Admittedly, the test data collected for this paper represents a small fraction of vehicles from different manufacturers, models and model years driven on the road. In addition, the test conditions are also a small representation of the large permutations of roadway and weather conditions these vehicles will encounter in real-life. Therefore, observations from the presented test results cannot be reliably extrapolated to draw general conclusions. Nonetheless, as ODDs expand for these systems rapidly with the launch of new models and model years of vehicles, test procedures and protocols must evolve accordingly. This study is a step towards this goal.

FUTURE WORK

Since this study was a first step towards developing more innovative test procedures and protocols for ADAS, there are a number of ways this work can grow. The foundational ability to characterize the dynamic roadway environment and to establish temporal correspondence with the recorded vehicle states can be exploited to provide deeper insights into current test procedures. For example, identifying control functions of the AEB system as the more probable root cause of failure in test 7 of Table 6 was made possible with the help of data provided by the DAQ system.

The DAQ system used in this study can provide rich situational awareness of the evolving roadway environment without the aid of elaborate support infrastructure only available in test-tracks. This opens up the possibility of conducting more naturalistic evaluation of ADAS features wherein a VUT can be driven on public roads under a mileage accumulation exercise. This will enable the ADAS to be exposed to numerous ADAS-relevant events and objects that structured test protocols do not cover in different weather and roadway conditions. By recording & subsequently evaluating vehicle and driver behavior in these events, performance of ADAS can be characterized with unprecedented statistical significance.

As driving automation features expand their capabilities, quantified specification of ODD is expected to be an increasingly important topic in driving automation testing activity. The multi-modal data provided by the DAQ system can facilitate research & development activities in this topic. In one example, the data can be used to examine ADAS performance as a function of ODD. In another example, the data can accelerate the development of objective methodologies for specifying ODD.

CONCLUSION

In a typical ADAS system, the sensor hardware provide raw data to the perception components that analyze the sensor data in order to detect and track relevant objects and events. If the perception components identify an unsafe driving condition, the control elements initiate a remedial action that may involve a warning provided to the human driver and/or a corrective action in the form of automated driving maneuver. Weather events affect all functional aspects of an ADAS system: sensing, perception, and control. Therefore, it is important to develop robust data acquisition methods to support test protocols that identify ADAS failure modes in adverse weather conditions. This study was conducted as a first step towards this goal.

This study utilized external perception sensors to characterize the test environment with rich definition, and characterized the performance of a representative ADAS system in different weather conditions. The opportunistic nature of this study did not allow for more tests. Nonetheless, lessons learned from this study will be invaluable in developing and designing the next evolution of ADAS testing.

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