A METHOD TO COMPARE THE SAFETY OF AUTONOMOUS VEHICLES TO HUMAN-DRIVEN NON-EXEMPT MOTOR VEHICLES IN THE UNITED STATES

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ABSTRACT

The objective of this technical paper is to present a method that characterizes autonomous vehicle (AV) safety performance through the application of risk-based validation that leverages existing crash incidence and severity data, physics based model and simulation, and U.S. Federal Motor Vehicle Safety Standard (FMVSS) benchmark metrics. The output of the proposed risk-based methodology is a framework that organizes the number and type of physical tests and model/simulation runs necessary to provide meaningful evidence of AV safety performance statistically equivalent to human-driven non-exempt motor vehicles.

INTRODUCTION

The lure of AVs promises elimination of vehicle crashes, injuries and fatalities. For consumers, passengers, and other road users to embrace AV technology, AVs must perform safely and reliably. A formidable challenge is measuring and quantifying the levels of safety offered by AVs. The debate of how safe is safe enough for AVs has been structured around a mindset of billions of miles traveled.

Common sense dictates the starting benchmark is the current level of safety performance; but how best is this measured? Traditionally, mechanical and physical safety have been measured in terms of compliance with government safety standards. AVs venture beyond this template in that the vehicles are loaded with complex sensor technologies and controlled by software. This paper proposes application of a risk-based methodology that leverages existing knowledge of vehicle performance characteristics and crash problem data with safety metrics to build a framework that compares an overall safety level between nonexempt vehicles and AVs.

Foundational Concepts

Defining AV safety metrics that are recognized and accepted industry wide by all stakeholders is an important first step. Four foundational concepts are in play: AVs must provide an overall safety level at least equal to the overall safety level of nonexempt motor vehicles; the Haddon Matrix, which is the most commonly used paradigm in the injury prevention field; all motor vehicles, including AVs, present as a system of systems; and safety is not reliability.

When determining if a vehicle presents an unreasonable risk to safety, probability of failure, consequence of failure, occurrence and severity of injury are the primary factors to consider. In a probabilistic risk assessment, there is a close relationship between safety and reliability. Yet, safety cannot generally be achieved through component or system reliability alone. The Federal Highway Administration (FHWA) version of the Haddon Matrix [3] illustrates the relationship between four factors of injury (human, vehicle/equipment, physical environment, and socioeconomic) and the phase of injury (pre-crash, crash, and post-crash).

If we consider the vehicle as a system of systems, one system would be the ‘driver,’ either in human form or in digital technology form. Vehicle systems such as powertrain, steering, braking, suspension, tires, fuel, occupant protection, and exterior lighting exist on all vehicles, whether AV or human driven. The primary differences between AVs and nonexempt vehicles will likely emerge in the driver system, in visibility and glazing systems, and interior human-machine interface (HMI) systems.

A Safety Network can be defined as shown in Equation 1.

$$Safety\ Network = Environment + Vehicle + Driver + Unknowns \qquad \text{(Equation 1)}$$

Reliability Concepts

Reliability is considered the absence of failures, and is predicated on how failure is defined. In the context of motor vehicle safety, we can describe a failure rate as both the crash rate and a function of system performance. Adopting the Advanced Product Quality Planning (APQP) and Control Plan manual definitions for reliability and confidence level supports analysis using key risk metrics. Reliability is defined as the probability that an item (i.e., vehicle) will continue to function at customer (i.e., roadway user) expectation levels at a measurement point, under specified environmental and duty cycle conditions. Confidence level refers to the percentage of all possible samples that can be expected to include the true population parameter. Additional reliability concepts include selecting an appropriate reliability distribution, sufficient sample size, and consideration of non-critical failures in the reliability analysis.

Several reliability distributions [7] appear to mirror the crash problem data, such as the binomial distribution, the exponential distribution, the Poisson distribution, and the Pareto distribution. Additionally, the bathtub distribution holds true for AVs in that sensor and camera initialization increases crash risk at the beginning of vehicle deployment. If certain crash avoidance data is collected from AVs, the normal and logistic continuous distributions offer the possibility to include the rate of crash events avoided, plotted as negative severity values. For any reliability distribution, key parameters (e.g., shape, scale, location) need to be confirmed. The distribution most appropriate for AVs may depend on the sample. In this paper, the sample was organized by vehicle classification, and the binomial distribution (with the assumption of replacement) was applied to count the number of successes (i.e., no crash) in a number of independent trials (i.e., VMT); if a crash occurs, then severity outcome is measured as no damage, property damage, injury, or fatality. The number of observations or trials must be sufficiently large.

Crash Problem

Utilizing the U.S. Department of Transportation data collections, databases and published statistical analysis, the crash problem on U.S. roadways in 2016 [4] was reported as 34,439 fatal police-reported crashes, 2,177,000 injury police reported crashes, and 5,065,000 property damage only (PDO) police-reported crashes, 37,461 people killed, 3,144,000 people injured, and 3,174 billion vehicle miles traveled. Additional crashes occurred that were not reported to the police; in 2010, the National Highway Traffic Safety Administration (NHTSA) estimated these unreported crashes as a 59.7% increase in PDO and a 39.7% increase in injury crashes [2]. Figure 1 shows a plot of the 2010 crash incidence versus severity. Ideally, future safety network analyses would be founded on the combined number of police-reported plus unreported crashes.

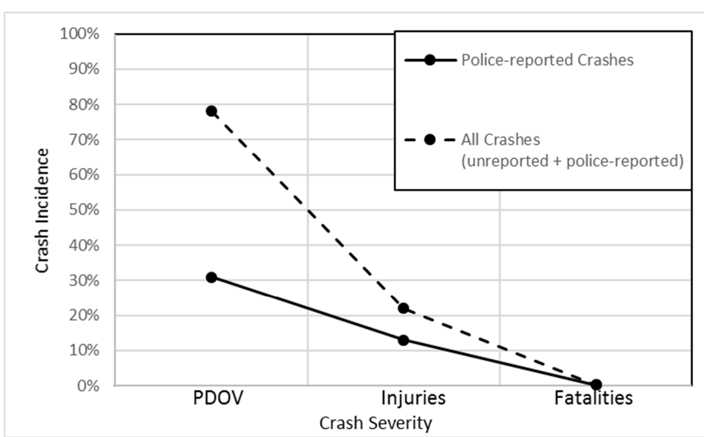

Figure 1. Crash Incidence versus Severity (2010 data; source: DOT HS 812 013)

Table 1 lists the police-reported crash incidence rates using 2016 data. Note that the crash per VMT rate for passenger cars, light trucks and buses are similar in magnitude as the total average. The police-reported crash incidence rate for large trucks is significantly lower, possibly due to these vehicles being operated by trained professional drivers.

Table 1.
Crash Incidence by Vehicle Classification (2016 data; sources: DOT HS 812 580 and [10])

Vehicle Classification	Police-reported Crashes (Fatal + Injury + PDO)	VMT (millions)	1 crash per (VMT)
Passenger Car	7,198,839	1,440,228	200,064
Light Truck	5,010,069	1,409,490	281,331
Large Truck	502,213	287,895	573,253
Motorcycle	129,421	20,445	157,973
Bus	71,227	16,350	229,548
Other/unknown	21,462	Not reported	-
	Total = 12,933,231	Total = 3,174,408	Total = 245,446

In 2015, NHTSA published findings from a statistical analysis of the National Motor Vehicle Crash Causation Survey (NMVCCS) [5], which collected on-scene information about the events and associated factors leading up to crashes involving light vehicles. NMVCCS is a weighted sample of 5,470 crashes, which represents an estimated 2,189,000 crashes nationwide. NHTSA found that the critical reason, which is the last event in the crash causal chain, was assigned to the driver in 94 percent (±2.2%) of the crashes. In about 2 percent (±0.7%) of the crashes, NHTSA found that the critical reason was assigned to a vehicle component's failure or degradation, and in 2 percent (±1.3%) of crashes, it was attributed to the environment (slick roads, weather, etc.). Among an estimated 2,046,000 drivers who were assigned critical reasons, NHTSA found recognition errors accounted for about 41 percent (±2.1%), decision errors 33 percent (±3.7%), and performance errors 11 percent (±2.7%) of the crashes.

METHODOLOGY

A technology-neutral approach to AVs would focus on safety aspects and system safety performance. Shifting the mindset to a system of systems construct with an emphasis on test and evaluation supports quantifying safety in terms of risk and performance. A test and evaluation strategy would include physical testing, modeling, simulation, verification, validation, and accreditation. Stakeholders would use this methodology to generate a sample size of test scenarios to which manufacturers would demonstrate the level of safety. Large statistical sample sizes will only be achieved through physical testing and modeling/simulation. The benchmark would be comprised of a combination of test trials plus simulation runs that vary key performance factors. Reliability theories were developed for aircraft components under a metric of flight time hours and are adapted here to VMT. This method describes how to statistically estimate the level of AV safety without billions of on-road demonstration miles. There exists tremendous opportunity to leverage modeling and simulation along with targeted testing to characterize AV safety performance in terms of a reliability distribution. Modeling and simulation supports enhancing the physical test scenarios through iterations that vary speed ranges, travel direction, traffic density, etc.

Key steps in this analysis are:

- Identify the most relevant set of risk metrics. For example, incidence (number of crashes, severity in terms of fatalities, injuries, and property damage), and vehicle miles traveled (VMT).
- Identify the data needed to support a risk-based analysis. For example, 2,967 billion VMT (2010 data) divided by 6,077,362 police-reported crashes (2010 data) results in 1 crash per 488,205 VMT. The average of 11,866 VMT per registered vehicle (2010 data) multiplied by an estimated average vehicle age of 10.8 years (passenger car vehicles, 2010 data) results in an available test time T_{test} of 128,153.
- Adapt the parametric binomial reliability distribution test by replacing the random variable of Time with vehicle miles traveled (VMT).
- Select the % reliability to be demonstrated. For example, '85% reliable.'
- Select the % confidence level. For example, 'with 90% confidence.'

- Select the number of test failures that can occur in the sample. For example, '1 failure allowed.'
- Calculate the sample size based on VMT and T_{test} to which AV manufactures would demonstrate the AV level of safety.
- Choose trials (e.g., tests and model/simulation runs) that characterize vehicle performance in steering, accelerating, braking, sensor recognition, causes of vehicle control loss, visibility, etc.

In this analysis, the independent test trials correspond to VMT, regardless of vehicle maneuver, speed, etc. An example of the typical resulting output is in the form: a sample size of 11 pedestrian detection system test trials with 0 failures occurring will demonstrate a reliability of 80% at the 90% confidence level. In other words, if the item reliability is < 80%, the chances of passing this test are < 10%.

Test Sample Size

Table 2 is a representative test sample size matrix which was populated by exercising a parametric binomial reliability demonstration test calculator [8] with mission time equal to 1 crash per 488,205 VMT (based on 2010 data) and the available test time equal to 128,153 hours (based on 2010 data). Setting the reliability and confidence levels is a subjective decision. If the current level of safety for nonexempt passenger cars and light trucks is estimated at 85% reliability with 95% confidence, then a test series for equivalent AV safety performance would require a sample size of 425 tests that allows one failure. An alternate approach is to conduct testing until one failure occurs, and then estimate the reliability and confidence level.

Table 2.
Example of a Test Sample Size Calculated using the Parametric Binomial Reliability Distribution

Passenger Cars & Light Trucks	Confidence with 1 Failure Allowed					
Reliability	**80%**	**85%**	**90%**	**95%**	**98%**	**99%**
99%	4,325	4,871	5,618	6,851	8,425	9,587
98%	2,152	2,423	2,795	3,409	4,192	4,770
95%	848	955	1,101	1,343	1,652	1,879
90%	413	465	537	654	804	915
85%	268	302	348	425	522	594
80%	196	220	254	309	380	433

Once the test sample size is determined, the test and evaluation strategy can be developed that describes the test scenarios and corresponding specific number of physical tests. Initially, test scenarios can be derived as a mix of existing FMVSS tests and AV sensor suite edge or challenging cases. Examination of sensor algorithms would assist in prioritizing tests and test scenarios that score high in risk assessment parameters probability of failure and consequence of failure. For example, low sun angle is a challenge for camera technologies. Therefore, of the 425 tests, a proportion representative of the risk would be allocated to low sun angle conditions for which the camera technology significantly contributes to vehicle control. Finally, the test and evaluation strategy can be tailored to a specific geographical region, such as state, city, county, geofenced area, or national level.

Building the Safety Framework

Consider building the safety framework by vehicle classification. The U.S. follows a self-certification system of compliance, in which vehicle and equipment manufacturers certify that their products meet applicable standards. Additionally, the manufacturer determines the vehicle classification – e.g., passenger car, large truck, bus, etc. Historically, stakeholders have considered self-certification to be demonstrated through physical test. AVs will likely propel stakeholders toward a new era of targeted physical testing supplemented with extensive modeling and simulation to demonstrate safety.

The values shown in Table 3 represent an example of a safety framework for nonexempt passenger cars and light trucks. The crash risk is derived from reference [9]. The reliability distributions were selected to reflect the network element risk. For example, U.S. DOT data shows high motor vehicle reliability with high confidence as demonstrated through the low number of crashes caused by vehicle failure, likely buttressed by NHTSA recall authority. The environment – e.g., roadway surface, markings, traffic communications (signage, lighting), etc. - has high reliability with high confidence, however, atmospheric conditions may contribute uncertainty and adversely impact reliability and confidence. Estimating the current level of safety for human drivers of nonexempt vehicles to be 85% reliability with 90% confidence reflects the NVMCCS analysis attributing 94% of passenger car and light truck crashes due to driver error. The unknown/uncertainty element gives stakeholders flexibility to examine competencies and scenarios of interest; for this paper, the reliability distribution of 80% / 85% was assigned as a minimum value.

Table 3.
Example of a Safety Framework for Passenger Cars & Light Trucks

Network Element	Crash Risk [Ref. #]	FMVSS	Reliability Distribution	Number of Tests: Parameter(s)
Environment	2%	301, 302, 303, 304, 305	90% / 95%	109 tests: rain, ice, snow
Vehicle	2%	All Standards	95% / 95%	220 tests: brakes, steering, occupant protection, etc.
Driver	94%	Recognition: 101, 103, 104, 108, 111, 113, 123, 125, 131, 138, 205 Decision: 102, 108, 124, 135, 209, 210, 213, 225, 401 Performance: 105, 106, 109, 110, 116, 117, 118 Non-Performance: 114 Other:	85% / 90%	17 tests: low sun angle 28 tests: speed, curves, intersections 7 tests: lane management, LTAP 3 tests: maneuvers near a "taco truck" with pedestrians 4 tests: see NMVCCS data
Unknown/ Uncertainty	2%	Varies	80% / 85%	37 tests: double parked, orange cone, etc.
				Total = 425 tests

Overall safety by vehicle class allows for differentiation in safety levels. A safety framework for large trucks would vary from Table 3 in the crash risk and reliability distributions, requiring additional data analysis. It is likely that trained professional drivers would be associated with a lower crash risk and a higher reliability distribution for the Driver element, and a safety level higher than passenger cars.

Table 3 shows data parsed into the NMVCCS categories which aligns better with the construct of "level of safety" for AVs because it treats the common vehicle systems (e.g., powertrain, steering, braking, etc.) separate from the Driver, and also allows for refinement of the driver behaviors (e.g., recognition, decision, performance, non-performance, and other). However, the NMVCCS sample is only light vehicles and this distribution cannot be projected directly onto NHTSA GES or CDS estimates for other vehicle classifications. An alternate option could be to parse the test sample by pre-crash scenario (Rear End, Crossing Paths, Road Departure, Pedestrian, Cyclist, etc.) which is a good fit for tracking how crashes occur and factoring system effectiveness.

Successful implementation depends on reaching consensus on the metrics, collecting and sharing relevant AV characterization data, and revisiting at regularly defined intervals.

CONCLUSIONS

All aspects of AV safety and reliability must be demonstrated before candidate AVs are deployed onto public roadways. This proposed methodology establishes a framework to quantify safety performance levels and includes the flexibility to incorporate new data describing driver performance or technological capabilities as AV technology evolves. To paraphrase Aristotle, the whole framework is greater than the sum of its parts. Blending established engineering concepts from motor vehicle safety, reliability, and systems engineering to form a new approach to specify benchmark test & evaluation scenarios places a reasonable burden on all stakeholders and is achievable well before driving billions of miles.

Table 4 lists one measure of vehicle incidence rates for different types of vehicles. Mindful that VMT and flight hours are not comparable metrics, the promise of AVs may be realized if it follows the trend of automated aviation safety.

Table 4.
Compilation of Vehicle Incidence Data

Vehicle	Incidence Data	
Police-reported Motor Vehicles Crashes	0.0205 crashes/ 10,000 VMT	[Ref. 2]
Estimate for All Motor Vehicles Crashes	0.0457 crashes / 10,000 VMT	[Ref. 2]
CA DMV AV Disengagements	38.6 disengagements / 10,000 AV VMT	[2017 data]
Automated Aviation	0.5 accidents / 1 million take-offs	[Ref. 6]
Commercial Aviation	0.149 accidents / 10,000 flight hours	[Ref. 6]
General Aviation	7.11 accidents / 10,000 flight hours	[Ref. 6]
Customs & Border Patrol Aviation	52.7 accidents / 10,000 flight hours	[Ref. 6]

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APPLYING LANE KEEPING SUPPORT TEST TRACK PERFORMANCE TO REAL-WORD CRASH DATA

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ABSTRACT

Lane Keeping Support (LKS) is an advanced driver assistance system (ADAS) technology intended to prevent a vehicle from drifting out of its travel lane. To assess the potential for LKS to reduce real-world crashes where the driver drifts out of their travel lane, test track performance was compared with the real-world crash data.

Five light vehicles equipped with LKS were evaluated on the test track using Lane Keeping Assist (LKA) test methods contained within the Euro NCAP Test Protocol - Lane Support Systems. Specifically, the procedures to evaluate a vehicle's response to an imminent departure over a solid white line were used; tests to evaluate LKS system response to an unmarked road edge were not performed. These tests identified performance differences between the vehicles, and were somewhat dependent on the lateral velocity used during test conduct.

Results from these tests were compared to relevant fatal crashes in the National Motor Vehicle Crash Causation Survey (NMVCCS) survey conducted by the National Highway Traffic Safety Administration from 2005-2007, and the agency's new Crash Investigation Sampling System (CISS). A review of the fatal 2005 – 2007 NMVCCS and 2017 CISS lane/roadway departure cases was performed to classify the shoulder type present on the side of the roadway from which the subject vehicle first departed from, and to estimate the shoulder width just after the departure, where applicable. The objective of this effort was to estimate whether LKS interventions could have potentially amended the real-world pre-crash path of the subject vehicle in the vicinity of the lane departure, given the system performance observed on the test track.

When the test track performance of the vehicles was considered in the context of the road shoulder widths and road/lane/shoulder characteristics present in the 43 fatal NMVCCS and 50 CISS crashes analyzed for this paper, estimating whether LKS could have affected the crash outcome was found to depend on a number of factors. From an input perspective, the lateral velocity of the vehicle as it is directed toward the boundary of the lane, and whether that boundary is comprised of a clearly defined painted line or simply a pavement edge, has the potential to affect whether an LKS intervention can even be expected.

Even if the input conditions are such that a vehicle's LKS activation criteria are satisfied, then the ability of the system to effectively address the pre-crash scenario is relevant, yet can depend on a number of factors. The amount of lateral deviation before or beyond the lane line and/or road edge, and the implications of it being too large, are important considerations. In the case of a right-side departure away from the travel lane, excessive lateral deviation may result in at least part of the vehicle leaving the paved roadway. Similarly, left-side departures with excessive lateral deviation have the potential to increase the risk of a head-on crash.

INTRODUCTION

Lane Departure Warning (LDW), Lane Keeping Support (LKS), and Lane Centering Control (LCC) are three advanced driver assistance system (ADAS) technologies intended to prevent vehicles from drifting out of their travel lane. All three systems utilize a camera-based vision system to monitor the vehicle's lateral position with respect to the roadway. Depending on the system design and system's level of intervention authority, the technology is intended to warn the driver that they are leaving the travel lane, redirect the lateral path of the vehicle to stay in the lane, or continuously maintain the lateral position of the vehicle within the lane of travel.

The run-out-of-lane pre-crash scenarios identified by Swanson, et al were used to estimate the target crash population of the ADAS systems discussed in this paper [Swanson, 2018]. In this work, a combination of the National Automotive Sampling System (NASS) General Estimates System (GES) and Fatality Analysis Reporting System (FARS) 2011-2015 crash databases were used to examine all police-reported crashes involving a light vehicle in the critical event of the crash or in the event that occurred which made the crash imminent. Light vehicles include all passenger cars, vans, minivans, sport utility vehicles, or light pickup trucks with gross vehicle weight ratings less than or equal to 10,000 pounds. Common crash types were analyzed to produce a list of representative pre-crash scenarios based upon NHTSA pre-crash variables (i.e., the pre-crash movement or the vehicle's action prior to an impending critical event or prior to impact if the driver did not make any action). From the pre-crash scenarios identified in the report, Table 1 lists those relevant to the inadvertent run-out-of-lane crash problem. This approach identified, on average, over 760,000 run-out-of-lane crashes annually; over 9,600 of which were fatal.

Table 1.
2011 – 2015 FARS and GES run-out-of-lane light vehicle target population

Scenario	Avg FARS	Avg GES
Road edge departure/No Maneuver	6,284	472,182
Opposite Direction/No Maneuver	2,983	96,095
Drifting/Same Direction	196	120,223
Object/No Maneuver	151	80,088
Total	9,615	768,588

To assess the potential effectiveness of countermeasures intended to prevent run-out-of-lane crashes, Wiacek, et al performed a study to better understand why drivers depart the roadway and under what conditions and circumstances the crashes occur [Wiacek, 2017]. Using fatal crashes from the National Motor Vehicle Crash Causation Survey (NMVCCS), this study identified 72 cases where the result of a subject vehicle departing the travel lane resulted in a crash where an occupant in an involved vehicle sustained fatal injuries. Of these, 43 cases where the subject vehicle drifted out of the lane and crashed were used to assess the real-world applicability of LDW/LKS/LCC crash avoidance technologies.

The study concluded that a robust LKS/LCC system with sufficiently high lateral control authority could have effectively prevented many of the 43 cases reviewed. In other words, unless there were other factors present which prevented the driver from reengaging in the driving task, a robust LKS/LCC system would likely have prevented the driver from running out of the lane, which started the chain of events that led to the fatal crashes. The study suggested that LKS/LCC systems appear to have more potential in crash reduction than LDW since the systems do not rely on alert modality effectiveness or driver responsiveness. Additionally, the mentioned the environmental and roadway conditions at the time of the crash would likely not have compromised the performance of the vision system to detect the roadway boundary at the moment the vehicle left the lane.

This paper builds upon the earlier work by comparing measured test track performance of vehicles equipped with LKS systems with the real-world crash data. The purpose was to measure the performance of the LKS systems under controlled conditions and estimate how the systems may have addressed the driving conditions preceding known crashes. The goal in doing this is to assess the efficacy.

Five light vehicles from different manufacturers were tested using Lane Keep Assist (LKA) test methods contained within the European New Car Assessment Programmed (Euro NCAP) Test Protocol - Lane Support Systems [Euro NCAP, 2015] to assess technology implementation differences. Euro NCAP uses LKA to describe systems NHTSA would describe as having LKS. For the sake of this paper, the terms can be used interchangeably. The following vehicles were tested:

- 2017 Cadillac CTS
- 2017 Ford Fusion
- 2017 Mercedes Benz C300
- 2017 Toyota Prius Prime
- 2017 Volvo XC90

For each vehicle, the test track performance was used to assess if the vehicles' LKS systems intervened, whether the interventions corrected the vehicle's heading back to the travel lane, and the maximum lateral deviation from the test lane line marking.

In addition to the vehicle tests, the crash data were also surveyed to assess how the technology would apply to the real-world. First, the 43 fatal NMVCCS cases from the previous study were reanalyzed. For each crash, on the side of the lane or roadway departure, the shoulder width of the road was estimated. To be consistent with the Euro NCAP LKA test procedure, the shoulder width measurement was estimated from the inside edge of the lane marking to the edge of the road surface. In those crashes where the shoulder width was not relevant because of the crash type or roadway surface, the side of the roadway or lane of travel was characterized.

Lastly, using the same methodology, a review of the run out of the lane fatal data was also analyzed using the 2017 NHTSA Crash Investigation Sampling System (CISS). CISS, which began pilot data collection is 2016, replaced the retired National Automotive Sampling System Crashworthiness Data System (NASS-CDS) as NHTSA's nationally-representative investigation-based data collection program. For these 50 cases, the shoulder width was measured or the side of the lane/roadway departure or was characterized. The results of this analysis will be presented and discussed in the context of the five vehicles tested.

VEHICLE TESTING

Test Procedure

The Euro NCAP LKA test procedure uses a series of trials performed with iteratively increasing lateral velocities towards the desired lane line. For all tests, a robotic steering controller was utilized to increase the repeatability of the procedure and reduce variability associated with manual steering inputs. Although the Euro NCAP LKA test protocol does not specify use of robotic steering controller, it does require tight path tolerances be satisfied by the vehicle as it approaches the desired lane marking during testing.

Pretest conditions

For each subject vehicle (SV), prior to testing, the vehicle manufacturers were asked to complete pre-test forms that included information to determine if any system initiation testing must take place prior to conducting the performance testing. If system initialization testing was needed, the vehicle manufacturer provided the recommended instruction to initialize the system.

Once the system was initialized, the SV's tires and brakes were pre-conditioned using a series of start and stops at predefined speeds and brake decelerations.

Test Maneuver

Each LKS trial began with the SV being driven at 72 km/h down a straight lane delineated by solid white and dashed white lines. The SV path was initially parallel to the lane lines, with an offset from the solid white line that depended on what lateral velocity would be used later in the maneuver (Figure 1).

After a short period of steady state driving, the steering machine was used to adjust the heading of the SV towards the solid white lane line using a path defined by a 1200 m radius curve. The amount of time the SV path remained on this curve depended on the lateral velocity desired for the test trial, and the heading angle associated with it. Once these parameters had been achieved, the steering machine returned the handwheel angle to zero, and was decoupled from the SV so as to allow the SV handwheel to move freely and independently.

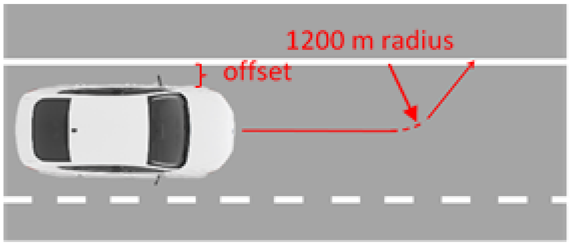

Figure 1. Left lane departure for LKS test

The lateral velocity of the SV approach towards the solid lane line (from both the left and right directions) was iteratively increased from 0.1 m/s. If acceptable LKS performance was realized, the lateral velocity used for the next trial was increased by 0.1 m/s. This continued until the SV was no longer able to satisfy the LKS performance criteria or until a maximum lateral velocity of 1.0 m/s was reached. The tests performed with lateral velocities from 0.1 - 0.5 m/s were used for the Euro NCAP performance assessment protocol, whereas those >0.5 m/s were used for research purposes. [Euro NCAP, 2015]

LKS Validity Criteria

The following validity criteria were applied to each test trial to insure the tests were properly performed:

• SV Speed: 72 km/h ± 1.0 km/h

• Lateral deviation from test path: ± 0.05 m

• Lane departure lateral velocity: ± 0.05 m/s from target lateral velocity

• Steering wheel velocity: ±15 deg/sec

LKS Performance Criteria

Acceptable LKS performance occurred when SV did not cross the inboard leading edge of the solid lane line by more than 0.4 m.

Results

The results from the five vehicles tested under the conditions described above will be presented. A summary of the data by vehicle and test condition is presented in Table 2. Per the test condition, the maximum lateral deviation is noted. Positive values indicate the maximum lateral deviation occurred prior to the vehicle crossing the inboard edge of the lane line. A negative value indicates the maximum lateral deviation occurred after the vehicle crossed the inboard line edge. No LKS intervention (No LKS) is noted on the summary table, as well as if a vehicle was not tested under a given condition (NDT).

Tests Performed with Lateral Velocities from 0.1 – 0.5 m/s

Of the five vehicles tested, only the Cadillac CTS and the Volvo XC90 satisfied the performance criteria for the first five lateral velocity iterations during both the left- and right-side lane line approaches. In the case of the Volvo XC90, the maximum lateral deviation occurred prior to the vehicle crossing the lane line, as indicated by the positive values in Table 2.

The Mercedes C300 satisfied the performance criteria during tests conducted with lateral velocities up to 0.3 m/s during left- and right-side approaches.

The Ford Fusion and Toyota Prius had asymmetrical performance where, under certain test conditions, the vehicles satisfied the performance criteria on one side but not the other for the same lateral velocity.

The Ford Fusion did not satisfy the performance criteria on the left-side approaches when lateral velocities of 0.1 and 0.4 m/s were used, but did for each right-side approach. For this vehicle, LKS did not activate during trials performed with a lateral velocity of 0.1 m/s (three repeated trials were performed, each with the same outcome) and while LKS did activate during the test performed with a 0.4 m/s lateral velocity, maximum lateral displacement exceeded 0.4 m.

The Toyota Prius satisfied the performance criteria at 0.2 m/s and 0.3 m/s on the right side, but exceeded the maximum lane deviation limit of 0.4 m on the left side.

Tests Performed with Lateral Velocities from ≥0.6 m/s
LKS interventions were observed during tests performed with lateral velocities of 0.6 to 0.9 m/s for three of the five vehicles tested in this paper. The Volvo XC90 satisfied the LKS performance criteria during left- and right-side approaches for lateral velocities up to 0.7 m/s, and only on the left side at 0.8 m/s. No further testing was conducted with the Volvo XC90.

The Cadillac CTS satisfied the LKS performance criteria during left- and right-side approaches performed with a lateral velocity of 0.6 m/s. Although LKS interventions were observed during left- and right-side approaches using lateral velocities up to 0.9 m/s, the vehicle exceeded the maximum lateral deviation threshold.

The LKS system on the Ford Fusion intervened when tested at the lateral velocity of 0.5 m/s, but the vehicle exceeded the maximum lateral deviation threshold on both the left- and right-side approaches. No further testing was conducted at higher lateral velocities.

For the Toyota Prius, testing at higher lateral velocities was only conducted on the right side because the performance criteria was not satisfied at lower lateral velocities during left-side approaches. The vehicle satisfied the maximum lateral deviation at 0.6 m/s, exceeded the criteria at higher lateral velocities on the left-side approach tests.

The Mercedes C300 was only tested on the right side at the lateral velocity of 0.5 m/s. The LKS did not engage during this trial, and no further testing was conducted. No vehicles were tested with lateral velocities at or above 1.0 m/s.

Figures 2 and 3 illustrate the performance differences among the five test vehicles during tests performed with the various lateral velocities. Lateral deviations greater than those specified by the LKS performance criteria are shaded in blue.

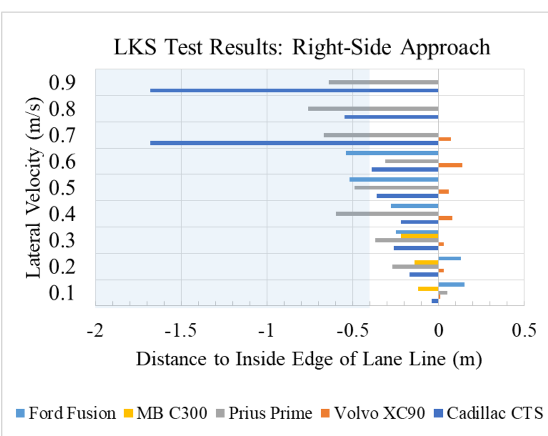

Figure 2. LKS test results – right side departure

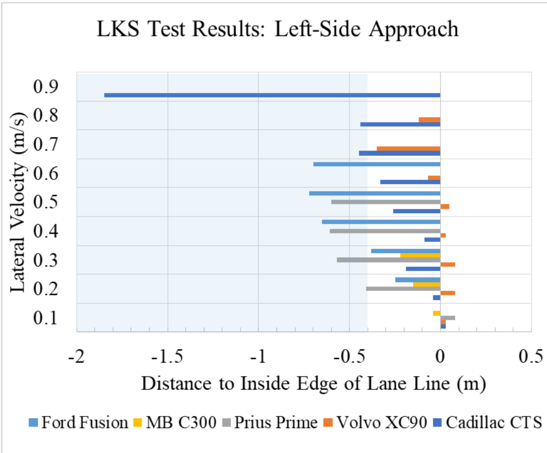

Figure 3. LKS test results – left side departure

Table 2.
Summary of test results by vehicle and test conditions

Maximum Lateral Deviation (m)	Lateral Velocity (m/s)									
	0.1		**0.2**		**0.3**		**0.4**		**0.5**	
	L	**R**	**L**	**R**	**L**	**R**	**L**	**R**	**L**	**R**
Cadillac CTS	0.03	-0.04	-0.04	-0.17	-0.19	-0.26	-0.09	-0.22	-0.26	-0.36
Ford Fusion	**No LKS**	0.15	-0.25	0.13	-0.38	-0.25	**-0.65**	-0.28	**-0.72**	**-0.52**
Mercedes Benz C300	-0.04	-0.12	-0.15	-0.14	-0.22	-0.22	**No LKS**	**No LKS**	**No LKS**	**No LKS**
Toyota Prius Prime	0.08	0.05	**-0.41**	-0.27	**-0.57**	-0.37	**-0.61**	**-0.6**	**-0.6**	**-0.49**
Volvo XC90	0.03	0.01	0.08	0.03	0.08	0.03	0.03	0.08	0.05	0.06
	0.6		**0.7**		**0.8**		**0.9**		**1.0**	
	L	**R**	**L**	**R**	**L**	**R**	**L**	**R**	**L**	**R**
Cadillac CTS	-0.33	-0.39	**-0.45**	**-1.68**	**-0.44**	**-0.55**	**-1.85**	**-1.68**	DNT	DNT
Ford Fusion	**-0.7**	**-0.54**	DNT	DNT	DNT	DNT	DNT	DNT	DNT	DNT
Mercedes Benz C300	DNT	**No LKS**	DNT	DNT	DNT	DNT	DNT	DNT	DNT	DNT
Toyota Prius Prime	DNT	-0.31	DNT	**-0.67**	DNT	**-0.76**	DNT	**-0.64**	DNT	DNT
Volvo XC90	-0.07	0.14	-0.35	0.07	-0.12	DNT	DNT	DNT	DNT	DNT

Figures 4 and 5 are screen shots from test video recorded during right-side approaches performed with a lateral velocity of 0.7 m/s, for the Volvo XC90 and the Cadillac CTS, respectively. LKS intervened during both trials. The maximum lateral deviation recorded for the Volvo XC90 was 0.07 m from the inboard edge of the lane marking (able to satisfy the LKS performance criteria), whereas it was 1.68 m for the Cadillac CTS (unable to able to satisfy the LKS performance criteria). The white arrows shown in Figures 4 and 5 indicate the reference lane marking.

Figure 4. Point of maximum lateral deviation observed during a right-side approach test performed with the Volvo XC90 and a 0.7 m/s lateral velocity

Figure 5. Point of maximum lateral deviation observed during a right-side approach test performed with the Cadillac CTS LKS and a 0.7 m/s lateral velocity

REAL-WORLD SHOULDER WIDTH ANALYSIS

A review of the fatal 2005 – 2007 NMVCCS and 2017 CISS lane/roadway departure cases was performed to classify the shoulder type present on the side of the roadway the subject vehicle first departed its travel lane, and to estimate the shoulder width just after the departure, where applicable. The objective of this effort was to estimate whether LKS interventions could have potentially amended the real-world pre-crash path of the subject vehicle near the lane departure, given the system performance observed on the test track.

NMVCCS Lane Width Analysis

Method To establish a baseline, the 43 previously analyzed fatal NMVCCS cases were reassessed. For these cases, it was previously established that the subject vehicle drifted out of the lane, resulted in a fatal crash, and was relevant to assessing the real-world applicability of LDW/LKS/LCC crash avoidance technologies. All the cases were reviewed and the side of the initial lane or roadway departure was identified. Once identified, the shoulder width distance was estimated for the side of the roadway departure. Examples will be discussed below followed by the results of the analysis.

To be consistent with the measurement convention used in the Euro NCAP LKA test procedure, and with the data reported in Table 2, the shoulder width estimates extracted from the NMVCCS and CISS cases were referenced from the inside edge of the lane marker to the end of the road surface at the location of the lane departure.

The side of the roadway was also characterized in those cases where a lane marking or shoulder was not present, such as when the vehicle traveled into an adjacent lane, rural or local roads where there were no markings and only a road edge and, intersections or when a curb was present that define the edge of the useable road surface.

Examples In NMVCCS Case Nos. 2006-045-063 and 2007-78-071 the drivers drifted out of the lane on the left side. For these types of cases the road shoulder width measurement was estimated from the inside edge of the lane marker to the end of the road surface. This was conducted by examining the scene diagram and the scene photos, using the lane line width as the reference for the measurement. (Figures 6 and 7)

Figure 6. NMVCCS Case No. 2006-045-063 shoulder width

Figure 7. NMVCCS Case No. 2007-078-071 shoulder width

NMVCCS Case No. 2005-76-035 is an example where the subject vehicle departed the lane of travel into the “adjacent lane.” In this case the driver drifted over the center line and departed the road on the left resulting in a rollover (Figure 8).

Figure 8. NMVCCS Case No. 2005-76-035 adjacent lane on the left

NMVCCS Case No. 2005-11-61 is an example of crash where the vehicle was traveling a straight, level, two-way, rural gravel roadway with no painted lines (Figure 9). The subject vehicle drifted and exited the roadway to the right.   This type of roadway was characterized by its "road edge."

Figure 9. NMVCCS Case No. 2005-11-61 road edge example

NMVCCS Case No. 2007-49-043 is an example of a roadway where there was no lane marking and just a curb at the end of the road surface on the side the vehicle departed the travel lane. In this case the subject vehicle was traveling east in left lane. After traveling through an intersection, the subject vehicle drove off the road to the left onto the curbed median striking a light pole (Figure 10). This crash also has some characteristics similar to the intersection crashes that were identified in the CISS data, and will be discussed later in this paper.

Figure 10. NMVCCS Case No. 2007-49-043 curb example

Results Using the method described above, the results of the analysis of the 43 NMVCCS cases are provided in Figure 11. For this analysis, the shoulder width measurement data was grouped by 0.1 m increments up to 0.4 m.

The data show that in 16 of the 25 crashes where a shoulder was present on the side of the road, and the vehicle departed the lane, the shoulder was greater than 0.4 m. In nine of the crashes, the shoulder width was equally distributed between the "greater than 0.1 m" and "equal to 0.4 m or less" groupings. There were no crashes where the shoulder was 0.1 m or less.

In this data set, there were three crashes where the subject vehicles left the road with no lane markings on the side of the roadway departure. It should be noted that in these cases, there was a clearly-defined road edge. Lastly, in 14 cases the vehicle drifted into the adjacent lane. These crashes resulted in the vehicle leaving the roadway after crossing into the oncoming lane or drifting into oncoming traffic

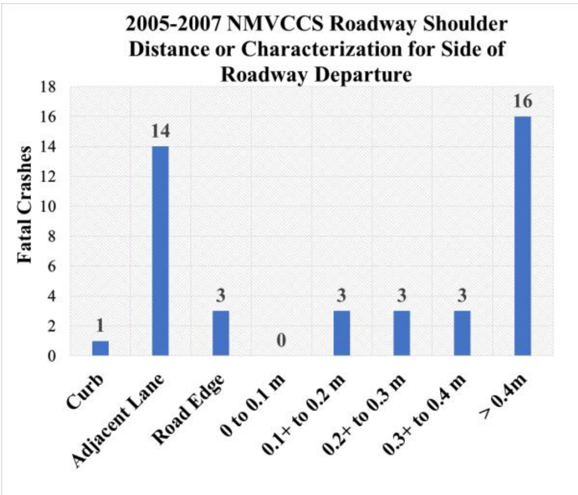

Figure 11. 2005 – 2007 NMVCCS roadway shoulder distance or characterization

CISS Lane Width Analysis

Method A second analysis of the real-world crash data was conducted using NHTSA's CISS. In response to a congressional directive to modernize its nationally representative crash databases, NHTSA concluded that the NASS-Crashworthiness Data System (NASS-CDS) program would be retired and replaced with the CISS. The new CISS program was designed to provide many improvements from its predecessor including, obtaining more accurate scene and vehicle measurements. [Mynatt, 2017] In addition to the improved measurement, the 2017 CISS dataset was the first year collected for the program. Given the NMVCCS data was older, the newer data could provide insight into changes to the roadways with respect to the efficacy of LKS.

As with the NMVCC study, all fatal cases from the 2017 CISS dataset that met the following Crash Type Code were selected: 01, 02, 04, 05, 06, 07, 09, 10, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 64, 65, 66, and 67 (a chart explaining the crash types is provided in the Appendix of this paper). As with the NMVCCS case selection, the intent was to capture fatal crashes resulting from the vehicle leaving the original travel lane. The CISS cases are also provided in the Appendix.

Fifty-seven cases met the criteria, however, upon review of the data, seven cases were excluded from the final analysis because the subject vehicles were traveling the wrong way on a one-way street or the vehicle lost control prior to departing the roadway. There were 50 cases in the final data set.

In CISS, all the crash scene measurements are now collected in three-dimensions using a Nikon Total Station electronic measuring devices, coupled with FARO® Blitz software. [Mynatt, 2017] As discussed in the NMVCC section, the cases were reviewed, and the side of the initial lane or roadway departure was identified. The NMVCCS shoulder width measurements were estimated using the scene diagrams and photos. In CISS, the shoulder widths were measured in the Blitz diagramming software near the roadway departure location. It should be noted that beginning in 2018, shoulder width measurements in CISS are coded in the data file. As with the NMVCCS cases, the side of the roadway departure was also characterized when applicable. Examples of the roadways will be provided below followed by a summary of the results.

Examples CISS Case No. 1-13-2017-127-01, the subject vehicle initially departed its lane of travel on the right side prior to returning and departing the lane on the left side, resulting in a crash with a vehicle traveling in the adjacent lane. (Figure 12). In this case, the lane departure occurred on a highway whose shoulder width was measured from the inboard edge of lane line to the end of the road surface on the far right.

Figure 12. CISS Case No. 1-13-2017-127-01 shoulder width example

CISS Case No. 1-19-2017-113-01 is an example of a vehicle leaving the lane of travel into the adjacent lane. In this case the subject vehicle was traveling east on the highway, departing the lane on the left. The vehicle departed the roadway on the left where it struck a concrete driveway, and rolled over before coming to rest on its side (Figure 13).

Figure 13. CISS Case No. 1-19-2017-113-01 adjacent lane

CISS Case No. 1-32-2017-013-01 was categorized as a vehicle parked on shoulder. In this case the subject vehicle was traveling on a major highway. The vehicle departed the roadway to the right, entering the road shoulder. The front of subject vehicle impacted the rear of a parked vehicle on the shoulder (Figure 14).

Figure 14. CISS Case No. 1-32-2017-013-01 parked vehicle

CISS Case No. 1-33-2017-025-01 is an example of a crash that occurred at an intersection. In this case, the subject vehicle drifted out of the travel lane into the adjacent lane. This occurred at an intersection where there were no lane markings. The vehicle proceeded to travel until it impacted a vehicle traveling in the opposite direction. Figure 15 shows the approach for the subject vehicle and the lack of lane markings at the intersection on the left side.

Figure 15. CISS Case No. 1-33-2017-025-01 intersection example

CISS Case No. 1-28-2017-046-01 is an example where there were no lane markings on a gravel road but a discernable road edge. In this case, the subject vehicle was negotiating a right curve. The vehicle departed the roadway to the left side and impacted a tree on the left side of the vehicle (Figure 16).

Figure 16. CISS Case No. 1-28-2017-046-01 road edge example

Results The results of the shoulder width measurements and roadway departure characterization for the 50 CISS cases are presented in Figure 17. As with the NMVCCS analysis, the shoulder width measurement data were grouped by 0.1 m increments up to 0.4 m.

The data show that in 16 of the 19 crashes where a shoulder was present on the side of the road, and the vehicle departed the lane, the shoulder width was greater than 0.4 m. In three of the crashes, the shoulder was greater than 0.1 m wide but equal to 0.3 m or less. There were no crashes where the shoulder was 0.1 m or less.

In this data set, there were seven crashes where the subject vehicle left the road with no lane markings on the side of the roadway departure. It should be noted that in these cases, there was a clearly defined road edge. There were four cases where the vehicle drifted out of the lane at an intersection where the lane markings were not present. In 18 cases, the vehicle drifted into the adjacent lane. As with the NMVCCS cases, generally these crashes resulted in the vehicle leaving the roadway after crossing into the oncoming lane or drifting into oncoming traffic. Lastly, there were two cases (CISS Case Nos. 1-32-2017-013-01 and 1-28-2017-039-01) where the subject vehicles impacted a vehicle parked on the shoulder.

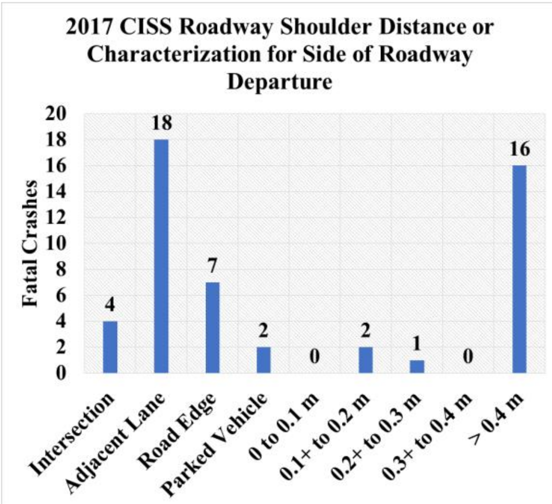

Figure 17. 2017 CISS roadway shoulder distance or characterization

DISCUSSION

This section will discuss the results of five vehicles tested with the Euro NCAP LKA procedure (i.e., those described earlier in this paper) in the context of the analysis of the real-world fatal crashes. Specifically, given the performance of the vehicles under the test conditions, discussion will be focused on whether the fatal crashes could have been potentially prevented for those cases where there was a shoulder, road edge, and adjacent lane.

With respect to the roadway shoulder width, NMVCCS and CISS results (which encompassed 93 fatal crashes that were collected approximately 10 years a part) were consistent and showed similar distributions. For that reason, the combined results are presented in Figure 18.

These real-world data were not assessed for the dynamic state of the vehicle and the lateral velocity of vehicle prior to the roadway departure. Any attempt to correlate that lateral velocity was beyond the scope of the study. It is also assumed that the travel speed of the subject vehicles met or exceeded the minimum activation speed for the LKS. The cases were identified by the vehicle appearing to drift out of the lane, and quantifying the shoulder width when applicable or characterization of the side of the roadway departure.

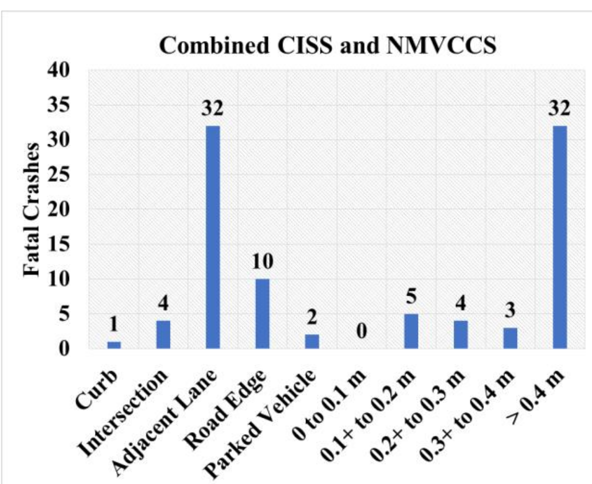

Figure 18. Combined CISS and NMVCCS roadway shoulder distance or characterization.

Lane Departure with Shoulder

CISS Case No. 1-19-2017-041-01, is an example of a roadway with a narrow shoulder that only an LKS that allows very limited lateral deviation from the travel lane would be expected to prevent at least part of the subject vehicle from departing the roadway. The subject vehicle in this example was traveling west and departed the roadway to the right. The vehicle, traveled down an embankment, across an adjacent roadway prior to impacting a tree.

From Figure 19, the shoulder width was measured in CISS to be approximately 0.15 m. The test track data previously presented in Table 2 indicated that only the Volvo XC90 LKS interventions consistently (i.e., over a wide range of lateral velocities) prevented right-side lateral deviations below that distance. Except for the lower lateral velocity conditions, the other test vehicles generally exceeded a lateral deviation of 0.15 m.

Figure 19. CISS Case No. 1-19-2017-041-01 vehicle approach

Lane Departure without Lane Markings

There were 10 crashes identified where there were no lane markings on the road or on the side of the road departure.

It is unknown whether any of the five vehicles tested were equipped with LKS systems capable of intervening in response to a circumstance where a lane departure is imminent, but only a road edge is present (i.e., no lane marker), as such conditions were not evaluated on the test track in this study. Euro NCAP has adopted a test procedure that includes a limit of 0.1 over a road edge, as shown in Figure 20 using a test procedure similar to the LKS test described earlier but without the lane line. [Euro NCAP, 2017]

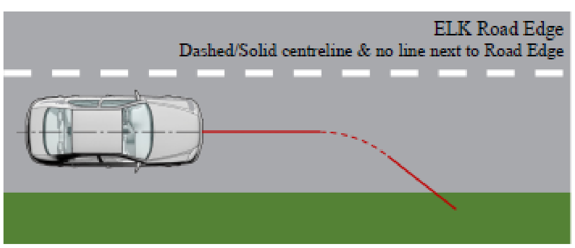

Figure 20. Euro NCAP road edge test condition

CISS Case No. 1-19-2017-097-01 is an example of a road edge case. In this fatal crash, the subject vehicle departed the roadway to the right where there was a disparate lane line and a discernable road edge (Figure 21). After departing the roadway, the vehicle traveled down a steep embankment, striking one or multiple trees and rolling over before coming to final rest. To prevent this type of crash, it is expected the most effective LKS intervention would occur prior to the vehicle leaving the road since pavement provides greater lateral force (turning) capacity than an unpaved deformable surface. With regards to intervention proximity to a lane line, the Volvo XC90 test track performance was indicative of this kind of operation; preventing the vehicle from traveling past the line in each of the right-side approaches. However, and as previously stated, it is unknown whether the Volvo XC90 LKS system has been configured to respond to an imminent road edge departure which, in this case, is essentially a lane departure without a clear marking delineating the right side of the lane. This case provides evidence of why it may be important for an LKS system to address lane and road departures, to maximize the overall potential safety benefits provided by these systems during real-world driving where clear markings are not always present.

Figure 21. CISS Case No. 1-19-2017-097-01 vehicle approach

Lane Departure into Adjacent Lane

Thirty-two of the ninety-three crashes shown in Figure 18 involved the subject vehicle drifting out of the initial travel lane into an adjacent lane. Crashes that involve the subject vehicle drifting out of its lane result in head-on crashes with an oncoming vehicle or a road departure from the adjacent lane.

With respect to LKS and the vehicles tested, it was determined that the roadway width in the adjacent lane was not a limiting factor as it exceeded the 0.4 m performance criteria. Specifically, for the single vehicle crashes where the vehicle departed the road on the right side, many of the same observations that were discussed in the shoulder width section remain true with respect to the performance of the LKS.   If the LKS engaged in the test condition, depending on the lateral velocity, the LKS may have been effective in preventing many of these adjacent lane crashes that did not involve another vehicle traveling in the opposite direction.

Of the 32 adjacent lane cases, over half were head-on crashes. Ten were identified in NMVCCS and eight in CISS. The analysis performed for this paper did not explore the location of the vehicles involved in head-on crashes relative to the lane marking at impact. However, assuming the opposing vehicle does not travel into the subject vehicle's lane, and if it can be assumed that if the subject vehicle's LKS does not allow the subject vehicle to cross into the adjacent lane, the head-on crash would likely not occur.

CISS Case No. 1-28-2017-032-01 is example where the subject vehicle encroaches into the adjacent lane and is involved in a fatal head-on collision. The subject vehicle was traveling west on a two lane non-divided roadway. A large truck was traveling east on the same roadway. The subject vehicle entered the truck's lane, and a head-on impact resulted (Figures 22 and 23).

Figure 22. CISS Case No. 1-28-2017-032-01 vehicle approach

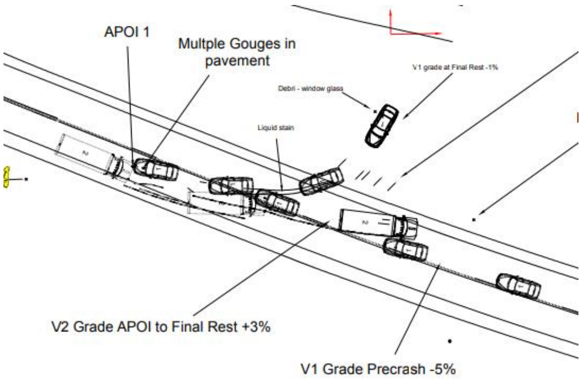

Figure 23. CISS Case No. 1-28-2017-032-01 scene diagram

Figure 24 presents the damage incurred by the subject vehicle. Based upon the crush pattern and interaction with the truck, the subject vehicle likely crossed over the centerline and into the adjacent lane by well over the 0.4 m allowance specified in the Euro NCAP LKA performance criteria.

Figure 24. CISS Case No. 1-28-2017-032-01 front end crush of subject vehicle

Other Lane Departure Cases

There were four crashes that occurred at intersections where there were no lane markings leading up to the location of the lane departure. It was apparent for each case, the subject vehicle was not turning and proceeding through the intersection. Otherwise, lane markings were present leading up to the intersection.

As discussed earlier (NMVCCS Case No. 2007-49-043) there was one crash where there were no lane markings on the side of the roadway departure and the road edge was delineated by a curb, over which the subject vehicle travelled. It is unknown how LKS may have affected the outcome of these crashes where the lane markings are not present.

Lastly, there were two cases (CISS Case Nos. 1-32-2017-013-01 and 1-28-2017-039-01), involving a vehicle parked on the shoulder. The assessment of the LKS performance was similar to the adjacent lane, head-on crashes discussed earlier. The effectiveness of the LKS is dependent on how far the vehicle deviates into the shoulder and the location of the parked vehicle. The only way to assure the crash is avoided during an imminent lane departure is to prevent or minimize how far the vehicle encroaches into the roadway's shoulder.

CONCLUSION

Five light vehicles equipped with LKS were evaluated on the test track using methods from the Euro NCAP LKA test procedure. Specifically, the procedures evaluated a vehicle's response to an imminent departure over a solid white line; tests to evaluate LKS system response to an unmarked road edge were not performed. These tests identified performance differences between the vehicles, and were somewhat dependent on the lateral velocity used during test conduct.

When the test track performance of the vehicles was considered in the context of the road shoulder widths and road/lane/shoulder characteristics present in the 43 fatal NMVCCS and 50 CISS crashes analyzed for this paper, estimating whether LKS could have affected the crash outcome was found to depend on a number of factors.

From an input perspective, the lateral velocity of the vehicle as it is directed toward the boundary of the lane, and whether that boundary is comprised of a clearly defined painted line or simply a pavement edge has the potential to affect whether an LKS intervention can even be expected.

Even if the input conditions are such that a vehicle's LKS activation criteria are satisfied, the ability of the system to effectively address the pre-crash scenario depends on a number of factors. The amount of lateral deviation before or beyond the lane line and/or road edge, and the implications of it being too large, are important considerations. In the case of a right-side departure away from the travel lane, excessive lateral deviation may result in at least part of the vehicle leaving the paved roadway. Similarly, left-side departures with excessive lateral deviation have the potential to increase the risk of a head-on crash.

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Appendix

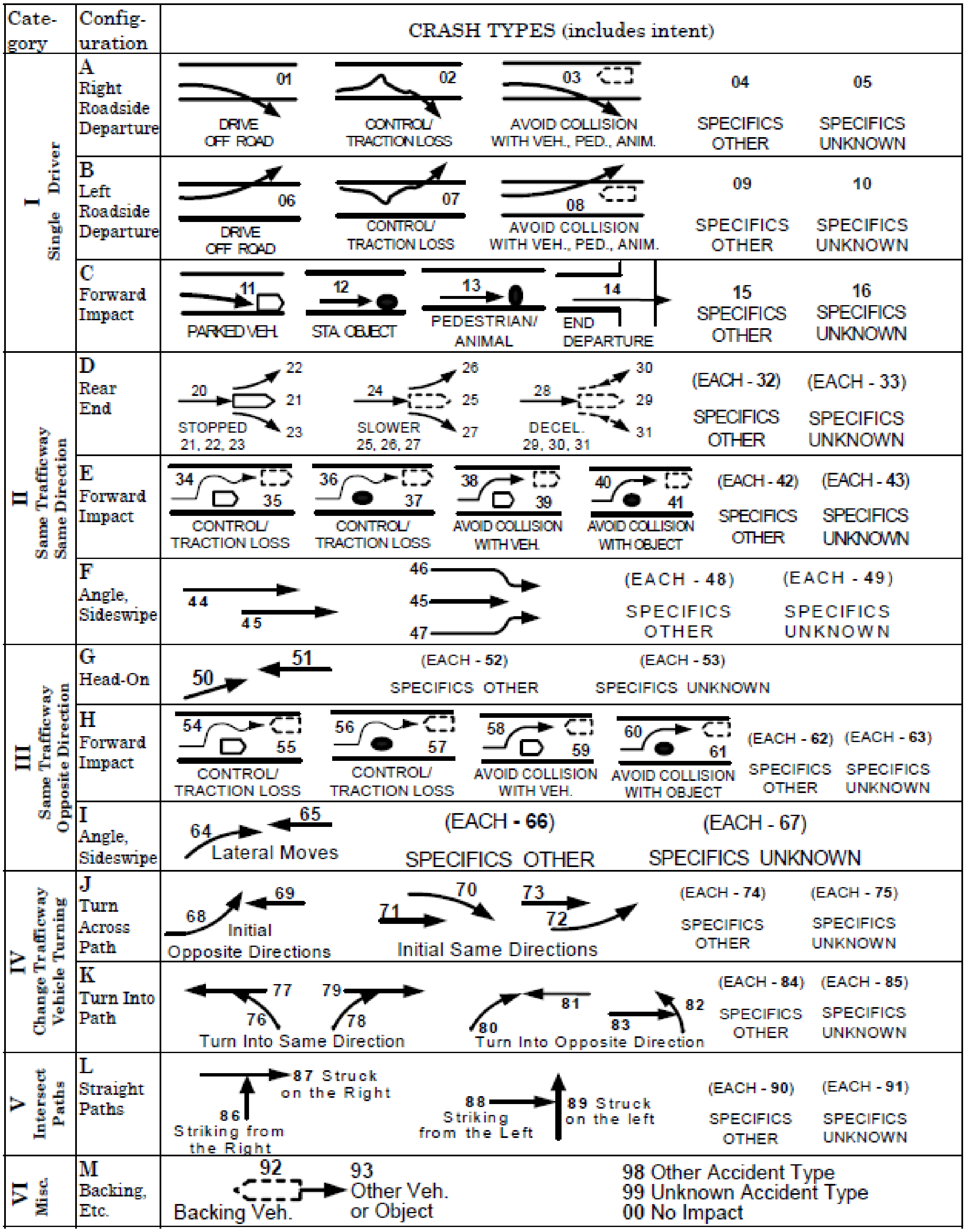

Figure A1. Crash type descriptions.

Table A1. CISS Cases

Case Number	Charcterization	Case Number	Charcterization
1-19-2017-041-01	0.15 m	1-22-2017-036-01	Adjacent lane
1-11-2017-020-01	0.18 m	1-19-2017-048-01	Adjacent lane
1-22-2017-050-01	0.3 m	1-13-2017-008-01	Adjacent lane
1-23-2017-064-01	0.48 m	1-24-2017-014-01	Adjacent lane
1-32-2017-152-01	0.6 m	1-22-2017-046-01	Adjacent lane
1-22-2017-083-01	0.82 m	1-16-2017-048-01	Adjacent lane
1-20-2017-006-01	0.85 m	1-28-2017-032-01	Adjacent lane
1-22-2017-119-01	0.87 m	1-11-2017-033-01	Adjacent lane
1-20-2017-042-01	0.92 m	1-20-2017-084-01	Adjacent lane
1-18-2017-054-01	0.96 m	1-25-2017-024-01	Adjacent lane
1-19-2017-029-01	1.03 m	1-20-2017-103-01	Adjacent lane
1-22-2017-062-01	1.27 m	1-33-2017-090-01	Adjacent lane
1-17-2017-086-01	1.3 m	1-23-2017-102-01	Adjacent lane
1-22-2017-052-01	1.32 m	1-19-2017-113-01	Adjacent lane
1-28-2017-008-01	1.33 m	1-21-2017-074-01	Adjacent lane
1-30-2017-094-01	1.69 m	1-18-2017-073-01	Adjacent lane
1-20-2017-013-01	1.95 m	1-23-2017-130-05	Adjacent lane
1-20-2017-024-01	2.0 m	1-17-2017-095-01	Adjacent lane
1-13-2017-127-01	3.0 m	1-28-2017-046-01	road edge
1-32-2017-013-01	Parked Vehicle	1-28-2017-047-01	road edge
1-28-2017-039-01	Parked Vehicle	1-28-2017-048-01	road edge
1-33-2017-025-01	Intersection	1-19-2017-097-01	road edge
1-24-2017-029-01	Intersection	1-22-2017-104-01	road edge
1-11-2017-017-01	Intersection	1-12-2017-070-01	road edge
1-22-2017-059-01	Intersection	1-19-2017-140-01	road edge

DETECTING POTENTIAL VEHICLE CONCERNS USING NATURAL LANGUAGE PROCESSING APPLIED TO AUTOMOTIVE BIG DATA

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Paper Number 19-000000

ABSTRACT

A large volume of unstructured data exists in the automotive industry and needs to be analyzed to detect potential vehicle concerns. Much of this data is textual in nature since customer complaints are made through call center interactions and warranty repairs. Current approaches to detect potential vehicle concerns in text data include various keyword search methods. In this paper, we apply Natural Language Processing (NLP) and shallow machine learning methods on text data to create classifiers to detect the potential vehicle concern of airbag non-deployment. For this potential vehicle concern, we show the performance of multinomial Naïve Bayes (NB), Support Vector Machine (SVM) and Gradient Boosted Trees (GBT) classifiers against keyword search methods. We present challenges of classification model development related to the nature of automotive data and limited training data. Our findings provide insights on robust text classification approaches that can improve identification of potential vehicle concerns.

INTRODUCTION

Automotive corporations and the U.S. federal government [1] are driving improvements in product safety through the collection and analysis of both structured and unstructured (text) data. Despite their efforts, a common problem facing large corporations today is how to extract meaningful insights about product safety from large volumes of unstructured, noisy data that they have accumulated in many disparate systems. These data systems present clear opportunities for analyzing actionable information regarding product complaints and potential defects, but are commonly referred to as "dark data" because they are not easily analyzed due to their unstructured nature [2]. Consider the text data of vehicle warranty claims, call center transactions, and product complaints on social media; these sources all contain valuable information that may describe potential vehicle concerns, but are not represented in a relational structure that can be easily queried. In addition, large corporations, such as General Motors (GM), spend resources maintaining these data systems and encounter challenges efficiently extracting actionable information from them because these systems were not originally created for safety event detection.

At the same time, the U.S. federal government has created several incident reporting and complaint collection systems for a variety of industries: the Food and Drug Administration's (FDA) Adverse Event Reporting System (AERS) [3] for the pharmaceutical industry, the Federal Aviation Administration's (FAA) Aviation Safety Reporting System (ASRS) [4] for the aviation industry, and the National Highway Traffic Safety Administration's (NHTSA) Vehicle Owner Questionnaire (VOQ) [5] and Transportation Recall Enhancement, Accountability and Documentation (TREAD) [6] for the automotive industry. The effort by the U.S. federal government in creating these systems is due to the public interest in ensuring that products created by these industries are safe for consumers. Yet, the fundamental problem still exists; all of these systems contain large volumes of dark data because they all have varying degrees of unstructured data in the form of text.

Ultimately, private industry and the U.S. federal government have a vested interest in developing techniques for the transformation of unstructured data into structured data to facilitate detection and monitoring of potential vehicle concerns within the automotive industry. For both private industry and the government there is a need to produce statistics that provide an overview of how certain types of product failures are reduced in response to their actions (product recalls, bulletins, etc.), but also to identify trends that should be addressed by those actions in the first place [7].

In this paper we will describe GM's efforts in utilizing Natural Language Processing (NLP) and shallow machine learning methods to transform unstructured text data into structured data that describes potential vehicle concerns [8]. The specific focus will be on the issue of airbag non-deployment, but we have expanded our approach to many other significant potential vehicle concerns. To the best of our knowledge, we believe this publication to be the first instance of NLP and shallow machine learning to be presented in the context of safety monitoring within the automotive industry.

Data for this effort originates from a variety of sources ranging from GM internal data (warranty claims, customer call center transactions) to public data managed by the U.S. government (NHTSA VOQ). For the scope of detecting narratives that involve airbag non-deployment, results presented in this paper will be constrained to NHTSA VOQ and TREAD data. Given their utility for the task of text classification, we present results for multinomial naïve Bayes, support vector machine and gradient boosted trees classifiers compared to traditional keyword-based pattern matching methods. We also discuss fundamental components of developing these classifiers, such as training set development and NLP pipeline development. Through the work described in this paper, it is our hope that we significantly advance the concept of detection and monitoring of potential vehicle concerns within the automotive industry.

BACKGROUND

In order to improve collision outcomes for occupants, front airbags work in concert with seat belts to restrain driver and front passenger seat occupants by inflating when vehicle sensors, measuring acceleration at various vehicle locations, indicate a moderate to severe frontal impact [9]. Airbag deployment is controlled during collision by a complex algorithm that assesses data from multiple vehicle sensors, such as occupant presence, change in velocity (delta V), time to max delta V, principal direction of force (PDOF) and others, to determine whether frontal airbags should deploy [9]. The complexity of the algorithm may contradict the assumption by vehicle occupants that the airbags were faulty in not deploying during a collision.

The value in detecting potential airbag non-deployment events is to enable investigation into these potential vehicle safety concerns by vehicle safety engineers. In the effort to decrease fatalities in frontal collisions related to potential system failure of frontal airbags, reliable, accurate, and robust detection methods in unstructured data are a critical first step.

Data Sources for Classification

Human-labeled datasets required for supervised methods were sourced from two corpora – NHTSA VOQ and TREAD data.

NHTSA VOQ is a publicly available dataset and consists of customer safety complaints about automotive products.

> JULY 20, 2016, WE WERE REAR ENDED BY A HONDA ACCORD DOING 40 MPH WHILE WE WERE STOPPED AT A LIGHT. THE IMPACT SLAMMED US INTO THE CHEVY SILVERADO IN FRONT OF US. NEITHER AIRBAG DEPLOYED.

The customer complaints dataset "contains all safety-related defect complaints received by NHTSA since January 1, 1995" [5]. NHTSA receives complaint documents from various sources including: (1) online submissions from by the general public, (2) vehicle owner questionnaire submitted by the general public, (3) the auto safety hotline submitted by the hotline operator and (4) consumer letters.

Figure 1. Sample NHTSA VOQ document describing a potential airbag non-deployment event.

TREAD is a GM-internal data source that is of interest for potential vehicle concern monitoring because it consolidates data from many disparate systems. The TREAD Act, which describes the requirements for GM's TREAD data system, was created in response to the Ford/Firestone issue and significantly changed the information automotive OEMs must report to the U.S. federal government [6]. The TREAD Act requires manufacturers to submit information related to substantially similar vehicles that may have different names, foreign fatalities, notices of foreign safety recalls and other safety campaign information and Early Warning Reporting (EWR). The EWR component of the TREAD Act results in GM compiling data from many disparate systems. As such, GM's TREAD data provides a broad cross-section of data from many business areas and large volumes of unstructured text data. The centralized nature of this data source is the primary motivating factor for its use in analyzing potential vehicle concerns.

Prior Detection Methods

Prior to the work described in this paper, potential vehicle concerns were monitored in both GM internal and public data sources using IBM Watson Explorer (previously known as IBM Content Analytics). Watson Explorer provides a proprietary version of Apache Lucene that employs an Unstructured Information Management Architecture (UIMA) pipeline for indexing, searching and analyzing text data. Watson Explorer annotators and dictionaries were used as the primary method for transforming unstructured data into structured data [10].

Annotators are compound rule sets for labeling text documents for a specific potential vehicle concern. Each rule within an annotator is designed to match a specific pattern of text. The pattern of text defined by an annotator may be a specific sequence or utilize Boolean logic to detect the presence of one or more words in a sentence, paragraph or document. Dictionaries are used to define the terms used in pattern matching.

An annotator defining airbag non-deployment could be applied to the document in Figure 1. Such an annotator would include a sequence rule matching a pattern of negation ("NEITHER"), followed by the airbag system ("AIRBAG"), followed by a mention of deployment ("DEPLOYED"). This complex rule would require a negation dictionary, an airbag system dictionary, and a deployment dictionary. All dictionaries would be required to include synonyms, misspellings and alternative forms of the base terms. For example, one would need to account for representations of the airbag system as "AIRBAG", "AIRBAGS", "AIR BAG", "SUPPLEMENTAL RESTRAINT SYSTEM", etc. A document stating, "AIRBAGS NEVER DEPLOYED" would not be flagged by the sequence rule because the airbag system is now in the first position of the pattern and negation is in the second position. To mitigate this issue, a Boolean rule would need to be developed that looks for airbag system, negation and deployment in the same sentence while ignoring sequencing. Utilizing Boolean logic loosens the pattern and can lead to tradeoffs between false positives and false negatives.

An IBM Watson Explorer annotator was designed to detect airbag non-deployment in NHTSA VOQ and TREAD. This annotator was developed using subject matter expertise and the same training data was used to develop machine learning methods described in later sections. The airbag non-deployment annotator serves as the baseline for comparing performance of machine learning methods.

METHODS

All document classification models combine supervised machine learning classification with the addition of standard Natural Language Processing (NLP) techniques to effectively transform unstructured text data into structured data. The general process used in this exercise consisted of: (1) training set development, (2) text preprocessing, (3) model development, and (4) and model assessment.

Training Data

Training sets were first developed to facilitate machine learning model development. Vehicle safety experts at GM collaborated to define airbag non-deployment events and related document characteristics. Potentially related document characteristics vary by dataset and consist of inclusion and exclusion criteria focused on terminology, key words, and circumstances described. Resulting definitions were documented and used as the basis for training data sampling and labeling.

The training set was developed for airbag non-deployment using NHTSA VOQ and TREAD data. Training samples from NHTSA VOQ were not restricted to GM manufactured vehicles since airbag non-deployment allegations are found among other automotive manufacturers. Qualitatively, the customer complaints describing airbag non-deployment within NHTSA VOQ were notably homogeneous across automotive manufacturers. The resultant labeled training set contained 2003 documents of which 1000 were sourced from NHTSA VOQ and 1003 were sourced from TREAD data. Within the overall labeled training set, there were 916 positive examples of airbag non-deployment and 1087 negative examples.

Text Preprocessing

Text preprocessing is commonly implemented in text analytics solutions. The goal of text preprocessing is to increase the homogeneity of the corpus through data standardization, aggregation of semantically similar terms and removal of words that contribute little to analysis.

Multiple text preprocessing techniques were used in this exercise including: (1) case standardization, (2) stop word removal, (3) contraction expansion, (4) lemmatization, (5) standardization of dollar values, units of speed and numbers and (6) removal of non-alpha-numeric characters. These techniques were applied to the labeled datasets prior to analysis using a custom developed Python program.

Model Development

NLP and machine learning pipelines were developed to evaluate the use of different machine learning methods to detect airbag non-deployment narratives. In text analytics, it is common that most effort in model development is spent on feature extraction. Features in this context are individual measurable properties extracted from the text that will be used to predict labels on documents (classification) [11]. Furthermore, features extracted in text analytics may include n-grams which are sequences of two or more words (i.e. “red wine” is a bi-gram, “engine control module” is a tri-gram). Pipelines are a collection of processes that can be used to transform data and fit classifiers in a defined sequence. Figure 2 depicts the steps included in the model fitting pipelines. Steps include: (1) feature extraction, (2) feature encoding, (3) feature selection and (4) classifier fitting. Pipeline parameters were tuned using grid search, evaluated using industry standard metrics, tested for generalizability using cross validation, and developed using open source data science technologies.

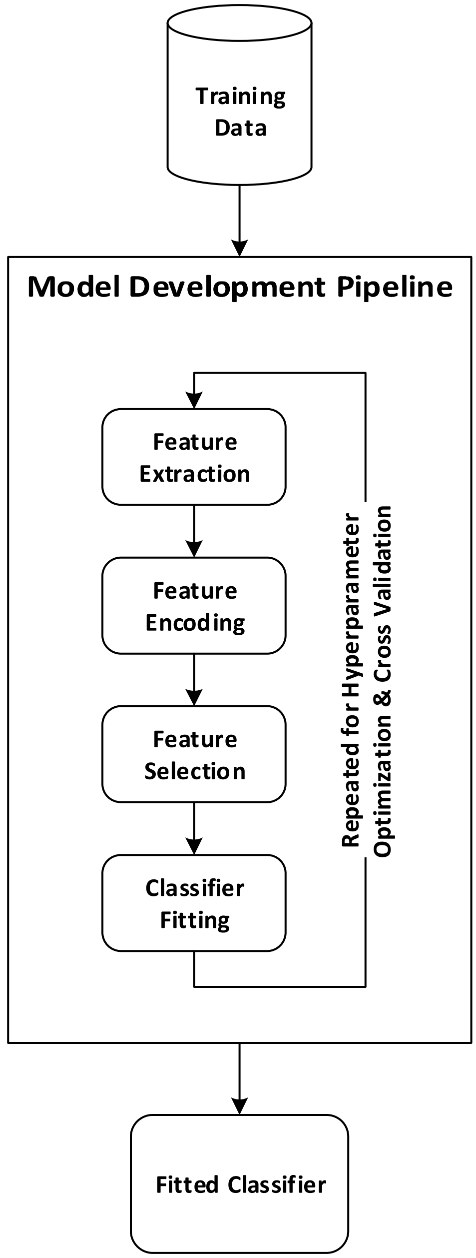

Figure 2. Model development pipeline.

Feature Extraction & Encoding: Features were extracted from the corpus as individual words and also included n-grams, which are a sequence of n adjoining words in a document. For example, if a document read "NEITHER AIRBAG DEPLOYED" bi-gram extraction, where n equals 2, would yield "NEITHER AIRBAG" and "AIRBAG DEPLOYED." Text features were restricted to bag of words (BOW) representations [12].

All features extracted from the labeled data were encoded using Term Frequency-Inverse Document Frequency (TF-IDF, Equation 1). TF-IDF is a feature encoding technique that weights how important a word is in a document within a corpus. Term Frequency ($tf_{t,d}$) describes the frequency of a term or token (t) within a particular document (d) while Inverse Document Frequency (idf_t) describes the inverse of the number of documents in the corpus that contain the term (t)

$$tf\text{-}idf_{t,d} = tf_{t,d} \times idf_t \quad \text{(Equation 1)}$$

Since both TF and IDF are raw frequency measures, it is common to utilize re-scaled and smoothed variants. Sublinear TF ($wf_{t,d}$) is described in Equation 2. A smoothed version of IDF is described in Equation 3 where n_d is the number of documents in the corpus.

$$wf_{t,d} = \begin{cases} 1 + log tf_{t,d} & if\ tf_{t,d} > 0 \\ 0 & otherwise \end{cases} \quad \text{(Equation 2)}$$

$$idf_t = log\frac{1+n_d}{1+df_t} + 1 \quad \text{(Equation 3)}$$

In general, frequently occurring terms have low TF-IDF weight and rare terms have a high TF-IDF weight. TF-IDF can be used to devalue words such as "VEHICLE" and "DRIVE" which frequently appear in automotive data but were not filtered out during text preprocessing. Furthermore, "DEPLOY" occurs in a considerable number of documents in the training data and would have a lower TF-IDF weight compared to other words.

Feature Selection: Feature selection is applied prior to classifier training to select the most relevant features for classification. The chi-squared test measures the dependence of the features on the classes being modeled. Features identified as being independent of a class will have a low chi-square test statistic and are not considered useful for classification. Each extracted feature is ranked by the chi-square test statistic from largest to smallest and the top q% of features are used for the model algorithm. The proportion of features selected, dictated by q, is one of the parameters varied in the model fitting pipelines.

Binary Classifiers: Given that detection of airbag non-deployment is a signal detection problem with a binary outcome/class (presence or absence, 1 or 0, yes or no), several binary classification machine learning algorithms were utilized in the model fitting pipelines. The objective in utilizing these algorithms is to fit a model on the extracted and selected features such that the model generates accurate predictions about the binary classes in the training data. These classifiers are discussed below.

Naïve Bayes: Multinomial Naïve Bayes (NB) is a widely used generative classifier in which the conditional probability is used to determine whether a document belongs to a class [12]. The most well-known use of NB in NLP is in sentiment analysis [12].

NB assumes independence for all features and can work well depending on the validity of this assumption. In NLP, NB feature independence would require a word in a document to occur independently of every other word. Since word independence is a false assumption regarding text, we included n-gram word sequences to partially capture word dependence.

Linear Support Vector Machines: Support vector machines (SVM) is a classifier that divides data into two classes using a hyperplane that maximizes the separation of data in each class [13, 14]. SVM has been used in text classification successfully and tests have shown it to be better than naïve Bayes in document classification [15]. SVM is well-suited for high-dimensional data and text feature extraction commonly results in hundreds of thousands of features.

Gradient Boosted Trees: Gradient Boosted Trees (GBT) is an ensemble model that uses several weak learners together to minimize the loss of the model [16]. The composition of the results from the weak learners is performed by gradient descent. New trees are iteratively added to the ensemble to reduce a loss function. Generating a GBT model is computationally expensive because each tree is a sub-classifier that is individually developed and the ensemble classifier is refitted at each iteration.

GBT have been used in sentiment analysis in situations in which there are insufficient data to train other classifiers successfully. For example, it has been used in sentiment analysis with the Greek language where data is not plentiful [17]. Since we are working with a relatively small amount of training data, this method could be optimal for our situation. The largest limitation of this method is the computational cost created by the high-dimensional feature space of NLP problems.

<u>Cross Validation & Hyperparameter Optimization:</u> A critical component of the model development process included the application of a rigorous and systematic method to find the optimal models and their respective parameters. Grid search is an exhaustive hyperparameter optimization technique where model pipelines are fitted using all possible combination of supplied parameters. To find the optimal parameters for the models described in this paper we applied a grid search over relevant parameters in the model pipeline. For example, we varied feature extraction and selection parameters, such as the chi-square proportional cutoff. Each of the models also had specific parameters relevant to those models. For example, the prior probability parameter was varied for the NB model and the slack parameter was varied for the SVM model.

Evaluation and testing is performed using k-fold cross-validation. In k-fold cross validation the data is divided into k groups. Five groups were used in this exercise. Four of the five groups are used to fit the model pipelines and the remaining group is used to evaluate the trained classifier. This process is repeated until each group is used for evaluation of the classifier. The pipeline with the highest average validation F1 score is determined by the grid search.

Model Assessment

The intersections of labeled and classifier predicted classes are depicted in Figure 3. In this case, true positives (TP) are occurrences where the classifier correctly indicated an airbag non-deployment event. True negatives (TN) are occurrences where the classifier correctly did not indicate an airbag non-deployment event. False positives (FP) are occurrences where the classifier incorrectly indicated an airbag non-deployment event. False negatives (FN) are occurrences where the classifier incorrectly did not indicate an airbag non-deployment event. False positives and false negatives are analogous to Type I and Type II errors in statistical hypothesis testing respectively.

		Classifier Predicted Classes	
		1	**0**
Labeled Classes	**1**	**True Positive (TP)**	**False Negative (FN)**
	0	**False Positive (FP)**	**True Negative (TN)**

Figure 3. Confusion matrix used to measure binary classification processes.

Precision, recall, and F1 are commonly used metrics to assess binary classification methods [15]. These metrics build upon test results described within the confusion matrix (Figure 3). Precision is a measure of model performance and is expressed in Equation 4 where precision is calculated by dividing true positive occurrences (TP) by the sum of TP and false positives (FP) occurrences.

$$precision = \frac{TP}{TP+FP} \text{ (Equation 4)}$$

Recall is a measure of completeness and is expressed in Equation 5 where recall is calculated by dividing true positive occurrences (TP) by the sum of TP and false negative (FN) occurrences.

$$recall = \frac{TP}{TP+FN} \text{ (Equation 5)}$$

F1 is the harmonic mean of recall and precision and was used to assess overall model performance in this exercise. Equation 6 states that F1 is two times the product of precision and recall divided by the sum of precision and recall.

$$F1 = 2 \cdot \frac{precision \cdot recall}{precision+recall} \text{ (Equation 6)}$$

RESULTS

Three machine learning classifiers, Multinomial Naïve Bayes (NB), Support Vector Machines (SVM), and Gradient Boosted Trees (GBT) were compared to text annotators to understand which method performed better in identifying potential airbag non-deployment events in text. The primary method of comparison was by F1 score.

Across all data, SVM and GBT showed a similar performance with identical F1 scores of 91.3% (Table 1, graphed in Figure 4). Consistent with identical F1 scores, both SVM and GBT had very similar recall (92.5% and 92.0%) and precision (90.2% and 90.7%) as shown (Table 1). The NB classifier had the poorest performance of the three tested machine learning models (F1 NB 87.8% compared to 93.1% for SVM and GBT, Table 1). Despite its poor performance, the NB classifier performed far better than the annotator across all the data (F1 62.4%, Table 1).

When analyzing by data source (Figure 5), the annotator shows a competitive performance for TREAD (F1 71.2%), which out-performs Naïve-Bayes (F1 64.2%). For VOQ, however, the annotator showed inferior performance (F1 59.1%, Table 2) versus NB (F1 92.3%, Table 2). The profile of TREAD, which is a collection of disparate data sources, is likely to be the reason for the reduced F1 classifier scores relative to the more consistent data exhibited by VOQ. In all cases, however, neither the annotator nor the NB model outperformed the SVM or GBT models (Table 2).

Table 1.
Comparative results of machine learning classifiers across all input data using F1, Recall and Precision.

	F1	Recall	Precision
Annotator	**62.4%**	**54.3%**	**73.5%**
NB	**87.8%**	**89.1%**	**86.6%**
SVM	**91.3%**	**92.5%**	**90.2%**
GBT	**91.3%**	**92.0%**	**90.7%**

Table 2.
Comparative results of machine learning classifiers by data source using F1.

F1	VOQ	TREAD
Annotator	**59.1%**	**71.2%**
NB	**93.4%**	**64.2%**
SVM	**95.0%**	**76.3%**
GBT	**94.6%**	**78.4%**

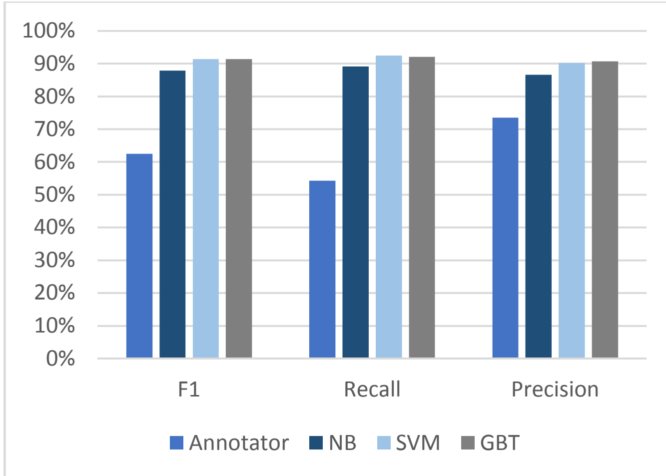

Figure 4. Graph of comparative results of machine learning classifiers across all input data using F1, Recall and Precision. Machine learning is represented by Naïve-Bayes (NB), Support Vector Machine (SVM) and Gradient Boosted Trees (GBT).

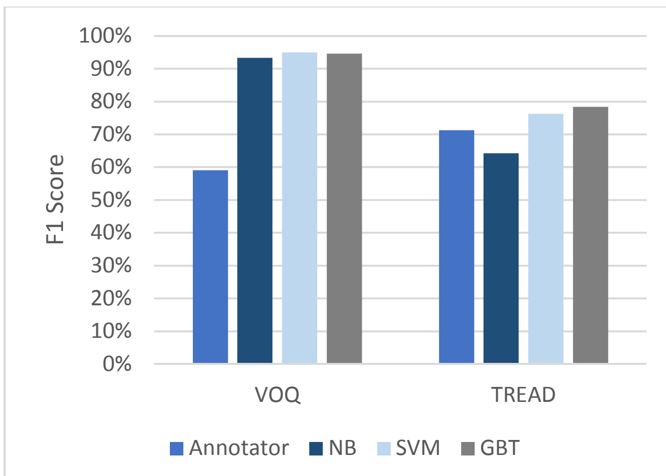

Figure 5. Graph of comparative results of machine learning classifiers by data source using F1. Machine learning is represented by Naïve-Bayes (NB), Support Vector Machine (SVM) and Gradient Boosted Trees (GBT).

CONCLUSIONS

The results shown in this paper illustrate the potential power for machine learning in transforming unstructured "dark data" into meaningful safety event detection. Machine learning methods demonstrated greatly improved classification performance (F1 score, precision, recall) in NHTSA VOQ and TREAD data than IBM Watson Explorer annotators for classification of airbag non-deployment narratives. This was true even in our scope, where training data was scarce and from a variety of data sources. Machine learning models also exhibited better balanced classification solutions compared to annotators which would tend towards having high recall at the cost of precision or vice versa.

The machine learning models yielded the worst classification performance on TREAD data. Indeed, the F1 scores for the three machine learning models tested were 16.2% to 29.2% worse for TREAD data relative to VOQ data. TREAD is the compilation of many disparate data sources at GM. We believe the reduced classification performance of TREAD is consistent with the heterogeneous nature of the data. It is likely that more training data will be required to increase TREAD classification performance since more TREAD data will include more of each of its constituent data sources.

Despite the improvement in detecting potential airbag non-deployment events, these methods have a number of limitations related to machine learning approaches in general. First, these supervised machine learning approaches require human-labeled data in large quantities to use for training data. Second, machine learning models can only account for features (words) that have been observed in training data. If GM, the U.S. federal government and/or the U.S. public at large were to develop a new term for an airbag, then that term would be unknown to the model described in this paper unless new training data with the new term in it were used to re-fit a new version of the model. Last, our methods ignore the structure of documents and additional information, such as parts of speech (POS), for words. Such grammatical information may improve the robustness and increase the performance of our predictive models.

The application of machine learning methods for detection of potential vehicle concerns presents a robust, reliable and accurate solution. The transformation of unstructured text data into structured data enables subsequent time series analysis of potential airbag non-deployment signals, including comparative trend analysis, anomaly detection, and control charting. Future work will also focus on methods to improve model performance and reduce potential training data bias. Extracting additional features from the text, such as word POS tags, Named Entity Recognition (NER) tagging or tagging text with an ontology, may provide significant performance gains. Additionally, word embeddings could be used as an alternative feature encoding scheme which would capture the semantic meaning of the words being modeled [18]. Utilizing the concept of "data programming" to create large training sets quickly may also enable the transition from shallow learning methods (NB, SVM and GBT) to deep learning methods, such as recurrent neural networks (RNN) utilizing long short-term memory (LSTM) [19].

The data sources used in this paper represent one public and one internal GM data source. Given the robustness of machine learning text classification methods, we intend to expand the application of these models to other publicly available and GM internal data sources. Social media data, such as Twitter, Facebook and automotive forums, contain similarly unstructured data that may describe airbag non-deployment events that are valuable to detect.

We have applied our NLP and machine learning methods to other areas of potential vehicle concern and have been able to increase safety event detection F1 scores by 8 – 24% (Figure 6). In addition, these increases in F1 score for safety event detection have occurred rapidly. While annotator development in IBM Watson Explorer required detailed development of a deterministic ruleset by a human over months, a machine learning algorithm arrives at an optimal solution in minutes. Given that training data is required for both approaches, the transition from annotators to machine learning methods was a natural one.

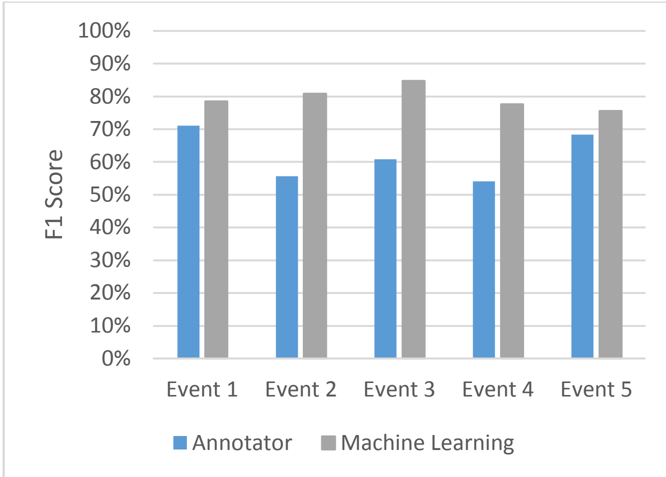

Figure 6. Classification performance improvements for other vehicle safety events. For each event, a specific machine learning model was developed. Each machine learning model is compared to an existing annotator based on F1 score.

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EVALUATION OF AEB EFFECTIVENESS USING COUNTERFACTUAL SIMULATIONS OF SHRP2 NATURALISTIC CRASHES

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ABSTRACT

Motor vehicle crashes remain a significant problem in the US and worldwide. Automatic emergency braking (AEB) is designed to mitigate the most common crash mode: rear-end striking crashes. However, assessing the efficacy of AEB in real-world crash scenarios is challenging given that avoided crashes are rarely documented except during naturalistic driving studies. Unfortunately, a large-scale naturalistic driving study involving AEB-equipped vehicles has yet to be conducted. In the absence of such data, AEB can be evaluated in real-world crash scenarios by retrospectively adding AEB to naturalistic crash data using counterfactual simulations. Previous counterfactual simulations have purported the potential benefit of AEB; however these studies often make simplified assumptions about vehicle dynamics. To this end, the current study aimed to conduct the most realistic AEB counterfactual simulations to date by using measured host and lead vehicle dynamics data and vehicle-specific AEB deceleration profiles as well as accounting for driver reaction and environmental conditions. The SHRP2 Naturalistic Driving Study was reviewed to identify rear-end striking crashes among teen (16-19 yrs), young adult (20-24 yrs), adult (35-54 yrs), and older (70+ yrs) drivers. Forty rear-end striking crashes that had reliable radar data were identified to serve as a basis for counterfactual simulations. Real-world AEB deceleration profiles were taken from IIHS AEB test data. IIHS AEB tests were matched to SHRP2 vehicles by selecting the most recent IIHS AEB test of the same make and vehicle class. AEB onset for SHRP2 crashes was based on a brake threat number (BTN) algorithm. The BTN was adjusted to match IIHS measured AEB onsets using minimum RMSE. AEB curves were then adjusted to match the speed of the subject vehicle at AEB onset. AEB deceleration curves were also scaled based on road surface conditions. Driver reaction was accounted for by beginning the deceleration curve at the current driver-initiated braking level. Counterfactual simulations were conducted using MATLAB to determine if AEB would have prevented the rear-end striking crash. AEB was found to be very effective, preventing 80% of rear-end striking crashes; greater than previously reported. Half of all crashes that were not prevented by AEB occurred during poor weather conditions. This study provides the most realistic counterfactual evaluation of AEB to date, utilizing real-world crash dynamics, driver reaction, road surface conditions, and measured AEB deceleration pulses. These data suggest that AEB is very effective at preventing rear-end striking crashes.

INTRODUCTION

Motor vehicle crashes continue to be a significant problem in the United States and worldwide. While the National Center for Statistics and Analysis found a decrease in the number and rate of fatal crashes in 2017 [1] as well as for the first half of 2018 [2] – bringing the US out of a multi-year increase in fatal crashes – motor vehicle crashes remain a leading cause of death for those 65 years and younger as well as the second leading cause of unintentional injury-related deaths [3]. Globally, road traffic fatalities remain a leading cause of death, particularly among low to middle-income countries [4].

Advanced driver assistance systems (ADAS), such as forward collision waring and lane keeping assist, have the potential to mitigate these crashes, reducing overall crash severity, injuries, and deaths. Previous injury reduction models have suggested that ADAS can prevent up to 57% of crashes and resulting injuries [6-12]. Automatic emergency braking (AEB) is designed to mitigate the most common crash mode: rear-end striking crashes. However, assessing the efficacy of AEB in real-world crash scenarios is challenging given that avoided crashes are rarely documented except during naturalistic driving studies. Several studies have attempted to illustrate the effectiveness of AEB using statistical models or counterfactual simulations. However, these studies have several limitations including (1) being based on archival data such as police reports and insurance claims which lack real-world vehicle dynamics data, (2) have used idealized AEB deceleration profiles including step or ramp pulses and have assumed constant jerk, (3) have assumed a static lead vehicle, and (4) have *not* accounted for road conditions or driver reaction. Naturalistic driving studies offer a unique opportunity to provide real-world data on these variables, which can serve as inputs for more realistic counterfactual simulations.

The Strategic Highway Research Program 2 (SHRP2) Naturalistic Driving Study (NDS) offers a unique opportunity to evaluate the potential efficacy of AEB on real-world crash scenarios. SHRP2 crashes include vehicle dynamic data such as radar data, vehicle velocity, and vehicle acceleration [13], which can be used to provide more realistic inputs to counterfactual simulations. Additionally, the Insurance Institute for Highway Safety conducts test-track-based AEB evaluations of currently available vehicles and provides year/make/model specific information on deceleration profiles and activation times through IIHS TechData [14]. Therefore, the current study aims to evaluate to efficacy of AEB by recreating SHRP2 rear-end striking crashes with the presence of AEB using measured deceleration profiles to determine if the application of AEB would have effectively prevented rear-end crashes.

METHODS

This study protocol was approved by the Institutional Review Board at the Children's Hospital of Philadelphia.

SHRP2 Dataset

A subset of the SHRP2 NDS data set was obtained via a data use license with the Virginia Tech Transportation Institute (VTTI). Scene videos, incident type, and times series data pre- and post-event including vehicle velocity, acceleration, and radar data were obtained for all crashes (n=1317) previously identified by VTTI for four age groups: teens (16-19 yrs), young adults (20-24 yrs), adults (35-54 yrs), and older adults (70+ yrs). Time series data ranged from 20 s prior to 10 s post event and were collected at 10 Hz.

Data Reduction

Rear-end striking crashes were defined as events where the subject vehicle contacted a lead vehicle. Rear-end striking crashes were identified using scene videos and event narratives by two independent video coders. Any discrepancies were reconciled by the study team. Rear-end striking crashes were then reviewed for reliable radar data. Events with missing or unreliable radar data were excluded from the analysis. Event data including vehicle velocity and acceleration, relative distance to the lead vehicle, and road surface conditions were used to conduct counterfactual simulations.

AEB Counterfactual Simulations

The SHRP2 database includes the year, make, and classification (*car, SUV/crossover, pickup, truck, van*) for each vehicle involved in the NDS. To generate realistic AEB deceleration profiles, measured deceleration curves for 20 kph and 40 kph AEB tests conducted by the Insurance Institute for Highway Safety (IIHS) [14] were downloaded from IIHS TechData (https://techdata.iihs.org) and used as inputs for the counterfactual simulations. IIHS AEB tests were matched to each SHRP2 rear-end striking events by selecting the most recent IIHS AEB test with the same vehicle make and classification. If a particular make or classification was not tested by IIHS or the SHRP2 subject vehicle was no longer in production, a classification-matched vehicle from the parent OEM was selected.

A brake threat number (BTN) algorithm [15] was used to determine the onset of AEB for each rear-end striking event. To increase the accuracy of the BTN algorithm, the BTN activation curve was scaled to match the AEB onset times measured during the IIHS AEB tests. Goodness of fit of the BTN activation curve was assessed using a minimum root mean square error (RMSE) criteria.

If the vehicle velocity at the time of AEB onset was ≤ 20 kph, the 20 kph IIHS AEB tests were used for the counterfactual simulation. Contrarily if the vehicle velocity at AEB onset was >20 kph, the 40 kph IIHS AEB tests were used. Counterfactual simulations were conducted in MATLAB 2015a. To account for changes in the AEB deceleration profile due to road surface conditions, the deceleration profile was scaled by a road surface friction factor [16]: dry=1.0, wet=0.7, snowy=0.3, icy=0.1. To account for the driver's braking reaction prior to AEB onset, the AEB deceleration curve was initiated at the vehicle's current braking level. To ensure that AEB deceleration profile was proportional to the subject vehicle's velocity at the time of AEB onset, the deceleration curves were either (1) truncated by proportionally scaling down the AEB curve in both magnitude and duration or (2) extrapolated by extending the steady-state portion of the AEB deceleration using a spline fit.

To simulate changes in vehicle dynamics due to AEB activation, the following equations were used:

$$\left.\begin{aligned} V_{aeb}(t) &= \int_{t_{aeb}}^{t_{crash}} A_{aeb}(t) + V_{SV}(t_{AEB}) && \text{(Equation 1)} \\ X_{aeb}(t) &= \int_{t_{aeb}}^{t_{crash}} \big(V_{SV}(t) - V_{aeb}(t)\big) + X_{LV}(t) && \text{(Equation 2)} \end{aligned}\right\} t_{aeb} \le t \le t_{crash}$$

t_{aeb} = time of AEB activation
t_{crash} = time of original SHRP2 crash
A_{aeb} = subject vehicle acceleration with AEB
V_{SV} = velocity of subject vehicle
V_{aeb} = velocity with AEB activation
X_{LV} = relative distance to lead vehicle
X_{aeb} = relative distance to lead vehicle with AEB activation

If V_{aeb} reached zero prior to the time of the original SHRP2 crash, it was concluded that AEB prevented the crash. If the addition of the AEB deceleration caused the simulation to extend beyond the time of the original SHRP2 crash, the lead vehicle velocity was assumed to be constant and the equations below were used:

$$V_{aeb}(t) = \int_{t_{crash}}^{t} A_{aeb}(t) + V_{SV}(t_{AEB}) \qquad \text{(Equation 3)}$$

$$X_{aeb}(t) = \int_{t_{crash}}^{t} \big(V_{LV}(t_{crash}) - V_{aeb}(t)\big) + X_{AEB}(t_{crash}) \qquad \text{(Equation 4)}$$

If V_{aeb} reached zero and $X_{aeb} > 0$, it was concluded that AEB prevented the crash.

RESULTS

A total of 99 rear-end striking crashes among 95 drivers were identified from the four age groups. Among these rear-end striking crashes, 30 events had no radar data. An additional 29 events were removed due to unreliable radar data. The final dataset for counterfactual simulations consisted of 40 rear-end striking crashes.

Exemplar counterfactual simulations for a prevented and non-prevented rear-end striking crash are shown in Figure 1. AEB was found to be very effective, preventing 80% (n=32) of simulated SHRP2 rear-end striking crashes with reliable radar data. Half (4 of 8) crashes that were *not* prevented occurred during poor weather conditions.

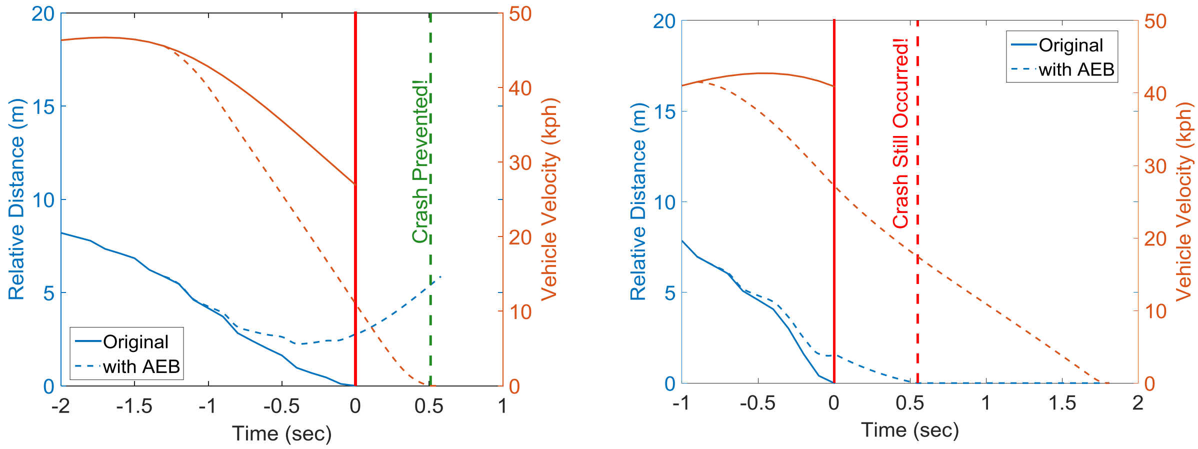

Figure 1. Exemplar prevented crash (left) and non-prevented crash (right).

LIMITATIONS

Several limitations warrant discussion. First, AEB is typically coupled with forward collision warning (FCW). The current study assumed the FCW did not alter the driver's reaction to the crash. Consequently, these counterfactual simulations represent the "worst-case" scenario for AEB. Of note, drivers executed an evasive braking maneuver in 33 (82%) of the simulated rear-end striking crashes. Furthermore, among the seven events where the driver had no evasive maneuver, AEB was capable of preventing all seven crashes. Consequently, the influence of FCW on these results is likely limited. The current study also assumed AEB activated at all speeds. However, this is not the case with all manufacturers. While some OEMs are releasing high-speed FCW and AEB systems, most low to moderate speed systems have a peak AEB activation speed of 36 mph. Consequently, the current study represents the potential of high-speed AEB to prevent rear-end striking crashes. Finally, radar data were only available for a subset (40%) of rear-end striking crashes. This possibly introduced selection bias because this subset may not be representative of all rear-end striking crashes in SHRP2.

CONCLUSIONS

To our knowledge, this study represents the most realistic counterfactual simulations of AEB effectiveness to date – utilizing measured vehicle dynamics, driver reaction, and road conditions from naturalistic data as well as measured AEB deceleration pulses. Our findings suggest that AEB is very effective at preventing rear-end striking crashes. However, AEB was less effective for crashes that occurred in poor weather conditions.

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Investigating Accidents Involving Highly Automated Vehicles: Concept of a Data Trustee and Data Model for Future Homologation

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ABSTRACT

According to statements by the EU Commission, 95% of all traffic accidents involve human error, and in 76% of accidents, humans are solely to blame [1]. A similar picture also emerges in the settlement of damages by Allianz Versicherungs-AG, and in detailed analyses of the accident research by Allianz Center for Technology.

At the same time, human drivers set high standards with regard to road traffic safety. Based on market figures over the past few years, in Germany, a passenger car causes material damage only every 250.000 km, and personal injury every 2.3 million km. Since the 1960s, the number of liability claims per passenger car has decreased to a third of the previous figure, and today the claims frequency is at around 60 claims per 1.000 insured units per year [2].

Above the level of high vehicle automation [3] from which the driver is no longer responsible for continuously monitoring the vehicle and the driving task, however, completely new issues will arise in the road traffic accident statistics. In the case of highly automated driving, extremely high requirements must be placed on vehicle safety and on protecting functions in order to not only keep road traffic safety at the current level, but actually improve it significantly. Unfortunately, accidents in the USA with vehicle prototypes in highly automated driving mode show that some accidents cannot be prevented with the current state of technology. Coupled with this is the question as to how cases can be investigated should an accident or criminal misconduct involving a highly automated vehicle occur after the legal authorization of highly automated driving functions and their introduction into the market in the EU.

As explained elsewhere [4], the German liability and insurance system is well suited to covering the risks that exist in the operation of highly automated vehicles. However, the selective operation of the vehicle by the driver and by a highly automated driving function raises fundamental questions concerning the investigation of cases in the event of accidents or traffic offenses.

Early on, Allianz already supported creating conditions so that accidents involving automated vehicles can be reconstructed in the future in order that victim protection, clarification of liability, and regress and product liability claims can still be ensured in a non-discriminatory manner. This is because, in the course of the motor vehicle insurer investigating a case and settling claims, particular importance is attached principally to the driving mode (highly automated driving/transfer phase/driver in control) in which the vehicle was moving at the time of the accident or the traffic offense. On the one hand, a driving error by the driver could be the cause of damage, on the other hand, errors by sensors, inadequate algorithms, deficient software quality or interoperability of systems cannot be ruled out as the cause of an accident. The driver's statement that a collision or non-compliance with traffic regulations occurred after handing over control to the vehicle cannot be verified or disproved without a sufficient set of relevant data.

DRIVING MODE RECORDER / DSSAD

Whereas standards for the data logged in vehicle event data memories have been established in the USA for several years (NHTSA DOT rule 49 CFR Part 563 [5]), outside the USA, there are no such standards to date. In the current stock of vehicles in the EU, reading accident data remains primarily a privilege afforded to the vehicle manufacturer. For external parties, for example experts, reading data is possible only – if at all – with high technical expertise, suitable reading devices, and still limited to some vehicle models.

This problem has been recognized by both the EU and the German government. Thus, in the course of amending the regulation UN ECE-R79 Steering systems, the "World Forum for Harmonization of Vehicle Regulations (WP.29)" develops continuous driving mode storage. The "Data Storage System for Automated Driving", or DSSAD for short, is intended to store data relating to [5]:

- GPS location and time
- Activation of the AD System (Automated Driving Function)
- Transition demands
- Activation of a "minimal risk maneuver"
- Takeover of the driving task by driver
- System error

These data elements are also required in § 63a StVG [7] of the German Road Traffic Act, amended in 2017, in the case a vehicle is equipped with a highly or fully automated function.

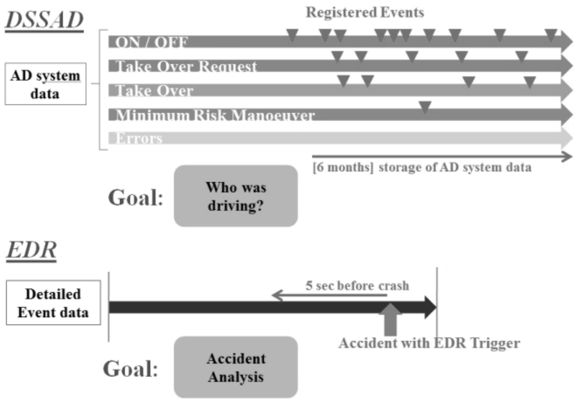

Figure 1: Difference between DSSAD and EDR

Figure 1 shows the difference between DSSAD and EDR. The DSSAD can clarify the question as to whether the vehicle or the driver is in control at a given time. But there is no trigger for data storage in an incident. Besides, it has not yet been determined how authorized persons or parties can access this data and in what location, internally in the vehicle or externally, said data have to be stored. Authorized persons or parties should have easy, tamper-proof, fair and non-discriminatory access to the relevant data elements. These requirements cannot be met when the data is solely stored in the vehicle. A brief example should illustrate this:
A person drives on the freeway in highly automated driving mode and, after this journey, receives a penalty notice as a result of having exceeded the maximum permitted speed by 20 km/h. If the data is stored only in the vehicle, the person in question would have to drive to a workshop or to an expert so that the data can be read in order to prove their innocence.
In the digital age, in which vehicles drive in a highly automated or even autonomous mode, this investment of money and time cannot be considered appropriate. Therefore, the data should be stored externally and should be accessible online, or available on request.

CONCEPT OF THE DATA TRUSTEE

Regulated external data storage and management could be ensured in practice by the concept of an independent data trustee. The data trustee must treat the encrypted raw data transmitted online impartially and check authorized access by interested parties. Figure 2 shows the advantages of double storage, i.e. in the vehicle and with an independent data trustee. Vehicle data that can be attributed to the occurrence of an accident or a criminal offense must not be made available exclusively to the driver, the insurer, the public prosecutors or the vehicle manufacturer. Independent data management by a trustee would ensure that the regulated dataset is accessible to all authorized persons or parties [2].

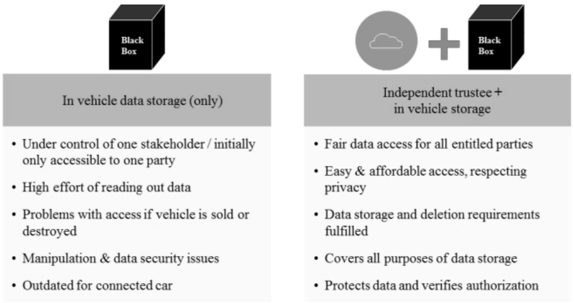

Figure 2: in vehicle storage versus data trustee and in vehicle storage

Example I:
In the case of a notification of a claim where responsibilities are to be clarified, the vehicle owner requests a clarification of the cause from the insurance company. On the basis of the owner's request and authorization and a specific loss event, the insurance company requests the data from the data trustee. In turn, the data trustee distributes the re-encrypted data to the insurance company via a secure channel for further analysis and, if necessary, to the OEM e.g. for product improvement (see Figure 3).
Since the request to the data trustee is ideally made only via a vehicle ID that is generated at the beginning of the authorization, it is not possible for the data trustee to establish a connection between the owner and the vehicle data.

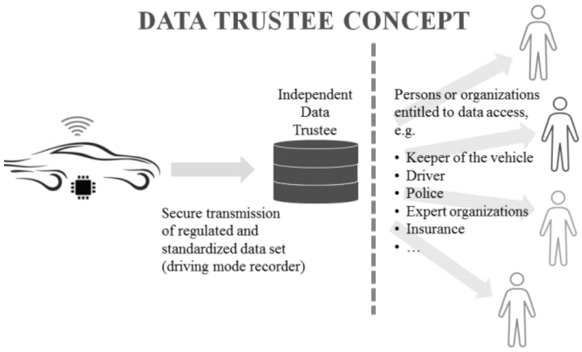

Figure 3: Data Trustee Concept

Example II:
If an owner wishes to view their data independently of the insurance company, e.g. to check for possible self-incrimination, they could make their request directly to the data trustee themselves or via the "Central Vehicle Register", via their attorneys or via an expert. As an alternative to personal requests, anonymous requests could also be answered in this way.
When data is transmitted to the data trustee, said trustee does not require any knowledge about the natural person with which a vehicle/driving mode memory is associated. From the perspective of the data trustee, the data is anonymous or under a pseudonym.
The data trustee should not have any direct contractual relationship with the data owner. Likewise, the data trustee should be independent and, in the relationship between the vehicle manufacturer, the vehicle owner, the driver, the other party involved in an accident (if applicable), and the insurance company, should represent a neutral party without own interests.

The data trustee guarantees the authenticity of the data (i.e. its origin and that it is unchanged) to the aforementioned parties and ensures that the (decrypted) data is provided

a) only to authorized parties,
b) only in authorized situations and
c) only in the regulated scope.

The trustee is also responsible for the security of the stored data against tampering, theft, etc.
Since the dataset as well as the access to data is defined by law, there is no need for the vehicle owner to sign a declaration of consent to storage. A data trustee would be able to provide the data to fulfill statutory require-

ments (e.g. a court order) without the permission of the data owner and, in standard circumstances, without access to the vehicle.
Technically, the requirements on data transmission can be met analogously, that is to say that the data transmission between the vehicle or the driving mode recorder and the trustee is carried out in a tamper-proof and tap-proof manner under any circumstances.
In this case, protecting the transmission via TLS (Transport Layer Security) is obvious, since this is an established protocol which, in addition to the encryption, also ensures that the vehicle's communication partner is also actually the chosen trustee. Additionally, a conventional asymmetric and symmetric encryption method could be used. Handling the data in this manner appears to be modern, convenient and fair.

NEED FOR ADDITIONAL DATA

As shown above some vehicle data have been subject to regulation, however the majority of vehicle data is not regulated in the EU. Figure 4 shows an overview of regulated and unregulated datasets in the EU. From the perspective of accident reconstruction, further standardization of the datasets would be desirable in order to clarify, in addition to the driving mode, the actual cause of the accident and additional questions of liability. An event data recorder is a prerequisite for:

- the ability of the driver and the vehicle owner to exonerate themselves where necessary and to assert product defects or service errors (e.g. in the case of updates and patches)
- protecting vehicle manufacturers and suppliers against unjustified claims
- a fair basis in any product liability cases/regress claims between the vehicle owner or the insurance company and the vehicle manufacturer or supplier

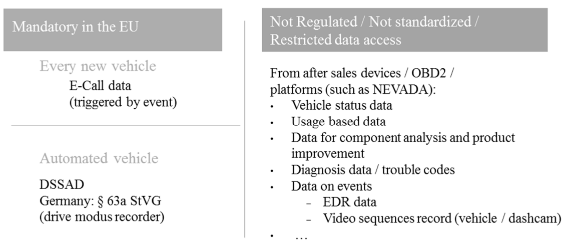

Figure 4: Overview of data handling in the EU

With a view to international harmonization of standards, the profile of requirements in NHTSA DOT rule 49 CFR Part 563 could be a starting point for standardized data logging. However, in the EU project VERONICA II [8] from 2007 to 2009, it has already been shown that this regulation also has its weaknesses in the triggering of an event and the correct interpretation of the data that is read. This also corresponds to the experiences in AZT [9]. In AZT crash tests, multiple tested vehicles from several manufacturers demonstrated good correlations with respect to the crash data when comparing external laboratory measuring equipment with the EDR data logged by the vehicle. The tests also show that it has to be provided that the limitations in data generation in the vehicle are recognized and taken into account.
The analysis of EDR protocols from real road traffic accidents shows that in particular the pre-collision speed data cannot always be interpreted unambiguously, and data elements (such as the turn signal) often are not available for inferring liability.

Regarding triggering an event, it should additionally be noted that the US regulation is not specifically adapted for the requirements of automated driving, but is rather focused on restraint systems being triggered by a change in speed of above approximately 8 km/h within 150 ms as a result of an impact. In the variety of collisions and accident types that are settled by vehicle insurers, from a present-day perspective in accordance with evaluations by Allianz Center for Technology, an airbag is triggered only in a very low percentage of less than 3% of the settled claims. Even fatal accidents involving vulnerable road users exceed the described trigger thresholds on urban road only in very few cases. However, based on 2016 data, in Germany, 27.8% of accidents with fatalities, 33.2% of accidents with severe injuries and 27.8% of accidents with minor injuries in road traffic were attributable to accidents involving cyclists and pedestrians [10]. In addition, a research initiative by Allianz, Continental and Munich University of Applied Sciences showed that approximately 40% of all passenger car accidents with material damage are parking and maneuvering accidents [11]. In these collisions as well, the change in speed of the passenger car as a result of an impact is generally below the trigger threshold of the US regulation.
With a view to protecting victims and clarifying questions of liability, in the future, a much higher percentage of accidents should be able to be captured and stored by an event data recorder in highly automated cars.

OUTLOOK FOR AHEAD DATA MODEL

Automated Driving requires a highly sophisticated degree of vehicle, event and accident information well above US-EDR standard for data capturing, period, recording, storage, retrieval and safety. The work group "AHEAD" (Aggregated Homologation-Proposal for Event-Recorder-Data for Automated Driving), established in 2017, a cooperation by Allianz, AXA, CARISSMA/TH Ingolstadt, Continental and DEKRA, has therefore committed to drafting detailed requirements for an event data recorder for vehicles with automated functions of level 3 and above. The aim is to develop a data model that allows transparent, non-discriminatory and tamper-proof accident reconstruction and is compatible with current data protection laws. Storing crucial vehicle data shall be limited to a short timeframe before, during and after a triggering an event with the goal of obtaining accurate, in-depth accident data. The technical level of EDR as defined in the VERONICA II Project (2007-09) and as referred to in the "European Parliament resolution of 27 September 2011 on European road safety 2011-2020 (2010/2235(INI))" is a good starting point. But with regard to Automated Driving it is not sufficient any more. AHEAD has set out to update the requirements. Building on the results from the EU project VERONICA II and taking into consideration the automated driving functions, AHEAD describes data elements and organizes them into four standardized categories. According to the AHEAD White Paper [**Error! Reference source not found.**] the AHEAD Data Model includes but is not limited to the following data:

- Driving Data
  - Vehicle Status, Operation Mode (e.g. manual, autonomous, remotely controlled), Speed, Yaw Angle, Control interventions of the assistance system, Takeover request
  - Diagnostic data of safety relevant systems and components (condition, status, system failures/ technical malfunction)…
- Driver Activity
  - Video feeds from cabin cameras, Steering, Seat Position, Pedal Positions, Driver Alertness…
- Surroundings- and Object Recognition
  - Video feeds from front and rear-facing cameras, Sensor Data, Classified Objects, Object Position, Object Direction, Object Speed, Calculated Movement…
- Crash
  - Date, Timestamp, Location, Acceleration, Collision Speed, Seat Belt Status, Airbag, Restraint System…
  - Sensor technology, e.g. advanced and sensitive trigger which recognizes accidents with low acceleration in order to detect and measure accidents with vulnerable road users involved, or parking/maneuvering accidents

Whereas the required driving data, the data elements relating to driver activity and the crash data can be described by individual signals, the data related to environment and object recognition consist of elements that may have already been merged, calculated and assessed, which make it possible to compare the generated model of the vehicle environment with the reality and to check the plausibility of the control commands of the vehicle. The process of generating a virtual world and moving in a real world provides a high potential for errors. A highly automated vehicle must therefore provide data relating to this process. Since the calculation algorithms of manufacturers' systems relating to sensor fusion, environmental model calculation and path planning of the highly automated ego-vehicle are strictly confidential, storing the raw sensor data is insufficient in this case.

The vehicle sensors, the vehicle cameras and other networking or communication channels of the highly automated and connected vehicle must be able to keep track of the entire vehicle environment. In practice, this means multiple overlapping and redundant “sensor cocoons” [13]. The detected sensor signals must be checked for plausibility, classified, provided with a time stamp, prioritized and annotated a thousand times per second. Lastly, in the generated environmental model, the location of the ego-vehicle relative to its environment must be determined in a repeatable manner and to within a centimeter. This processing of the signals can no longer take place by means of the bus systems used up to now, but rather must be processed by means of software blocks, which contain corresponding algorithms, on sensor platforms. The situational awareness of the highly automated vehicle which is calculated on said platforms part of the basis for the standardized data storage according to AHEAD.
The raw data supplied by the sensors (camera, laser scanner, radar, ultra sound) is prepared and evaluated by a number of different algorithms. The environment with the objects located in it must be classified and located by different methods. Thus the actual state of the vehicle environment is determined on the basis of a model, taking into consideration weather and visibility conditions. By means of GPS data, HD card data, the inertial sensor, the cameras, the laser scanner, the radar and ultrasound sensors, the ego-vehicle can locate itself in said environment. So that the ego-vehicle can also move in this environmental model, the future must also be calculated. For this purpose, numerous assumptions about the movements of other objects must be made. If the system has decided on path planning at a certain speed, this can ultimately be implemented in the form of control commands to the longitudinal and lateral control.
One of the greatest challenges for AHEAD will be getting this variety of data to a suitable level and an enforceable standard. This must also be done in accordance with the following AHEAD Guiding Principles for access to vehicle data:

- Consent
- Fair and undistorted competition
- Data privacy and data protection
- Tamper proof access and liability
- Data economy
- Standardized interface
- Crash resistance of data storage system in vehicle
- Event Data Storage for limited period of time before and after an incident (~ 30 sec)

Therefore the individual data elements required are continuously validated on the basis of real accidents and crash tests and evaluated and publicly discussed in various discussion groups. The AHEAD members invite stakeholders involved in setting the rules and requirements for Automated Driving (Parliament, Commission, Member States and others) to enter into dialogue.

CONCLUSIONS

An EU wide regulation with respect to a driving mode recorder, access to the data via a data trustee in combination with the introduction of an event data recorder for highly automated driving functions would have considerable advantages for the parties involved:

- The main focus would be on the public interest in integrity and victim protection.
- The ability of the driver and the vehicle owner to exonerate themselves where necessary and to assert product defects.
- Protecting vehicle manufacturers and suppliers against unjustified claims.
- Access to data would be politically endorsed and legitimized.
- Fairness for all parties.

In order for highly and fully automated driving to be widely accepted by society, the driver must only be able to be prosecuted for his own misconduct. It must therefore always be possible to clarify who is responsible (if the system has failed or if the person has failed). This driving mode data must be available for investigation through storage in order to clarify whether the vehicle was controlled by the automated system at the time of the incident or by the driver or was in the handover phase between the human driver and the automated system.
The necessary data must be in the hands of a neutral, independent third party (data trustee) in order to allow all authorized persons access to the data under the same legal conditions. In addition to storing the data in the vehicle itself, transmission to an independent third party is therefore mandatory. In the event of a vehicle being sold or after the vehicle has been destroyed in an accident, the data trustee is the only source of clarification in the interest of all parties involved.

Moreover, for highly automated vehicles (Level 3 and higher), a standardized event data set from the vehicle in the event of an incident is required. Only in this way will it be possible in future to clarify accidents or legally punishable events involving automated vehicles in a proper and transparent manner. The AHEAD working group develops parameters for such a data set. The data model includes elements on the vehicle status, driving environment, driving situation and driver activity which are defined for accident clarification. In addition trigger thresholds are defined with the goal of storing crucial vehicle data limited to a short timeframe before, during and after relevant events.

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PASSENGER CAR SAFETY BEYOND ADAS: DEFINING REMAINING ACCIDENT CONFIGURATIONS AS FUTURE PRIORITIES

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ABSTRACT

New vehicles are increasingly equipped with a variety of Advanced Driver Assistance Systems (ADASs). As these systems have the potential to prevent accidents, accidents of the future will differ from those of today. Predicting the type and characteristics of these future accidents is therefore essential to current research and development in the occupant restraint and new ADAS fields.

In this study, accident avoidance of 15 ADASs was modelled using simple deterministic rules for each, creating both a conservative and an optimistic ruleset to account for current limitations and future possibilities. The rulesets were applied to the US National Automotive Sampling System Crashworthiness Data System data from 1995-2015 and verified through the literature. The residual passenger vehicle to passenger vehicle accidents were analysed, treating all accidents and accidents with at least moderate injuries in modern passenger vehicles (model year 2007 and later) separately.

Many accidents were found to be avoided through such systems, and their combined effectiveness ranged from 51% to 97% depending on ruleset. Electronic Stability Control (ESC), Lane Keep Assist (LKA), and Crossing and Rear End Automated Emergency Braking (AEB) were highly effective, individually preventing over 25% of accidents in the optimistic calculation. Importantly, remaining accidents will have a different distribution across accident types compared to today: rear end collisions will reduce, leaving turning and crossing scenarios to dominate future accidents.

For passenger vehicle to passenger vehicle accidents with at least moderate injuries in modern vehicles, four accident types alone were found to account for 93% of all remaining accidents in the optimistic estimate: Head On, Turn Across Path, Turn Into Path Opposite Direction and Straight Crossing Paths; the latter three are intersection-related and together represent three quarters of all remaining accidents.

The intersection accidents are analysed further for deformation pattern, impact direction, 90% cumulative delta velocity and injured occupant position in order to identify possible new impact conditions to be used when evaluating occupant restraints. The well-established frontal and side impacts will still generate many AIS2+ injuries, while new more oblique impact conditions will also be needed to represent the variety of intersection accidents remaining.

The description of future accidents and impact conditions presented here can serve as a basis for the research and design of future ADASs and occupant restraints. We propose virtual assessment methods with Human Body Models (HBM) based on these impact conditions.

INTRODUCTION

More than six million police-reported motor vehicle accidents occurred in the United States in 2016; of the 37 461 fatalities, 23 714 (63%) were occupants of passenger vehicles [1]. Over recent years, many Advanced Driver Assistance Systems (ADASs) have been introduced to the market, including Automated Emergency Braking (AEB) for rear end collisions and pedestrian impacts and Lane Keeping Assist (LKA), which are estimated to reduce the number of accidents significantly [2-8]. To reduce this number further, additional ADASs, such as AEB for intersections and Evasive Steering Assist (ESA), are under development as a stepwise progression to fully autonomous driving. Society of Automotive Engineers (SAE) describes these steps at five levels [9], where level 0 means no driving automation and level 5 means full driving automation. Most ADASs today are designed for level 2, partial automation, which means that the driver needs to be fully engaged but the vehicle has automated emergency functions like braking and steering. Through monitoring the driver, driving environment and surrounding traffic, these functions intervene to prevent traffic accidents and support safe driving.

With the number of ADASs in the vehicle fleet increasing, the frequency distribution of accident types will change over time. It is of importance to be able to predict which accident types will remain and which will predominate; this is needed not only to guide the development of new or improved driver assistance systems, but also to guide the development of occupant restraints. However, the real-world effect of new ADASs is difficult to determine since they are not yet widely deployed to the market. Attempts to evaluate this may broadly be categorized as either retrospective or prospective, as follows.

Retrospective analyses tell what has happened. This is done by direct comparison of vehicles with and without the ADAS in question. Several researchers have reported on the number of accidents that could be prevented by various ADASs [3, 5, 10-14] using such an approach; however, newer ADASs like ESA, Driver Monitoring Systems (DMS), Traffic Jam Assist (TJA) and Highway Assist (HA) have not yet been evaluated as these have a rather low installation rate, making a retrospective investigation hard to execute. Retrospective analysis is also hard to execute if vehicles are equipped with several ADASs because any of the systems present may have prevented the accident and thus attributing the benefit to a specific ADAS is not clear-cut.

Prospective analyses tell what will happen. Alvarez et al. (2017) define four levels of prospective analyses from level 0, “Use of expert opinion to estimate the potentially addressed situations”, to level 3, “Use of simulation to generate reference situations (RS) and modified situations (MS) from the understanding and characterization of processes” [15]. Prospective analyses take in-depth accident data from accident scenes and then apply an intervention to assess its potential benefit. Such predictions are either made by detailed simulations or by some type of estimation. Simulation is used when a detailed understanding is needed, in which case a thorough set up of the accident boundary conditions is made. The ADAS is then applied to the situation to evaluate whether it prevents the accident or not. When simulating, it is also possible to vary the situation boundaries to evaluate situations that could have happened or to vary the magnitude of the intervention [16-18]. This method is by nature limited to the detailed data available and is time consuming since it requires the creation and validation of a simulation model as well as at least two simulation runs per accident, one reference and one modified with the ADAS. In contrast to this, the use of estimates for given situations gives an overall understanding of the potential of an ADAS [2, 19-21]. Assuming that a range of safety systems will be able to intervene in the future — for example, through the implementation of ADASs — one can model each of these interventions in low detail, apply this to historical crash data, and get estimations regarding future crashes which can be used to prioritize interventions and plan for subsequent ones [22]. This method has been validated for a 10-year time horizon using Swedish fatality data [23]. Although the result is not as detailed as for a simulation, it is nonetheless a significantly faster process.

The objective of this study is to investigate which passenger vehicle to passenger vehicle accident types will remain, and how the impacted vehicles are deformed, in a future when today’s known Level 2 ADASs have been implemented. New impact conditions, guiding the evaluations of occupant restraints, are defined based on these deformations. A prospective approach is taken using estimates to examine the effectiveness of 15 ADASs in avoiding accidents.

METHOD

The method used in this study contains five steps: data collection; definition of ADAS rulesets; verification of ADAS rulesets; accident description; and analysis of the deformation pattern of the remaining impacted vehicles (Fig. 1). First, data regarding passenger vehicle to passenger vehicle accidents and single passenger vehicle accidents were extracted from the National Automotive Sampling System Crashworthiness Data System (NASS CDS). In the second step, two deterministic rulesets, one optimistic and one conservative, were created for today’s known ADASs, 15 in total. The rulesets were then applied to the data to calculate the effectiveness in avoiding accidents of each ADAS alone and in combination. The third step verified the rulesets by comparing the computed effectiveness to the literature for accident avoidance, irrespective of injury severity. In the fourth step, the accidents were analysed in terms of accident scenario and general area of deformation. This analysis was only done for passenger vehicle to passenger vehicle accidents where at least one occupant sustained a moderate injury, i.e. a number equal or higher than two on the Abbreviated Injury Scale (AIS). In the fifth and final step, the accidents still remaining after the optimistic ruleset had been applied were analysed in terms of accident type, delta velocities, corresponding Collision Deformation Classification (CDC) codes and the position of injured occupants.

Definition of terms

Accident scenario: Accident scenarios describe the overall kinematics before and during an impact of both vehicles involved. Accident scenarios are taken as the combination of two NASS CDS variables: crash category and crash configuration [24]. Examples are Same Direction – Rear End, Intersection Path – Straight Path and Vehicle Turning – Turn Across Path.

Accident type: Accident scenarios are divided into specific accident types (crash types in NASS CDS, in which 99 different crash types are described) with each vehicle involved being allocated a type. Examples of accident types are Drive Off Road, Turn Into Opposite Directions and Striking from the Right. An accident having two vehicles is described by a combination: for example, one vehicle is described as “Striking from the Right” and the other by “Struck on the Right”.

Deformation pattern: Deformation patterns describe each vehicle’s General Area of Damage (GAD), Principal Direction of Force (PDOF), and the Specific Longitudinal or Lateral Location of Deformation [25].

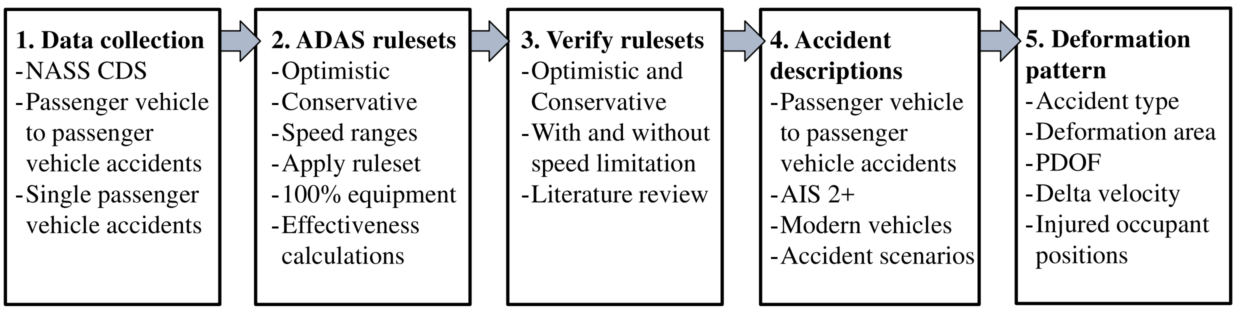


***Figure 1.* Description of the five steps used in the study**

1. Data collection

Data regarding passenger vehicle to passenger vehicle accidents and single passenger vehicle accidents were collected from the NASS CDS database, a US nationwide accident data-collection program sponsored by the U.S. Department of Transportation. NASS CDS includes police reported accidents in which at least one involved vehicle is towed away due to damage. Details of around 5 000 accidents are collected every year and consist of accident scene reconstructions, interviews with police and vehicle occupants, medical charts, and detailed information about the vehicles involved. Data are collected on a representative stratified sample of minor, serious, and fatal accidents involving passenger vehicles (passenger cars, pickup trucks, and vans), large trucks, motorcycles, bicyclists, and pedestrians [26].

The data from 1995 to 2015 were extracted on accident level and weighted according to weighting factors provided in the NASS CDS (RATWGT) to compensate for sampling bias. Very heavily weighted accidents (greater than 5000) were removed from the dataset since such cases could influence the results in a disproportionate way [27]. This gave in total 83 038 unweighted and 33 022 646 weighted accidents, of which passenger vehicle to passenger vehicle accidents accounted for 52 462 (63.2%) unweighted and 22 308 978 (67.6%) weighted accidents. Passenger vehicle – Object/Run off/Rollover accounted for 30 576 (36.8%) unweighted and 10 713 668 (32.4%) weighted accidents.

2. ADAS rulesets

Today’s known ADASs, 15 in total, were modelled to address a broad range of accident scenarios. Functions were grouped where possible. As an example, Forward Collisions Warning (FCW) and Brake Assist System (BAS) were assumed to be included in the AEB Rear End, and Lane Departure Warning (LDW) included in LKA. A conservative and an optimistic ruleset were created for each ADAS to take into account its limitations and its potentially improved future performance [28]. The conservative ruleset contained limitations which, if present in the accident scenario, would prevent an ADAS from avoiding an accident. These limitations include harsh weather, poor road conditions, including snow and ice on the road, missing lane markings, and unstable vehicle dynamics from skidding or speeding. Each ruleset also has a specific speed range within which the ADAS intervenes. If all the conditions in the rulesets were met, the accident was removed from the dataset, i.e. the ADAS prevented the accident. If the accident scene included a limitation, that specific accident was not avoided in the conservative estimate.

It was assumed that all passenger vehicles in the dataset were equipped with all the ADASs; the rules did not take into account manual overriding. When calculating the effectiveness of all ADASs together, i.e. the combined effectiveness, an accident was only removed once. For example, a lane change related accident can hypothetically be avoided by both Lane Change Assist (LCA) and Blind Spot Detection (BSD), but it will only be counted once. For combined effectiveness, four groups were created, optimistic and conservative with and without speed limitation. The purpose was to identify what limited the effectiveness of the ADASs, i.e. the speed range or the conservative limitations.

Input for speed range and limitations was derived from Euro NCAP assessment procedures [29-30], Euro NCAP test results [31], driver manuals [32-34] and web pages [35-37]. Each ADAS is listed in Table 1 with a brief description of which accident scenario it addresses. A concise description of how the ADAS rulesets were created using NASS CDS variables [25, 38] can be found in Appendix A and B.

3. Ruleset verification and ADAS effectiveness in avoiding passenger vehicle accidents
Rulesets were verified using reference values obtained from literature based on US data only. This was done to keep the conditions as similar as possible to those in the dataset and to minimize noise factors that could affect the result, such as differences in traffic environment or vehicle fleet. Both retrospective and prospective references were used in the verification process to get a range that could be compared to the conservative and optimistic rulesets. Retrospective studies normally give lower effectiveness estimates because they by design include all ADASs limitations. Table 1 lists the 15 ADASs with descriptions and estimates of their effectiveness in avoiding single passenger vehicle and passenger vehicle to passenger vehicle accidents.

4. Accident description
In this step all passenger vehicle to passenger vehicle AIS2+ accidents were selected from the dataset and described by their accident scenario and general area of deformation, where each accident could either be:

- Front–Front, both vehicles had damage to their fronts, coded blue.
- Front–Rear, one of the vehicles had a damage to the front and the other had a damage to the rear, coded green.
- Front–Side, one of the vehicles had a damage to the front and the other had a side damage to left or right side, coded red.
- Other, the accident could be a Side–Side or Rear–Side impact, or be missing such data, coded brown.

Accident scenario and general area of deformation were then combined to give an overview of the accidents (see Fig 3). This was done for this for four groups A–D:

A. All passenger vehicle to passenger vehicle AIS2+ accidents, N = 14 351 accidents, weighted to 2 005 362 accidents.
B. All passenger vehicle to passenger vehicle AIS2+ accidents with model year 2007 and later, N = 1 391 accidents, weighted to 215 184 accidents.
C. The residual of the conservative ruleset with speed limitation of group B, N = 761 accidents, weighted to 117 463 accidents.
D. The residual of the optimistic ruleset with speed limitation of group B, N = 251 accidents, weighted to 42 407 accidents.

5. Analysis of accident type and deformation pattern of the remaining impacted vehicles
To study the optimistic safety potential of the 15 ADASs, the accidents in group D were analysed by accident type to determine the most frequent ones. For the most frequent accident types, the vehicles with an AIS2+ injured occupant were then described in terms of the deformation pattern, 90% cumulative delta velocity, and injured occupant position.

Table 1.
Investigated ADAS, description and its effectiveness

ADAS	ADAS description	Effectiveness from literature
Lane Keep Assist (LKA)	Detects if the vehicle is about to drift beyond the edge of the road or into oncoming or overtaking traffic in the adjacent lane and automatically steers back.	1 - 3 % [2, 4-6]
Lane Change Assist (LCA)	Detects when a is car entering the blind spot while the driver is switching lanes.	Not found
Blind Spot Detection (BSD)	Detects vehicles diagonally behind and to the side of the car, typically when the car is being overtaken by other vehicles.	3% - 7% [2, 10]
Advanced Front Lighting System (AFLS)	Includes special auxiliary optical systems within the vehicle's headlamp housings and measures steering angle and vehicle speed and swivels the headlamps accordingly.	2% [2]
Electronic Stability Control (ESC)	Detects loss of steering control and automatically applies the brakes to help "steer" the vehicle where the driver intends to go. This ruleset was only applied to vehicles with model year earlier than 2010 since newer cars are equipped with ESC due to regulation.	7% - 8% [12, 14]
AEB Rear End	Detects stationary vehicles or vehicles being approached while driving ahead in the same lane. The driver is warned and if does not react, braking is activated.	16% - 21% [2-4]
AEB Reversing	Detects the presence of vehicles or obstructions behind and automatically initiates braking or prevents acceleration while reversing.	0.7% - 2% [11,13]
AEB Crossing	Detects crossing vehicles at an intersection. The driver is warned and if does not react, braking is activated.	2% - 8% [17-18]
Emergency Steering (ES)	Steering assistance upon risk of head-on accident: detects oncoming traffic and intervenes by steering and/or braking within the lane to prevent narrow overlap head-on accidents.	Not found
Driver initiated Evasive Steering Assist (ESA)	Detects oncoming traffic and provides assistance by adding steering torque to support the movement of the steering wheel, swerve or evasive action by driver.	Not found
Driver Monitoring System (DMS	Detects impaired and distracted driving and gives appropriate warning and takes effective action.	Not found
Intelligent speed adaption (ISA)	Detects if the vehicle speed exceeds a safe or legally enforced speed.	Not found
Traffic Jam Assist (TJA)	Detects the vehicle in front of your own vehicle and paces it to automatically maintain a steady following distance. In combination with that it also steers to stay within the lane.	Not found
Highway Assist (HA)	Longitudinal and lateral control on divided roads.	Not found
Alcohol interlock	Prevents the driver from driving when affected by alcohol.	Not found

RESULTS

The results were obtained in a three-step approach corresponding to steps three to five outlined in the method. The first step presents the single and combined effectiveness of each ADAS, with and without limitations, to the full dataset, i.e. to all single passenger vehicle and passenger vehicle to passenger vehicle accidents. It also includes a comparison with the effectiveness found in the literature. In the second step, groups A-D are described regarding accident scenario and impact direction. In the third step, group D accidents are analysed regarding deformation pattern, 90% cumulative delta velocity, and injured occupant position.

Ruleset verification and ADAS effectiveness in avoiding passenger vehicle accidents
Effectiveness in avoiding single passenger vehicle and passenger vehicle to passenger vehicle accidents was calculated for each ADAS (Fig. 2) and, additionally, the combined ADAS effectiveness for the four combinations, the optimistic and conservative rulesets each with and without speed limitation, was assessed. For the optimistic ruleset without speed limitation the combined ADAS effectiveness was 97%. The ADASs with the greatest potential to avoid accidents are AEB crossing (38%), Rear End AEB (24%), Electronic Stability Control (27%) and Lane Keep Assist (27%) (see Fig. 2). However, it was found that the NASS CDS variables that were queried in the ruleset for the ESA and DMS systems included many cases with missing information about the steering before the crash and driver state before the crash, 35% and more than 50%, respectively, which rendered the defined rules inapplicable. This might lead to underestimating effectiveness of these two ADASs in our study.

When the speed limitation was applied to the optimistic rulesets, the combined effectiveness was reduced to 88%. The ADASs most affected by the speed limitation were LKA, AEB reversing and TJA, which saw their effectiveness reduced by 40% to 70% (Fig. 2). Speed limitation was not applied to AFLS, ESC, DMS and Alcohol interlock.

The combined effectiveness for the conservative ruleset without speed limitation was 72%, a reduction of 26% compared to the optimistic ruleset without speed limitation. However, the effectiveness of many of the ADASs was reduced by between 40% and 70%. One exception was ISA whose effectiveness was reduced by 95%, dropping from 8% to less than 1% (Fig. 2). The reason for this substantial reduction was that skidding often occurs in combination with speeding, and as the conservative rule includes the limitation to not prevent the accident if skidding occurs, these accidents are no longer avoided.

Finally, for the conservative ruleset with speed limitations, the combined effectiveness decreased to 51%. The ADASs that were most impacted by this were the same as for the optimistic ruleset, i.e. LKA, AEB reversing and TJA, and, in addition, AEB crossing, LCA and ESA also decreased. The effectiveness of these ADASs was reduced by between 40% and 70% (Fig. 2).

Compared to the reference literature, the optimistic effectiveness truly is an optimistic representation. The ADASs whose effectiveness in the literature reaches these levels were BSD and AEB Rear End. On the other hand, the conservative values were truly conservative, underpredicting effectiveness for BSD, AFLS and AEB Rear End. The effectiveness of LKA, ESC and AEB crossing was overpredicted even with the conservative ruleset. For AEB reversing, the values were in line with the literature. For LCA, Emergency steering, Evasive steering assist, DMS, ISA, TJA, HA and Alco interlock, no reference values were found in the literature.

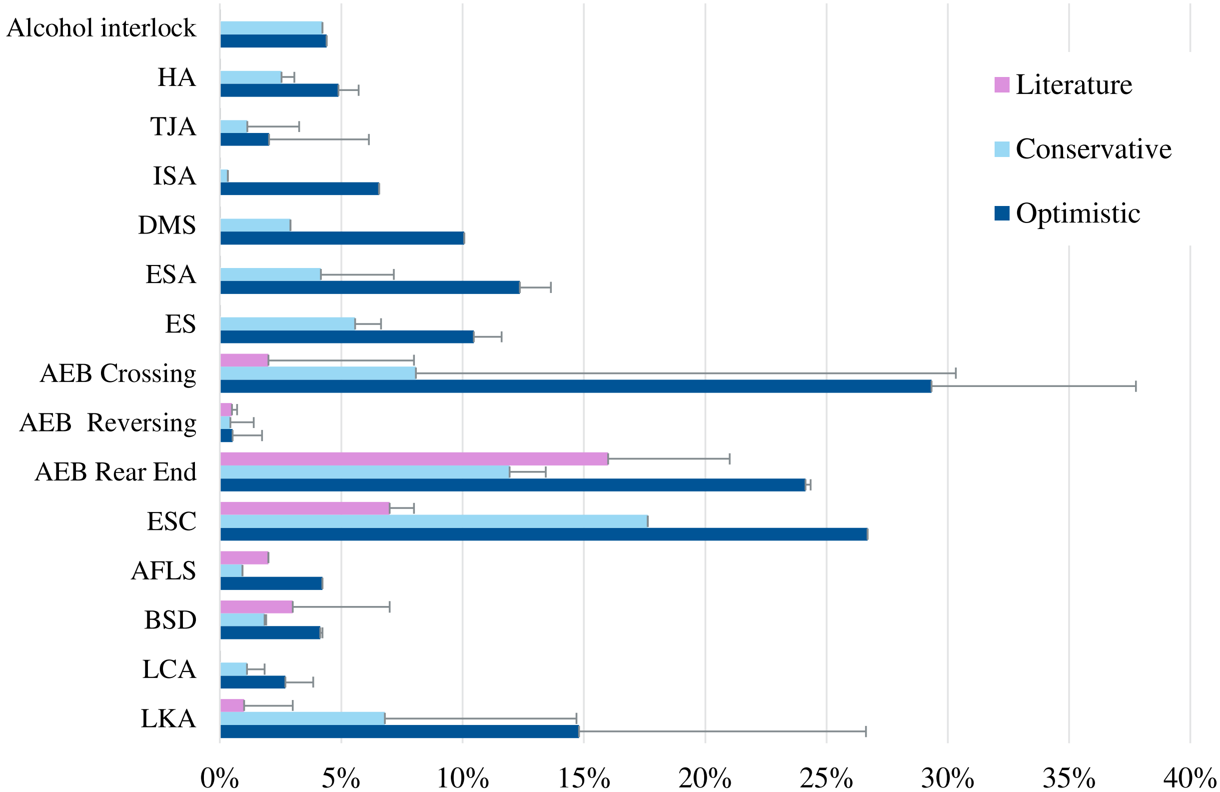


***Figure 2*. ADAS effectiveness and reference values from the literature. For conservative and optimistic rulesets, the error bars represent the effectiveness values without speed limitation. For the Literature the error bars represent the upper and lower values found.**

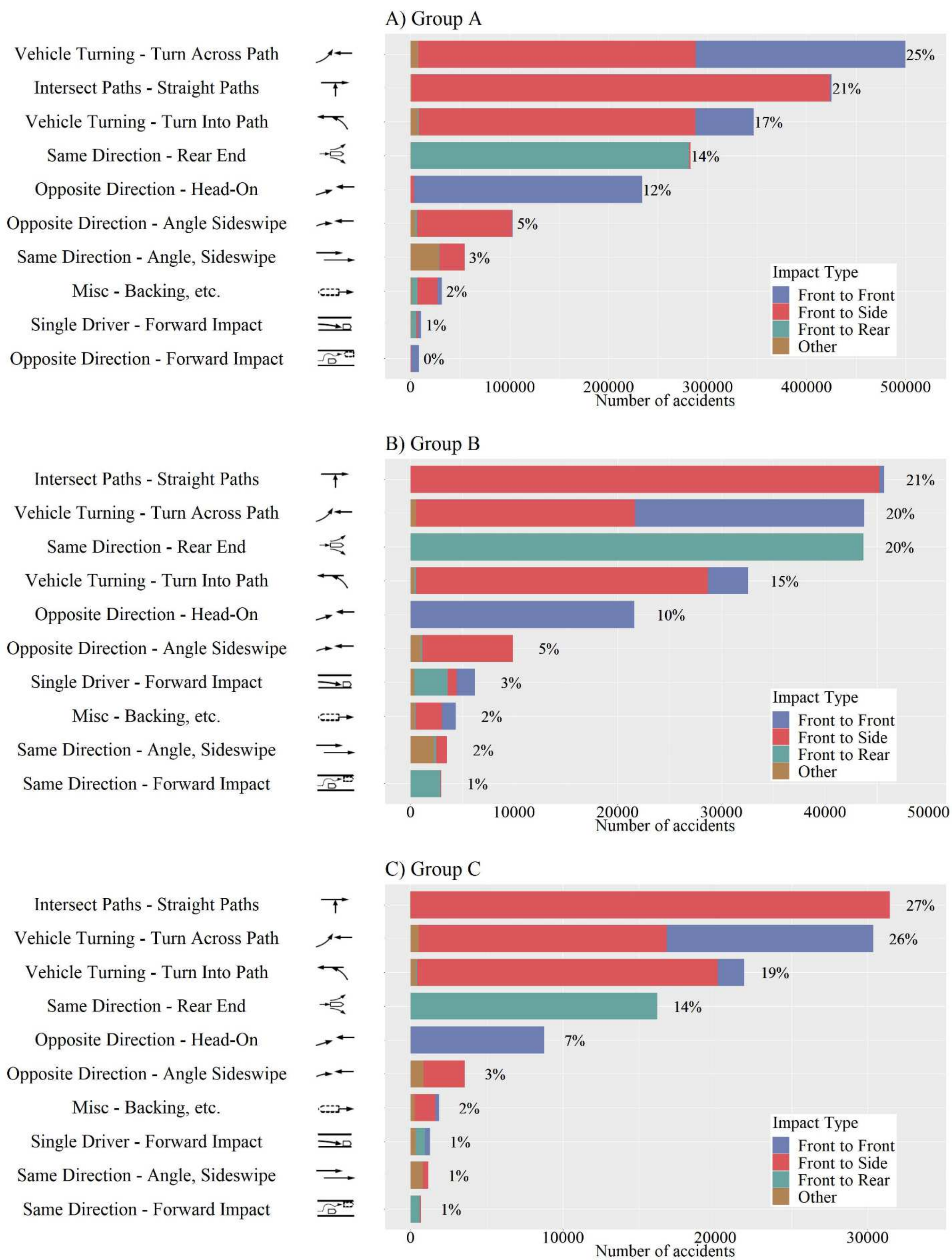
Accident description

Fig. 3 A) illustrates the breakdown of accident scenarios for group A, all passenger vehicle to passenger vehicle AIS2+. The top four accident scenarios are: Vehicles Turning – Turn Across Path, representing 25%; Intersection Path – Straight Path, 21%; Vehicle turning – Turn into path, 17%; and Same Direction – Rear End, 14%.

Fig. 3 B) illustrates this for group B, which is the same as group A but restricted to modern cars, model year (MY) 2007 or later. The same top four accident scenarios remain but with a small variation in percentage and order: as an example, Same Direction – Rear End increases to 20% and Vehicles Turning – Turn Across Path decreases to 20%.

Fig. 3 C) illustrates this for group C, the remaining modern passenger vehicle to passenger vehicle AIS2+ accidents with the conservative ruleset with speed limitations. The top four accident scenarios remain the same but Same Direction – Rear End accidents were reduced to 14% and Intersection Paths – Straight Path and Vehicle Turning – Turn Across Path increased to 27% and 26%, respectively.

Fig. 3 D) illustrates this for group D, which is as group C but with the optimistic ruleset with speed limitations. Same Direction – Rear End accidents are almost eliminated, and Vehicle Turning – Turn Across Path dominate the data. The new top four scenarios are Vehicle Turning – Turn Across Path, Vehicle Turning – Turn Into Path, Intersection Paths – Straight Paths and Opposite Direction Head. Together, these four accident scenarios represent 93% of all remaining accidents, with Vehicle Turning – Turn Across Path accounting for almost half.


A) Group A
Vehicle Turning - Turn Across Path
Intersect Paths - Straight Paths
Vehicle Turning - Turn Into Path
Same Direction - Rear End
Opposite Direction - Head-On
Opposite Direction - Angle Sideswipe
Same Direction - Angle, Sideswipe
Misc - Backing, etc.
Single Driver - Forward Impact
Opposite Direction - Forward Impact
25%
21%
17%
14%
12%
5%
3%
2%
1%
0%
Impact Type
Front to Front
Front to Side
Front to Rear
Other
0
100000
200000
300000
400000
500000
Number of accidents
B) Group B
Intersect Paths - Straight Paths
Vehicle Turning - Turn Across Path
Same Direction - Rear End
Vehicle Turning - Turn Into Path
Opposite Direction - Head-On
Opposite Direction - Angle Sideswipe
Single Driver - Forward Impact
Misc - Backing, etc.
Same Direction - Angle, Sideswipe
Same Direction - Forward Impact
21%
20%
20%
15%
10%
5%
3%
2%
2%
1%
Impact Type
Front to Front
Front to Side
Front to Rear
Other
0
10000
20000
30000
40000
50000
Number of accidents
C) Group C
Intersect Paths - Straight Paths
Vehicle Turning - Turn Across Path
Vehicle Turning - Turn Into Path
Same Direction - Rear End
Opposite Direction - Head-On
Opposite Direction - Angle Sideswipe
Misc - Backing, etc.
Single Driver - Forward Impact
Same Direction - Angle, Sideswipe
Same Direction - Forward Impact
27%
26%
19%
14%
7%
3%
2%
1%
1%
1%
Impact Type
Front to Front
Front to Side
Front to Rear
Other
0
10000
20000
30000
Number of accidents

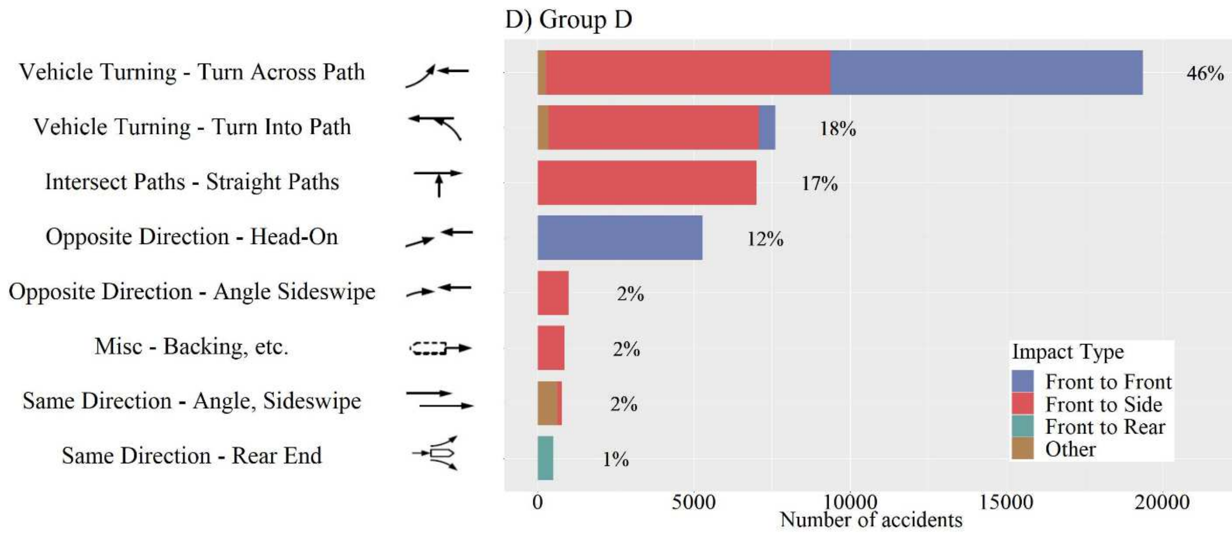


Figure 3. **Top 10 Accident scenarios for AIS2+ passenger vehicle to passenger vehicle accidents with colour code: Blue = Front to Front, Red = Front to Side, Green = Front to Rear, Brown = Other. A) Group A: All passenger vehicle to passenger vehicle AIS2+ accidents, initial population, no ADAS applied, N=2 005 362. B) Group B: All modern passenger vehicle to passenger vehicle AIS2+ accidents, no ADAS applied, N=215 184. C) Group C: Conservative residual with speed limitation of all modern passenger vehicle to passenger vehicle AIS2+ accidents, N=117 463. D) Group D: Optimistic residual with speed limitation of all modern passenger vehicle to passenger vehicle AIS2+ accidents, N=42 407.**

Analysis of accident type and deformation pattern of the remaining impacted vehicles
Accident scenarios are groups of accident types (see above) and breaking down Group D (remaining accidents from the optimistic rule set) further into accident types reveals that four predominate: Head On (12%), Turn Across Path (45%), Turn Into Path Opposite Direction (15%) and Straight Crossing Path (14%). Together these four accident types cover almost 90% of the group D accidents, almost three-quarters of which are intersection accidents.

Even though the intersection accidents are defined by accident type, how the vehicles actually impact each other will vary. To understand the deformation pattern for vehicles that had an AIS2+ injured occupant and were involved in an intersection accident, their CDC code was analysed and, based on their general area of deformation, they were divided into having frontal, left or right impacts. It was found that 54% sustained frontal impacts, 25% left impacts, and 19% right (Fig. 4), while 2% of these accidents were missing this type of information. The frontal, left and right cases were further investigated in four regards: the distribution of longitudinal or lateral location of the deformation; principal direction of force (PDOF); 90% cumulative delta velocity; and position of the injured occupant (Fig. 4).

All vehicles with frontal impacts had a distributed deformation involving 75% or more of the front with PDOF of between 11 and 1 o'clock, with the main part, 60%, at 12 o'clock. The 90% cumulative delta velocity is 39 km/h. 76% of the injured occupants are drivers and 23% are front seat passengers (see Fig. 4, left).

For the vehicles with left-side deformation, all vehicles sustained deformation to the part in front of the occupant compartment, i.e. the left wing, with 19% sustaining deformation to this part only. Just above half of the impacts have a PDOF that is perpendicular to the vehicle with the remainder being at 10 and 11 o'clock. The 90% cumulative delta velocity for the left-side impact is 45 km/h. 87% of the injured occupants are drivers and 5% are front seat passengers (see Fig. 4, mid).

Lastly, of the vehicles with right-side impacts, almost all (97%) had an impact that involved the occupant compartment. Most impacts have a PDOF of 2 o'clock. The 90% cumulative delta velocity for the right-side impact is 33 km/h. Of the injured occupants, 92% are drivers and 6% are front seat passengers (see Fig. 4, right).

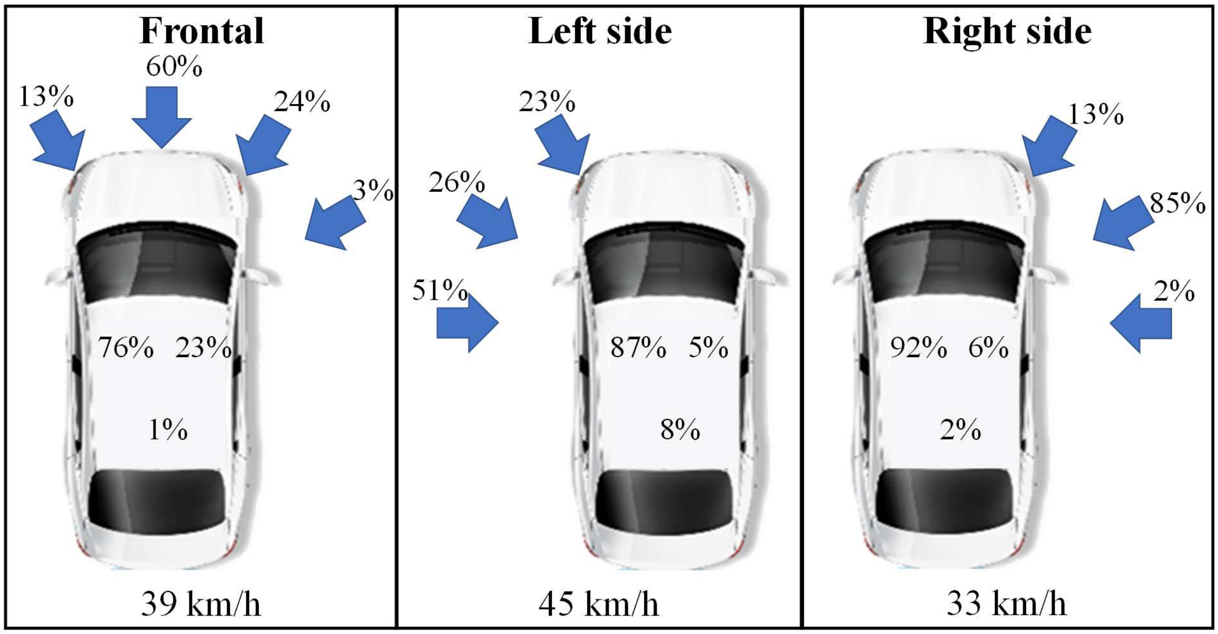


Figure 4. **Longitudinal and lateral deformation area, PDOF, 90% cumulative delta velocity and position of the injured occupant. Left: Frontal impacts. Mid: Left-side impacts. Right: Right-side impacts.**

DISCUSSION

We have presented estimates of the potential for accident reduction of current ADASs, and have included conservative estimates as well as future, optimistic estimates. The use of deterministic rules to create estimates for the effectiveness of an ADAS has a number of limitations but is straight forward, and data from the literature indicate that the calculated values are reasonable and sufficiently accurate for the purpose.

Applying the ADAS rulesets to the AIS2+ passenger vehicle to passenger vehicle accidents shows that to achieve a major change in the accident scenarios, the optimistic ruleset needs to be applied (Fig. 3). With the conservative ruleset, 55% of the accidents would still have occurred, compared to only 20% for the optimistic ruleset, and there is no clear change in the distribution of accident scenarios.

Factors that limit effectiveness

One way to analyse the ADAS effectiveness findings is to figure out what the limiting factor is: the speed range limitation, or the conservative ruleset, in which the limitations stem from either technical limitations of the sensors or vehicle dynamics. It was shown that both factors have a large effect on the total number of accidents avoided, and even more on individual ADAS effectiveness. This indicates that using more generous speed ranges can open the way for improvements in effectiveness, even without technical sensor improvements.

Single ADAS effectiveness and verification of the ADAS rulesets

The four ADASs that address most accidents are ESC, LKA, AEB crossing and Rear End AEB, each having an effectiveness of 25% or above in the most optimistic calculations. ESC has been mandatory in the US since 2010 in passenger vehicles [39] and when comparing accidents involving passenger vehicles older than MY 2010 to those involving newer passenger vehicles, 25% of the older passenger vehicles are coded as skidding prior to the accident compared to 5% of the newer passenger vehicles. This confirms that ESC has a positive effect in reducing accidents. LKA in this study shows an effectiveness of between 7% and 27%. This is much higher than that reported in other studies, which find an effectiveness of 1% to 3% [2, 4-6]. The NASS CDS variable queried here was PREEVENT equals to 10, 11, 12 and 13, which states whether the initial critical pre-crash event was that the passenger vehicle crossed a line (road lane marking) or ran off the road. This seems to be too optimistic a way to simulate LKA, given the findings from previous research, or, alternatively, could be seen as indicating potential for improvement. AEB crossing also gives very optimistic results unless the conservative ruleset with speed limitation is applied, which reduces its effectiveness to a level comparable with findings from the literature. This indicates potential in allowing higher speeds for the AEB crossing. The Rear End AEB gave a result that is directly comparable with the literature with an effectiveness of between 12% and 24%. However, for many of the ADASs there were no references found in the literature and it is therefore hard to evaluate whether a method with a deterministic ruleset is sufficiently accurate.

Need for a new assessment crash test?

When looking at the remaining intersection accidents, and comparing the observed deformation patterns with regulation and consumer ratings [40-41], we see that the full frontal and side impact conditions are well covered by existing crash tests. It is also noteworthy that angled right-side impacts with the driver getting injured represent 17% of the remaining cases, which is a similar impact condition to that of the upcoming Euro NCAP far side crash test [42].

However, it is important to note that both front and side impacts occur at speeds well below the current regulatory and rating speeds yet still generate AIS2+ injuries in the remaining accidents. This indicates that human variations and sensibility to loadings are not fully covered by the current crash dummies, injury criteria and injury thresholds. The remaining injuries are further analysed in terms of occupant characteristics, accident type and injured body region in [43].

We also see oblique front and side impacts remaining which are not covered in current regulation and consumer crash tests. Evaluating these types of impacts would require vehicle dynamics that are hard to replicate in current crash test labs. It is also likely that current crash dummies (developed for pure frontal or side impact) will not respond in a biofidelic way when the load direction is not purely frontal or from the side. New ways of evaluating crashes are therefore required; an alternative might be to use virtual methods and human body models (HBMs). HBMs are by design more valid for omnidirectional loading than current crash dummies. To take this step would require the development of a new virtual assessment method as proposed by [44-46]. Applying these types of impact conditions would most likely also demonstrate a need for new and improved occupant restraints to protect the occupants. Such improved restraint systems are likely to include both pre-crash and in-crash activated components. For example, motorised belts have the potential to keep occupants in position during lateral pre-crash manoeuvres [47] and inflatable shoulder belts have the potential to avoid the shoulder slipping out of the belt, preventing the head and thorax from impacting various components of the vehicle interior [48].

Limitations

The estimations were based on the NASS CDS database which contains data from accidents occurring in the United States. Accident distributions may therefore not be representative of other areas where the driving environment and vehicle fleet differ. In addition, the database may include some degree of misclassification of the key variables used, or omit pertinent data, or may not include sufficient details to determine the true conditions. One such variable is vehicle speed, which is often not reported. In this study, the speed limit of the location was used if the vehicle speed was not reported. This could be one reason for the relatively low level of effectiveness obtained for Intelligent Speed Adaptation (ISA) as the speed may, in the real event, have been higher.

Using deterministic rulesets has some inherent limitations. In our implementation, an accident can only be prevented or not. In reality, accidents that are not prevented can still be mitigated. When analysing accidents with AIS2+ injuries, this is important because reducing the impact speed might also reduce the injury severity. This cannot be captured in this study.

Another example of an inherent limitation is that an ADAS can intervene in driving through braking or steering, thereby affecting the trajectory of the vehicle, and in consequence may not only avoid accidents but also cause new types of accident or modify deformation distributions; again, this cannot be accounted for in this study.

For some of the level 2 ADASs, drivers need to accept and use the information given by the system and respond appropriately. Drivers may, in fact, switch the system off, not trust it or, in a critical situation, be overwhelmed by the information and not take appropriate action, thus reducing the effectiveness of the ADAS from its potential [49-50]. This can also be seen in the literature, with retrospective analyses often giving a more conservative response than prospective studies. The method used here does not take into account inappropriate driver action.

Implementation rate

This study has assumed that all passenger vehicles in the vehicle fleet are equipped with all ADASs. In reality, it takes a long time for high implementation rates of a given ADAS to be attained [51]. However, the implementation rates of new systems might speed up in the near future through software updates during a vehicle's lifetime. This can be done if a vehicle is equipped with sensors that recognise the driving conditions and driving environment and has the computing power to take the sensor data and make decisions [52].

CONCLUSIONS

The benefit of ADASs in reducing the number of passenger vehicle accidents is impressive. Still, even with a 100% implementation in passenger vehicles of the systems in use or under development today, accidents will occur. Occupant restraints, therefore, will still be needed to mitigate occupant's injuries into the future.

After applying today's known ADASs, 15 in total, to modern passenger vehicle accidents with severe injury outcome, almost 90% of the remaining accidents were found to fall into four accident types: Head On, Turn Across Path, Turn Into Path Opposite Direction and Straight Crossing Paths. The latter three are intersection accidents and represent as much as three quarters of all remaining accidents.

The detailed analysis of these remaining intersection accidents presented here indicates a need for new oblique impact conditions targeting lower impact speeds. These oblique impacts are a necessary complement to the existing and still relevant frontal and side crash tests to reduce the number of AIS2+ injuries. The impact conditions may be evaluated in virtual assessments with HBM and can guide the development of tomorrow's occupant restraint systems.

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APPENDIX A

Table 2.
ADAS accident prevention conservative rulesets

ADAS	Ruleset using NASS CDS variables	Ruleset in text
LKA, Lane Keep Assist Typical accident scenarios that can be avoided are running off the road, drifting into oncoming vehicle and side swipes.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREEVENT == (10,11,12,13) LANES != 99999 WEATHER == 0 or CLIMATE == (16,18,19) PREISTAB == 1 SURCOND != (3,4) PREEVENT !=5 PREEVENT != 6 TRAVELSP>= 60	Passenger vehicle Initial critical pre-crash event No missing lane marks No precipitation No skidding prior to accident No ice or snow on the road Good road condition No speeding Speed > 60 km/h
LCA, Lane Change Assist Typical accident scenarios that can be avoided are side swipes and rear end accidents when changing lane.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREMOVE == 15 LANES != 99999 WEATHER == 0 or CLIMATE == (16,18,19) PREISTAB == 1 SURCOND != (3,4) PREEVENT !=5 PREEVENT ! =6 speeding TRAVELSP >= 60)	Passenger vehicle Pre-event movement: Changing lane No missing lane marks No precipitation No skidding prior to accident No ice or snow on the road Good road condition No speeding Speed > 60 km/h
BSD, Blind Spot Detection Typical accident scenarios that can be avoided are side swipes and rear end accidents when changing lanes or merging.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREMOVE == (15,16) WEATHER == 0 or CLIMATE == (16,18,19) PREISTAB = 1 SURCOND != (3,4) PREEVENT != 5 TRAVELSP >= 10	Passenger vehicle Pre-event movement: Changing lane or merging accident No precipitation No skidding prior to accident No ice or snow on the road Good road condition Speed > 10 km/h
AFLS, Advanced Front Lighting System Typical accident scenarios that can be avoided are running off roads in dark conditions	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") LGTCOND == 2 ALIGNMNT == (2,3) WEATHER == 0 or CLIMATE == (16,18,19) PREISTAB == 1 PREEVENT != 6	Passenger vehicles Light condition equal to dark Curve to right or left No precipitation No skidding prior to accident No speeding
ESC, Electronic Stability Control Typical accident scenarios that can be avoided are skidding accidents.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREISTAB == (2,3,4) MY =< 2010 SURCOND ! = (3,4) PREEVENT != 5 PREEVENT != 6.	Passenger vehicles Skidding prior to accident Model year earlier than 2010 No ice or snow on the road Good road condition No speeding
AEB Rear End, Autonomous Emergency Braking Rear End	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") GADEV1 == "R"	Passenger vehicles General Area of Damage equal to rear

 Typical accident scenarios that can be avoided are impacts to rear end of vehicle in same lane.	GADEV2 == "F" WEATHER == 0 or CLIMATE == (16,18,19) SURCOND != (3,4) PREEVENT != 5 PREISTAB == 1 (TRAVELSP-TRAVELSP_OPP) <= 70	General Area of Damage equal to front No precipitation No ice or snow on the road Good road condition No skidding prior to accident Relative speed < 70 km/h
AEB reversing, Autonomous Emergency Braking Reversing Typical accident scenarios that can be avoided are impacts to another vehicle when reversing.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") ACCTYPE == (92, 93, 98, 99) WEATHER == 0 or CLIMATE == (16,18,19) TRAVELSP<= 30	Passenger vehicles Backing accidents No precipitation Speed < 30 km/h
AEB Crossing, Autonomous Emergency Braking Crossing Typical accident scenarios that can be avoided are crossing and turning at intersections.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREEVENT == (15,16,17,65,66,67,68) WEATHER == 0 or CLIMATE == (16,18,19) SURCOND != (3,4) PREEVENT !=5 PREISTAB == 1 TRAVELSP <= 30.	Passenger vehicles Initial critical pre-accident event crossing scenarios No precipitation No ice or snow on the road Good road condition No skidding prior to accident Speed < 30 km/h
Emergency Steering (ES) upon risk of head-on accident Typical accident scenarios that can be avoided are head on scenarios where the driver is not performing any maneuverer.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") GADEV1 == "F" ? SHL == (“L”,”R”) MANEUVER != (6-9,11,12) WEATHER == 0 or CLIMATE == (16,18,19) SURCOND != (3,4) PREEVENT != 5 PREISTAB == 1 TRAVELSP <= 100 & TRAVELSP >= 40	Passenger vehicles General Area of Damage equal to front Specific longitudinal or lateral deformation location equals to left or right Driver is not initiating a maneuverer No precipitation No ice or snow on the road Good road condition Not skidding prior to accident 40km/h < Speed < 100 km/h
Driver initiated Evasive steering assist Typical accident scenarios that can be avoided are head on scenarios where the driver is not steering enough to avoid the accident.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") GADEV1 == "F" MANEUVER == (6-9,11,12 WEATHER == 0 or CLIMATE == (16,18,19) SURCOND != (3,4) PREEVENT != 5 PREISTAB == 1 TRAVELSP <= 70 & TRAVELSP >= 20	Passenger vehicles General Area of Damage first vehicle equal to front Driver is initiating a manoeuvre No precipitation No ice or snow on the road Good road condition No skidding prior to accident 20km/h < Speed < 70 km/h
DMS, Driver drowsiness/distraction monitoring	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") DRIVDIST == 11 PREEVENT ! = 6	Passenger vehicles Driver sleepy No speeding

All types of accidents where driver is distracted can be addressed.		
ISA, Intelligent Speed Adaptation Accidents where the cause is speeding can be addressed	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREEVENT == 6 WEATHER == 0 or CLIMATE == (16,18,19) SURCOND != (3,4) PREEVENT !=5 PREISTAB == 1	Passenger vehicles Speeding accident No precipitation No ice or snow on the road Good road condition No skidding prior to accident
TJA, Traffic jam assist Typical accident scenarios that can be avoided are low speed side swipes and rear end impacts.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") GADEV1 == ("F", "L", "R") TRAFFLOW == (1, 2, 3) RELINTER == (0, 3) WEATHER == 0 or CLIMATE == (16,18,19) SURCOND != (3,4) PREEVENT != 5 PREISTAB == 1 TRAVELSP <= 65	Passenger vehicles General Area of Damage first vehicle equal to front, left or right Divided road with and without barrier Traffic way not related to junction No precipitation No ice or snow on the road Good road condition No skidding prior to accident Speed < 65 km/h
HA, Highway Assist Typical accident scenarios that can be avoided are high speed side swipes and rear end impacts on highways.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") GADEV1 == ("F", "L", "R") SPLIMIT > 50mph (80km/h) RELINTER == (0, 3) TRAFFLOW== (1,2,3) WEATHER == 0 or CLIMATE == (16,18,19) SURCOND != (3,4) PREEVENT !=5 PREISTAB == 1 PREEVENT != 6 TRAVELSP >= 80	Passenger vehicles General Area of Damage first vehicle equal to front, left or right Speed limit > 50 mph Traffic way not related to junction Divided road with or without barrier No precipitation No ice or snow on the road Good road condition No skidding prior to accident No speeding Speed > 80 km/h
Alcohol interlock Prevents the driver from driving when affected by alcohol.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") DRINKING == 1 ALCTEST > 8 & ALCTEST< 200	Passenger vehicles Police reported alcohol presence Alcohol test result

APPENDIX B

Table 3.
ADAS accident prevention optimistic rulesets

ADAS	**Ruleset using NASS CDS variables**	**Ruleset in text**
LKA, Lane Keep Assist Typical accident scenarios that can be avoided are running off the road, drifting into oncoming vehicle and side swipes.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREEVENT == (10,11,12,13) TRAVELSP>= 60	Passenger vehicle Initial critical pre-crash event Speed > 60 km/h
LCA, Lane Change Assist Typical accident scenarios that can be avoided are side swipes and rear end accidents when changing lane.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREMOVE == 15 TRAVELSP >= 60)	Passenger vehicle Pre-event movement Changing lane Speed > 60 km/h
BSD, Blind Spot Detection Typical accident scenarios that can be avoided are side swipes and rear end accidents when changing lanes or merging.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREMOVE == (15,16) TRAVELSP >= 10	Passenger vehicle Pre-event movement Changing lane change or merging accident Speed > 10 km/h
AFLS, Advanced Front Lighting System Typical accident scenarios that can be avoided are running off roads in dark conditions	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") LGTCOND == 2 ALIGNMNT == (2,3)	Passenger vehicles Light condition equal to dark Curve to right or left
ESC, Electronic Stability Control Typical accident scenarios that can be avoided are skidding accidents.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREISTAB == (2,3,4) MY =< 2010	Passenger vehicles Skidding prior to accident Model year earlier than 2010
AEB Rear End, Autonomous Emergency Braking Rear End	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") GADEV1 == "R" GADEV2 == "F"	Passenger vehicles General Area of Damage equal to rear

Typical accident scenarios that can be avoided are impacts to rear end of vehicle in same lane.	(TRAVELSP-TRAVELSP_OPP) <= 100	General Area of Damage equal to front Relative speed < 100 km/h
AEB reversing, Autonomous Emergency Braking Reversing Typical accident scenarios that can be avoided are impacts to another vehicle when reversing.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") ACCTYPE == (92, 93, 98, 99) TRAVELSP<= 30	Passenger vehicles Backing accidents Speed < 30 km/h
AEB Crossing, Autonomous Emergency Braking Crossing Typical accident scenarios that can be avoided are crossing and turning at intersections.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") PREEVENT == (15,16,17,65,66,67,68) TRAVELSP <= 60	Passenger vehicles Initial critical pre-accident event crossing scenarios Speed < 60 km/h
Emergency Steering (ES) upon risk of head-on accident Typical accident scenarios that can be avoided are head on scenarios where the driver is not performing any maneuverer.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") GADEV1 == "F" ? SHL == (“L”,”R”) MANEUVER != (6-9,11,12) TRAVELSP <= 140 & TRAVELSP >= 40	Passenger vehicles General Area of Damage equal to front Specific longitudinal or lateral deformation location equals to left or right Driver is not initiating a manoeuvre 40km/h < Speed < 140 km/h
Driver initiated Evasive steering assist Typical accident scenarios that can be avoided are head on scenarios where the driver is not steering enough to avoid the accident.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") GADEV1 == "F" MANEUVER == (6-9,11,12 TRAVELSP <= 100 & TRAVELSP >= 20	Passenger vehicles General Area of Damage first vehicle equal to front Driver is initiating a manoeuvre 20km/h < Speed < 100 km/h
DMS, Driver drowsiness/distraction monitoring All types of accidents where driver is distracted can be addressed.	BODYTYPE == ("Cars","SUV","Van","Pickup_Truck") DRIVDIST == 3-8,11,12,13	Passenger vehicles Driver distraction

<table>
<tr><td>ISA, Intelligent Speed Adaptation

Accidents where the cause is speeding can be addressed</td><td>BODYTYPE ==
("Cars","SUV","Van","Pickup_Truck")
PREEVENT == 6</td><td>Passenger vehicles

Speeding accident</td></tr>
<tr><td>TJA, Traffic jam assist

Typical accident scenarios that can be avoided are low speed side swipes and rear end impacts.</td><td>BODYTYPE ==
("Cars","SUV","Van","Pickup_Truck")
GADEV1 == ("F", "L", "R")

TRAFFLOW == (1, 2, 3)

RELINTER == (0, 3)
TRAVELSP <= 65</td><td>Passenger vehicles

General Area of Damage first vehicle equal to front, left or right
Divided road with and without barrier
Traffic way not related to junction
Speed < 65 km/h</td></tr>
<tr><td>HA, Highway Assist

Typical accident scenarios that can be avoided are high speed side swipes and rear end impacts on highways.</td><td>BODYTYPE ==
("Cars","SUV","Van","Pickup_Truck")
GADEV1 == ("F", "L", "R")

SPLIMIT > 50mph (80km/h)
RELINTER == (0, 3)
TRAFFLOW== (1,2,3)
TRAVELSP >= 80</td><td>Passenger vehicles

General Area of Damage first vehicle equal to front, left or right
Speed limit > 50 mph
Traffic way not related to junction
Divided road with or without barrier
Speed > 80 km/h</td></tr>
<tr><td>Alcohol interlock

Prevents the driver from driving when affected by alcohol.</td><td>BODYTYPE ==
("Cars","SUV","Van","Pickup_Truck")
DRINKING == 1
ALCTEST > 8 & ALCTEST< 200</td><td>Passenger vehicles

Police reported alcohol presence
Alcohol test result</td></tr>
</table>

PROSPECTIVE EFFECTIVENESS ASSESSMENT OF ROAD VEHICLE AUTOMATION BASED ON DRIVER PERFORMANCE MODELS

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ABSTRACT

One of the major challenges for enabling market introduction of automated driving is to identify risks and benefits of these functions. For this purpose, a new framework for assessing the safety impact of automated driving functions (ADFs) has been investigated. This framework is based on accident- and field operational test- (FOT-) data while using simulations for assessment of ADFs with respect to a certain baseline. According to the German Ethics Commission for Automated and Connected Driving, this baseline has to be human manual driver performance. For modelling of this baseline in simulations, so-called driver performance models are introduced in this publication and incorporated in an overall framework for effectiveness assessment.

The main idea of the developed framework is that the types of driving scenarios, respectively physical accident constellations, do not change with automated driving. However, since ADFs are continuously controlling the behavior of the vehicle, it is possible that ADFs will get involved less frequently in accident scenarios playing a major role at human driving, e.g. rear-end accident scenarios. On the other hand, it is likely that other previously irrelevant accident types will rise. Consequently, the frequency of occurrence and the severity of the addressed driving scenarios may change with automated driving although the types of driving scenarios stay the same. To investigate the change of severity in a driving scenario, accident re-simulations are used. The changes in frequency of occurrence of driving scenarios are analyzed by using traffic simulations. In this work, so-called driver performance models are introduced for modelling human baseline in accident re-simulations. Key findings concerning the structure of these driver performance models are presented.

The developed method and models are applied on two generic ADFs, a generic “Motorway-Chauffeur” (SAE level 3) and a generic “Urban Robot-Taxi” (SAE level 4). The results indicate that, e.g. a Motorway-Chauffeur at a market penetration of 50 % has a potential for reducing about 31 % of all accidents on German motorways resulting in personal injury. This equals 2 % of all accidents on German roads.

INTRODUCTION

In the last decade various automotive functions for supporting the driver have been developed. These so-called advanced driver assistance systems (ADAS) are supporting the driver on different levels of the driving task. Driven by recent developments in algorithms for environment perception and decision making, the ultimate goal of vehicle automation seems to be a solvable task as shown by several demonstrations [1].

However, due to an increasing complexity of decision making algorithms of these complex functions, identifying benefits and drawbacks will be challenging. Hence, new safety effectiveness assessment methods have to be designed which are based on detailed accident-, FOT- and simulation data and that are assessing the ADFs with respect to a certain baseline. Since automated driving will not be able to avoid all accidents on roads, e.g. due to the misbehavior of other traffic participants and physical limits, a baseline for assessment has to be defined. According to the German Ethics Commission for Automated and Connected Driving,

> *"[..] the licensing of automated systems is not justifiable unless it promises to produce at least a diminution in harm compared with human driving, in other words a positive balance of risks [..]"* [2]

Consequently, the reference for safety impact assessment needs to be human driver performance. In order to assess ADFs with respect to human driver performance, this paper introduces a method for safety effectiveness assessment. The basic idea of this framework is that the types of accident constellations and thus driving scenarios do not change with automated driving. However, the severity and frequency of occurrence of these driving scenarios may change with automated driving.

BACKGROUND

For effectiveness assessment of (advanced) driver assistance systems with environment perception, many different methods have been used in the past. All these methods have in common, that they compare driving situations without the system with driving situations, in which the system is activated. One valid approach for determining the effectiveness of ADAS is the accident re-simulation on basis of in-depth accident data, e.g. as applied in [3]. In this case, reconstructed accident scenarios from detailed accident data, such as the German-in-depth accident database (GIDAS) [4], are simulated with and without the considered function. The difference in performance in the situation, e.g. probability of severe injuries, is considered as the benefit of the function. An alternative to re-simulation of single accident situations is provided by stochastic approaches describing the situational variables of a driving scenario by Monte Carlo sampling of synthetic driving situations from probability distributions as presented in [5]. A disadvantage of accident re-simulations is that new induced driving scenarios by automated driving cannot be considered, because these are not represented in the accident data. Another approach for safety impact assessment based on recorded data is the field operational test (FOT) as presented in [5]. Here, huge amounts of driving data without function (control condition) and with activated function (experimental condition) are collected. The effectiveness of the considered function is analyzed by investigating the change in frequency of occurrence of incidents and near-crashes compared to the baseline. For effectiveness assessment of a function in defined situations, driving simulator studies can be used as well. This approach allows a detailed investigation of human driver performance with and without the considered function as demonstrated in [6], but requires a selection of situation parameters to be presented to the drivers. As described previously, ADFs need to be assessed in the whole entity of possible driving situations in their operational design domain. Hence, simulations of these functions in the whole traffic are a promising approach as presented in [7]. However, validation of these simulations remains challenging because of the variety and complexity of models necessary for safety impact assessment.
Based on the available methods presented previously, a suitable method for assessing the effectiveness of road vehicle automation is defined. Although accident re-simulation based on detailed accident data is a valid approach, it will not be suitable for assessing ADFs since this approach is based on previously recorded detailed accident data from human driving. In order to identify new driving situations induced by ADFs, a FOT would be suitable. However, considering the necessary resources difficult to realize. Thus, a holistic approach including accident re-simulations for investigation of changes in severity and traffic simulations for assessing changes in frequency of driving scenarios is developed for effectiveness assessment of ADFs.

FRAMEWORK FOR EFFECTIVENESS ASSESSMENT

Built on previously recorded accident- and FOT-data and extended by simulation data, the effectiveness of a defined ADF is assessed by considering the changes in severity and frequency of addressed driving scenarios, see Figure 1. Based on a definition of the ADF and the addressed driving scenarios the effectiveness fields – all addressed accidents and relevant driving situations – are identified in the input data. To this end, the absolute number of accidents per driving scenario is extracted form accident statistics for upscaling. By this, the results derived from detailed data can be projected upon the effectiveness on a national level. The parameters spaces (e.g. probability density function of velocity of involved traffic participants) are extracted from in-depth accident- and FOT-data for determination of the changes in severity of driving scenarios due to the function.

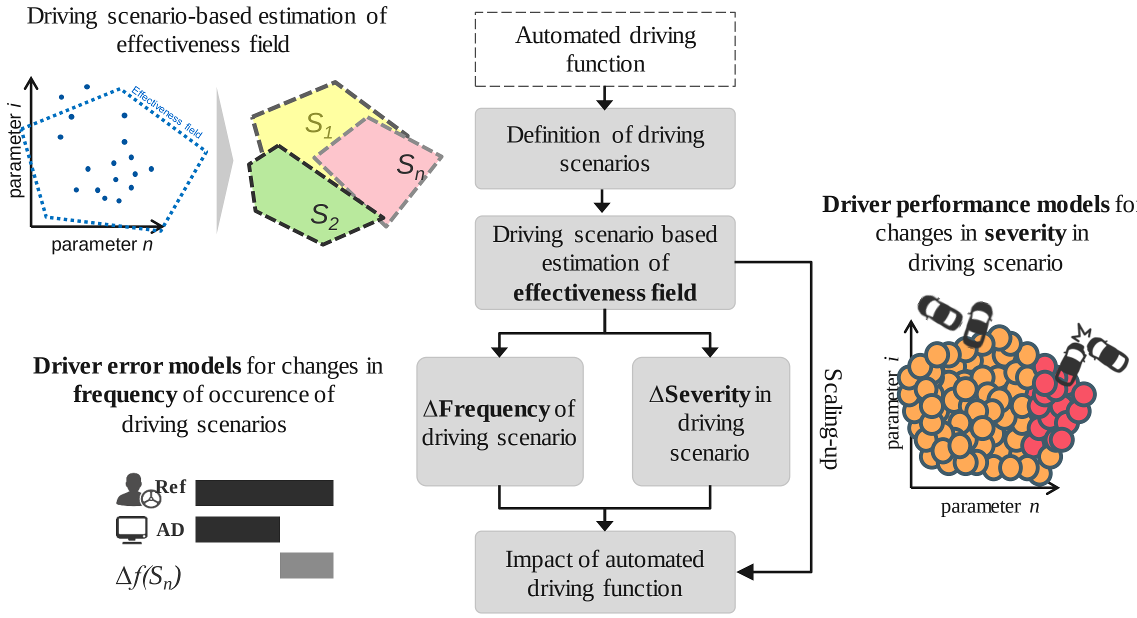


Figure 1. Framework for Effectiveness Assessment of Road Vehicle Automation.

Afterwards, the changes in frequencies of occurrence of the defined driving scenarios are assessed by using traffic simulations. Here, so-called driver error models are used to model critical driving situations in traffic simulations. To identify the changes in severity in the defined driving scenarios, these are simulated with and without ADF while the reference performance is modelled by human driver performance models. The effectiveness E of an ADF in terms of safety can be derived based on a consideration of the accident risk $R_{Scenario}$ by the severity $I_{Scenario}$ and the frequency of occurrence $f_{Scenario}$ for each driving scenario.

$$R_{Scenario} = I_{Scenario} \cdot f_{Scenario}$$

The effectiveness E in a scenario i is defined as the difference of risks ΔR_i.

$$E_i = \Delta R_i = R_{ADF,i} - R_{Human,i}$$

Substituting the risk R_i by severity I_i and frequency f_i results in:

$$E_i = I_{ADF,i} \cdot f_{ADF,i} - I_{Human,i} \cdot f_{Human,i}$$

With the change in severity $\Delta I = I_{ADF}/I_{Human}$ and the change in frequency of occurrence $\Delta f = f_{ADF}/f_{Human}$, the effectiveness E is derived for all scenarios n by:

$$E = \sum_{i=1}^{n} I_{Human,i} \cdot f_{Human,i} \ (\Delta I_i \cdot \Delta f_i - 1)$$

Definition of Driving Scenarios based on Accident Type Catalogue

The developed framework assumes that the defined driving scenarios cover all physical possible accidents constellations. For this purpose, the driving scenarios are derived from the German accident type catalogue [9] that includes a classification scheme for all accidents by a three-digit code built upon decades of experience by the German police. In consequence, almost all accident constellations that are physical possible are included in this catalogue. The considered driving scenarios are derived from this catalogue by assigning each three-digit accident types $UTYP3$ to a driving scenario. This process is illustrated on the example of a "cut-in" driving scenario in Figure 2.

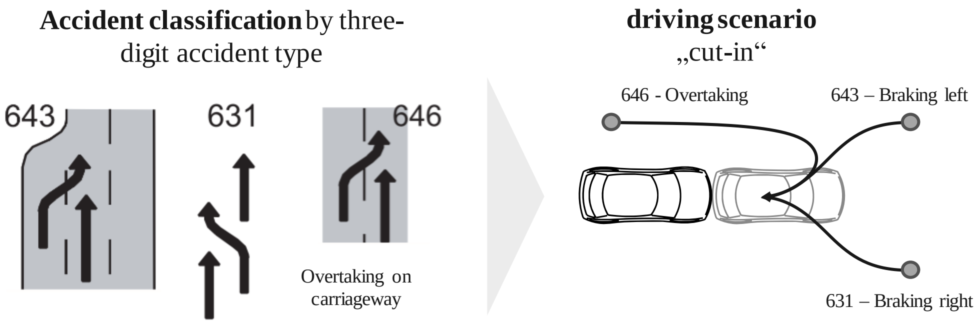
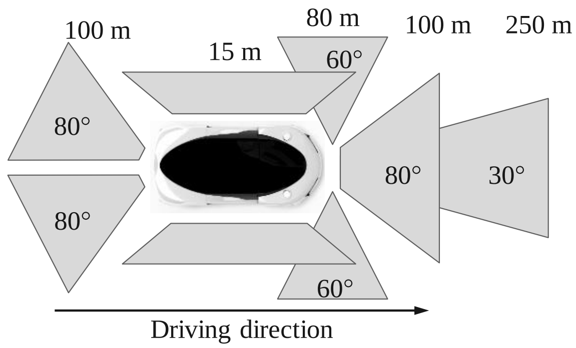


Figure 2. Derivation of driving scenarios based on three-digit accident classification on the example of a "cut-in" driving scenario.

Description of Automated Driving Function

The previously derived driving scenarios are used to describe the functional scope of the assessed ADF. In this sense, to describe an Urban Robot-Taxi, only driving scenarios on urban roads within the operational design domain of the Urban Robot-Taxi will be linked to the function. In addition, functional limitations, e.g. due to environmental conditions (fog, heavy rain, snow) are included in the description of the ADF and can be used to limit the addressed accidents. An exemplary description of an Urban Robot-Taxi is given in Table 1.

Table 1.
Description of automated driving functions and their operational design domain (ODD) on the example of the Urban Robot-Taxi.

Parameter	***Value***
Name	Urban Robot-Taxi
Level of automation according to [SAE16]	4
Sensor view range	
Adressed driving scenarios	• Driving without influence from leading vehicle • Approaching static object • Approaching leading vehicle • Approaching lateral moving object • Approaching traffic jam • Cut-in • Lane change • Turning • Crossing • U-Turn
Road types and speed range	• Inside city-limits: 0 - 50 km/h
Functional limitations	• None

Driving Scenario-based Identification of Effectiveness Fields

After describing the assessed ADFs including their applicable driving scenarios, the effectiveness fields – the accidents and driving situations where the ADFs have a potential impact - are estimated. For in-depth accident data and national accident statistics, the three-digit accident type can be used to select the driving scenarios. FOT-data is not labelled with a three-digit accident type as it contains time series data. To cluster FOT-data, the driving scenario classification algorithms based on machine learning introduced in [9] can be used. Here, the relative motion included in the three-digit accident type is used to detect the driving scenarios in time series data.

The effectiveness fields can be limited regarding road types and limitations of the ADFs. The classification of driving scenarios results in a number of accidents per driving scenario (see Figure 4) that enables to investigate the change in frequency of the driving scenarios as well as the parameter spaces necessary to determine the change in severity per driving scenario (see Figure 5). Figure 3 illustrates the whole definition process of a driving scenario-based estimation of the effectiveness fields exemplified for a "cut-in" driving scenario.

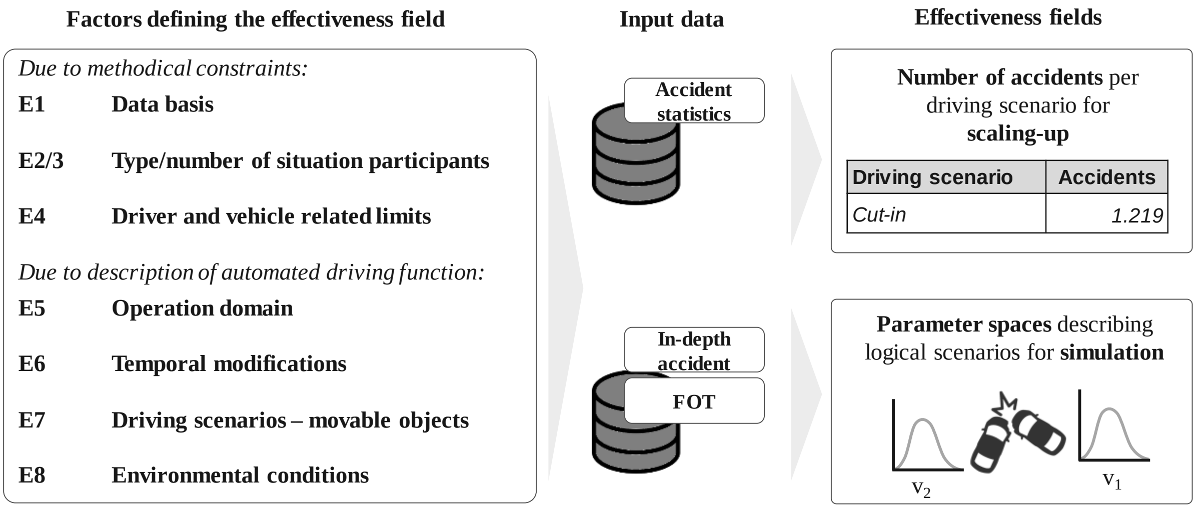


Figure 3. Process for driving scenario-based estimation of effectiveness fields due to methodical constraints and description of the ADF. The effectiveness fields include the number of accidents as well as the parameter spaces per driving scenario.

For example, from all accidents with personal injuries A(P) occurring within city limits in Germany (70 % of all accidents), an Urban Robot-Taxi is addressing 66 %. The other accidents in the domain cannot be addressed due to the reason that driving scenarios are not covered by the functional scope of the automated driving function (14 %), driver and vehicle related limits such as technical failures or alcohol use (3 %) and no car involvement in the accident (17 %), see Figure 4.

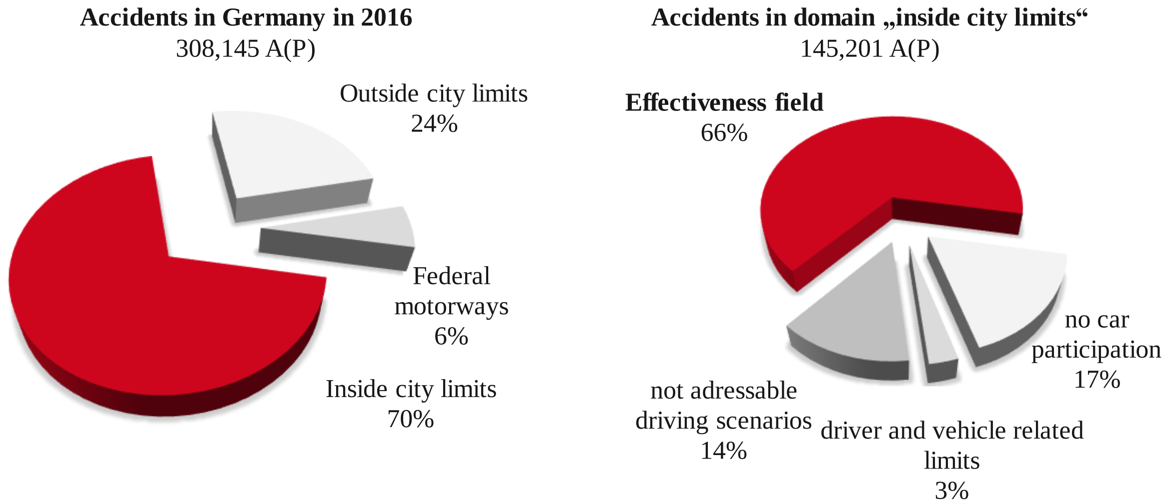


Figure 4. Numbers of addressed accidents resulting from effectiveness field of Urban Robot-Taxi in German national accident statistics DESTATIS.

Next to the number of accidents resulting from the effectiveness fields, the parameter spaces describing the driving scenarios for estimation of the changes in severity are extracted from FOT- and in-depth accident data. The parameter spaces are represented as Kernel Density Estimation (KDE) obtained from the probability density functions of situational variables of in-depth accident data and FOT-data. Using Monte-Carlo sampling techniques according to [11], concrete scenarios that can be simulated are randomly "drawn" from the logical scenarios. Exemplary parameter spaces of situational variables such as "ego velocity" describing the logical scenario "cut-in" are presented in Figure 5.

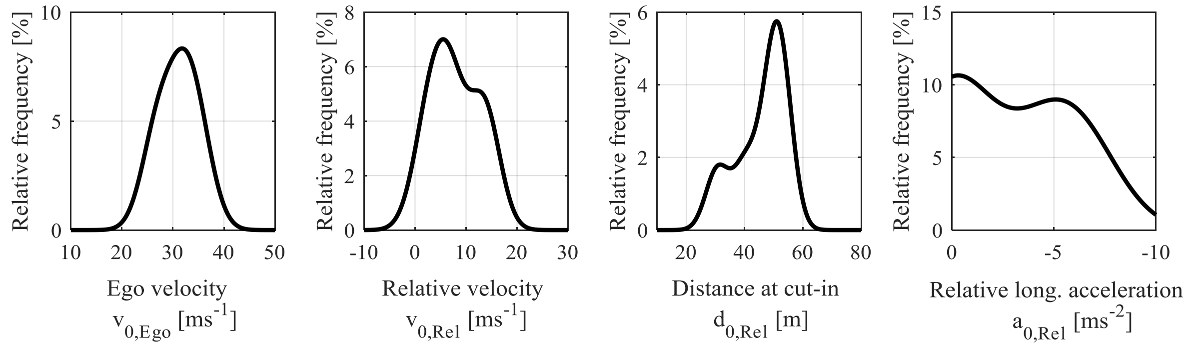


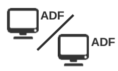
Figure 5. Parameter spaces for describing the logical scenario "cut.in" for estimation of the changes in severity by simulation.

Both number of accidents per driving scenario and the parameter spaces describing the driving scenario for simulation are used in the following to estimate the effectiveness in terms of a change in accidents per driving scenarios.

Driver Error Models in Traffic Simulations for Changes in Frequency of Driving Scenarios

Traffic simulations are used to identify the changes in frequency of occurrence Δf of driving scenarios. For considering the effects within mixed traffic conditions of human driven and automated vehicles, it is distinguished whether a human driven or an automated vehicle has induced or "caused" a certain driving scenario. For example, a human driver cutting-in in front of the automated vehicle can cause a "cut-in" driving situation. In this case, the human driver induced the driving situation while the automated vehicle was involved in it. Based on this principle, a classification scheme for driving situations is introduced, see Table 2.

Table 2.
Types of interactions in driving scenarios in mixed-traffic conditions

Type of interaction	Type of vehicle driving scenario **induced** by	Type of vehicle **involved:**	Illustration
HUM-HUM	Human driver	Human driver	
HUM-ADF	Human driver	Automated driving function	
ADF-HUM	Automated driving function	Human driver	
ADF-ADF	Automated driving function	Automated driving function	

The changes of frequencies for all four defined types of interactions are analyzed by using traffic simulation data of human driven and automated vehicles for several market penetration rates of automated vehicles. For traffic simulation, a 26 km long section of the German motorway A2 around Hanover is used, see Figure 7 (left).

Modelling the behavior of human traffic participants is one of the most crucial parts in traffic simulations. Although a tremendous variety of driver models is available [12], [13], [14] the main purpose of these existing models are traffic flow investigations and not investigations related to traffic safety. The main limitation of the available models is that they do not require to reflect human behavior in critical and uncommon situations but that they have been designed to represent the trained "normal" driving behavior. Special driver models are therefore needed to realistically represent human driving behavior in incident situations.

Consequently, so-called driver error models are developed that are modelling human errors causing incident driving situations in traffic simulations.

To model how humans induce incident situations in traffic simulations, the principles leading to human errors have to be incorporated in the simulation models. The existing driver models, e.g. [14], that assume an ideal recognition and decision of humans, are extended by probabilistic error models that represent uncertainties in recognition and decision. According to the findings of [15], human drivers are able to perceive Time-to-Collision (TTC) and Time Headway (THW) to other objects in their surroundings. For example, the human eye is capable of perceiving the TTC to an object by detecting changes in its retinal projection [15]. A similar principle is assumed for perceiving the THW [15]. For modelling driver errors, it is assumed that the perception of TTC and THW is afflicted with uncertainties. Therefore, the perceived $TTC_{perceived}$ might differ from the real TTC_{real} in a driving situation ending up in a misjudgment of the situation by the driver that can lead to an incident situation, see Figure 6.

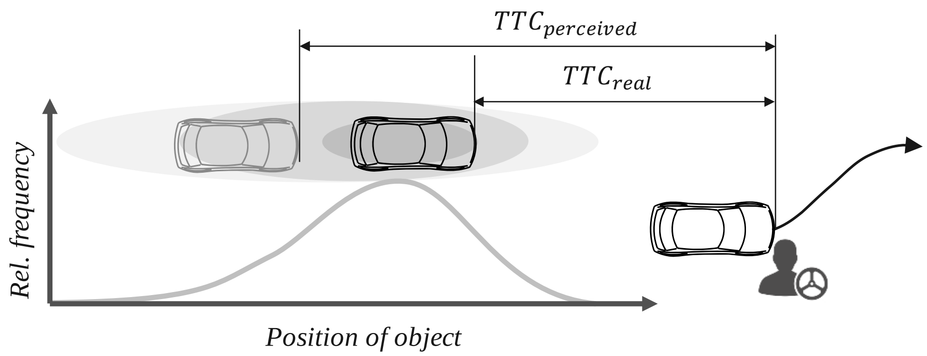


Figure 6. Probabilistic modelling of uncertainties in recognition and decision for the induction of incident driving scenarios.

It is assumed that these uncertainties in recognition of other traffic participants of the driving scenario are gamma distributed. Based on Monte-Carlo sampling [11] of the gamma probability distributions, for each explicit driving situation occurring in simulation uncertainties in THW and TTC can be generated. While most of the sampled uncertainties will be few and not lead to incident situations, potential incident "cut-in" driving situations will occur according to the probability for high uncertainties represented in the gamma probability distributions. The resulting exemplary changes of frequency for an "approaching leading vehicle" driving scenario are shown in Figure 7 (right).

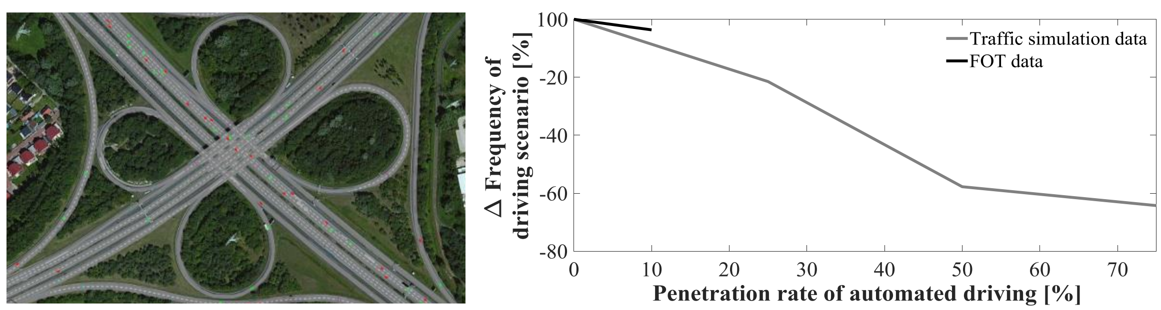


Figure 7. Traffic scenario for estimation of changes in frequencies of driving scenarios (left) and change of frequency of "approaching leading vehicle" driving scenario (right).

Driver Performance Models for Changes in Severity of Driving Scenarios

If an automated vehicle gets involved in an incident driving situation, the changes in severity ΔI induced by the ADF are assessed. For this purpose, driving situations with explicit parameters are simulated with an ADF and with human driver performance models as a reference. The process is illustrated in Figure 8. The difference in performance between human and ADFs is defined as the change in severity. This is measured by the likelihood for severe injuries (MAIS2+) that is derived by injury risk curves based on the relative collision speed. The parameter spaces resulting from the driving scenario-based estimation of effectiveness fields (see Figure 5) are used to generate concrete scenarios with explicit parameters that can be simulated.

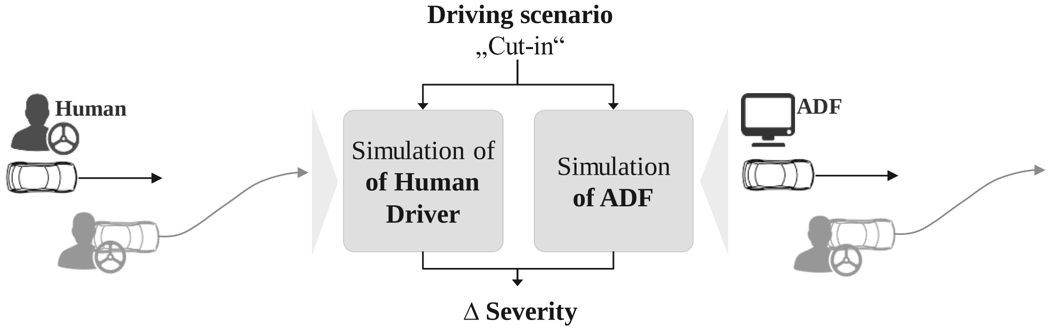


Figure 8. Simulation method for estimating the changes in severity in driving scenarios on the example of a “cut-in” driving scenario.

For human reference performance, quantitative driver models for modelling human driving performance in defined driving scenarios from [16] are used. The structure of the models is split into perception, information processing and action. Human drivers are acting in unexpected driving situations based on their knowledge rather than on the actual situational variables according to [17]. Thus, human action is modelled with an initial feedforward impulse and a feedback control to stabilize the vehicle afterwards. The initial feedforward reaction is described by reaction time and -intensity and is sampled from gamma distributions representing a driver population. The structure of the developed driver performance models is validated based on simulator studies with 35 test subjects [16]. Finally, the developed models are verified based on in-depth accident data for ensuring that they can be applied for the respective driving scenario. The structure of the models is presented in Figure 9.

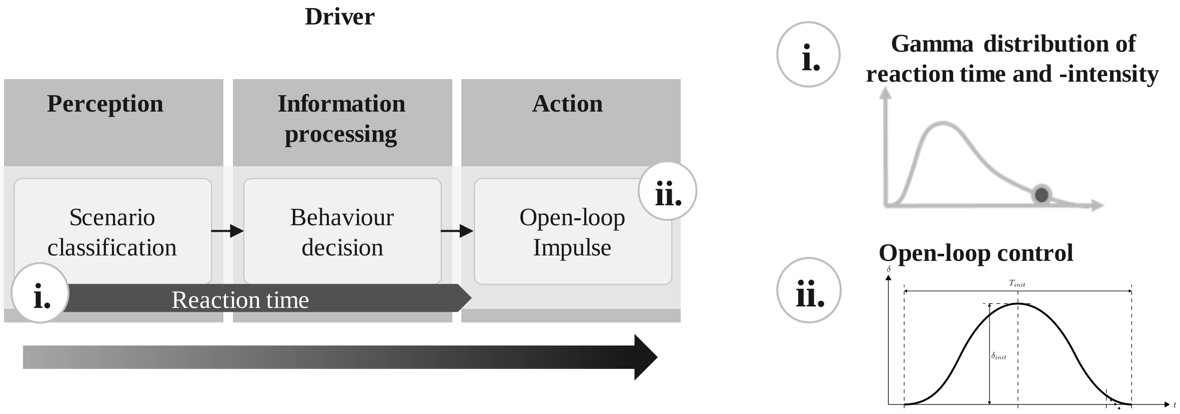


Figure 9. Framework for human driver performance models consisting of perception, information processing and action.

These driver performance models are developed for all covered driving scenarios. For example, in the driving scenario “cut-in” the likelihood for severe injuries (MAIS2+) can be reduced by 42.3 % by the Motorway-Chauffeur.

Effectiveness of Automated Driving Function

Finally, the effectiveness of the automated driving function in the effectiveness field is derived based on the changes in frequencies of all driving scenarios and the changes in severity in all driving scenarios. This process is illustrated on the example of the “cut-in” driving scenario at 50 % market penetration of the Motorway-Chauffeur.

The results of the analysis of changes in frequency of occurrence based on traffic scenario level showed a decrease in accidents by 28.2 %, as presented in Figure 10. According to the traffic simulation (see Section 7.3), human drivers induced all resulting in 71.8 % of accidents on traffic scenario level. From all accidents on traffic scenario level induced by human drivers, 43.5 % are with involvement of a human driver (“HUM-HUM”) while the remaining incidents are with involvement of an ADF (“HUM-ADF”)

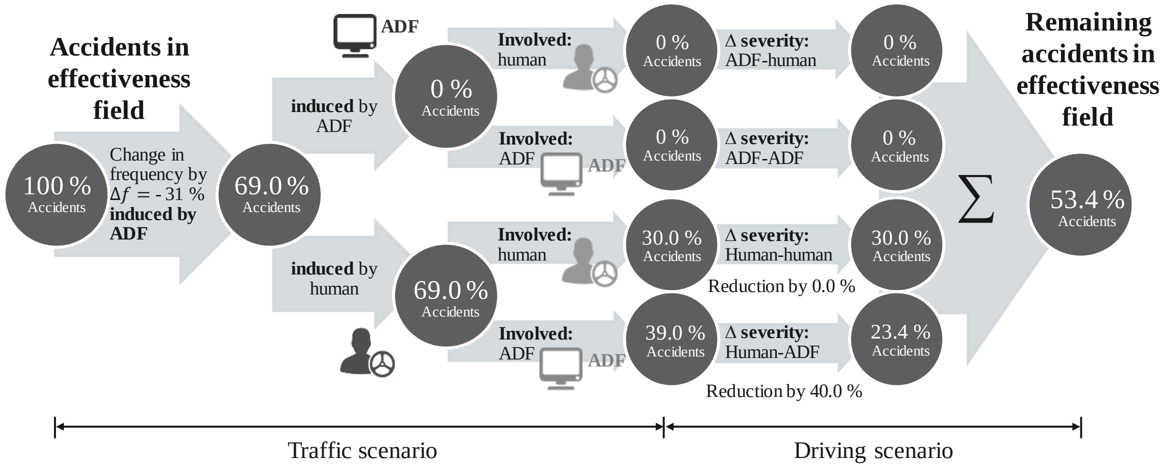


Figure 10. Effectiveness of an ADF on traffic- and driving scenario level on the example of a "cut-in" driving scenario and a market penetration of 50 %.

In the next step, the changes in severity on driving scenario level are analyzed. According to the results of the re-simulation (see Section 7.4), all accidents with involvement of ADF can be reduced by 40 % to 23.4 % of accidents. For the case in which only human drivers were involved, the 31.2 % of accidents do not change with ADF. In total, from the initial 100 % of accidents, the ADFs reduces to 53.4 % of accidents which consequently results in an effectiveness of 46.6 % for the driving scenario "cut-in" at a market penetration rate of 50 %.

RESULTS

The simulation-based estimated effectiveness for the different ADFs is scaled-up on national level for the Federal Republic of Germany. Since the effectiveness of the ADF is determined based on detailed GIDAS accident data that is only available for a limited geographical region in Germany the effects have to be corrected and projected by using the national accident statistics. For this purpose, the correction factors per driving scenario are derived based on the frequency of occurrence of the defined driving scenarios in GIDAS detailed accident and national accident statistics by using the three-digit accident type. On basis of the Urban Robot-Taxi the results presented in Figure 8 will be explained. In the operation domain of the Urban Robot-Taxi 205,321 accidents with personal injuries occurred in 2016. Since only ADFs of passenger cars are considered, just those accidents can be addressed where at least one passenger car is among the first two participants of the accidents. These 36,486 accident cannot be addressed (see light gray area). Furthermore, 47,487 accidents per year are outside the functional limits of the Urban Robot-Taxi (see dark gray area) due to not addressed driving scenarios, alcohol and drug use, technical failures and limitations of the Urban Robot-Taxi (rain, fog, ice, construction sites).

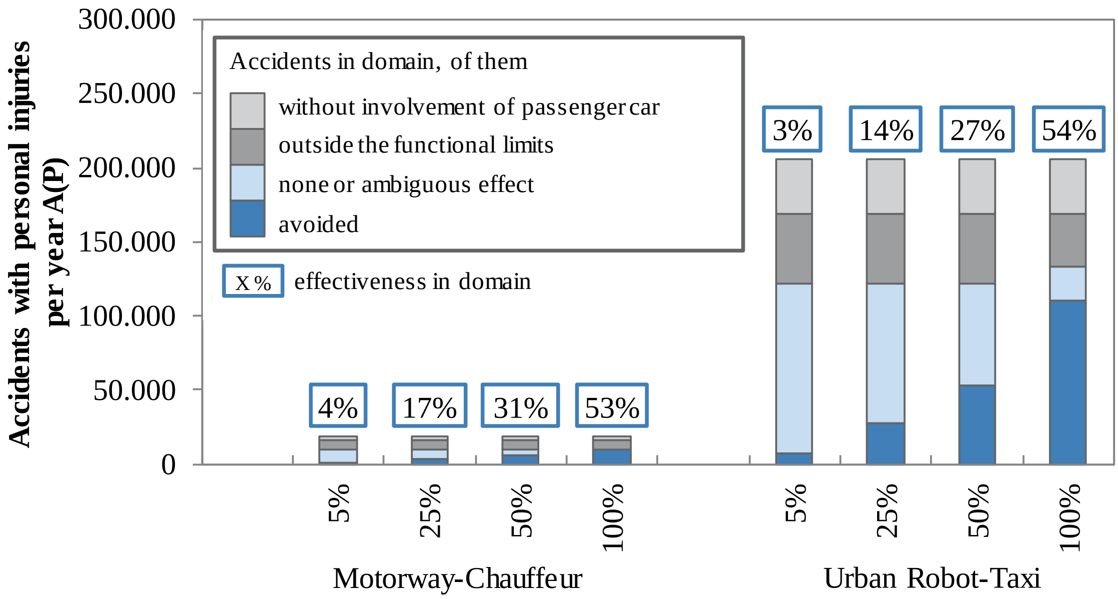


Figure 11. Effectiveness in terms of avoided accidents of Motorway-Chauffeur and Urban Robot-Taxi [18]**.**

The light blue area represents the number of accidents that are potentially addressable, but cannot be avoided according to the simulation results. These are for example accidents that cannot be avoided due to physical constraints. However, the severity of these accidents possibly can be reduced by a reduction of the collision speed. The dark blue area represents the number of avoided accidents. Hence, the Urban Robot-Taxi can avoid 52,517 accidents at a market penetration of 50 %. This equals an effectiveness of 27 % of all accidents in the operation domain.

DISCUSSION

In contrast to existing approaches in literature that define driving scenarios based on ontologies created by expert knowledge, in this work the driving scenarios are derived from the three-digit accident type covering all potential physical accident constellations known to accident research for decades. A set of 13 driving scenarios has been identified from the accident type catalogue. The definition of the driving scenarios by the three-digit accident type reveals tremendous gains. Since both national accident statistics (in five German federal states) and GIDAS in depth accident data feature the three digit-accident type, the driving scenarios can be classified in both types of data. Consequently, both, the number of accidents on national level per driving scenario and the parameter spaces for deriving the change in severity induced by ADFs can be determined with the developed concept. The presented concept in this thesis limited the available number of traffic participants by a number of two that covers 90 % of accidents. A possible enlargement of the presented driving scenarios to cover the remaining 10 % of accidents is to extend the number of traffic participants per driving scenario to more than two. Beyond that, a more detailed clustering into more than 13 driving scenarios can be realized. However, it has to be considered that the efforts for assessment are increasing with the number of driving scenarios.

CONCLUSIONS

According to the statements in [2], automated driving functions need to show a positive risk-balance compared to human driving in terms of traffic safety. Therefore, a framework for effectiveness assessment of road vehicle automation has been introduced in this work. The basic idea of this framework is that the types of accident constellations and thus driving scenarios do not change with automated driving. Though, the severity and frequency of occurrence of these driving scenarios may change with automated driving. Traffic simulations with automated driving functions are investigating the changes in frequency of occurrence. For determination of the change in severity in relevant driving scenarios, accident re-simulations were used. After determining the effectiveness of the automated driving functions, they are projected and depicted over the whole territory of the Federal Republic of Germany. The results indicate that, e.g. a Motorway-Chauffeur at a market penetration of 50 % has a potential for reducing about 31 % of all accidents on German motorways resulting in personal injury. This equals 2 % of all accidents on German roads. The Urban Robot-Taxi can avoid 27 % of all accidents with personal injury within city-limits at a market penetration of 50 %. This equals 17 % of all accidents on German roads.

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REAL-WORLD EVALUATION OF DRIVER ASSISTANCE SYSTEMS FOR VULNERABLE ROAD USERS BASED ON INSURANCE CRASH DATA IN SWEDEN

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ABSTRACT

In 2010 Volvo cars introduced advanced driver assistance systems (ADAS) designed to detect vulnerable road users (VRUs) in specific conflict situations. The aim of this study was to evaluate the first generation of the optionally mounted Pedestrian ADAS, which covers car-to-pedestrian collisions, and Cyclist ADAS, which covers car-to-cyclist collisions.

Data from collisions in Sweden between passenger cars and pedestrians or cyclists were collected from 2015-2017. Crashes involving Volvo cars with third-party liability insurance at If P&C Insurance/Volvia were included in the dataset, and cars with these ADAS were compared to crashes involving cars without the systems. A total exposure of 490,000 insured vehicle years was used in the evaluation.

Overall, the number of collisions for cars with the Pedestrian ADAS system was 21% less than the number for cars without it. When studying straight crossing path crashes only, which accounted for more than half of all car-to-pedestrian collisions in Sweden, these were reduced by 36%. However, the results are not statistically significant due to the low number of crashes. For the ADAS, which covers car-to-cyclist collisions, an overview of data available for retrospective performance evaluation is discussed.

One clear restriction in the evaluation of VRU ADAS at this point in time is the relatively low number of cars equipped with the system together with the low rates of car-to-cyclist collisions (≈ 0.0002 per insured vehicle year) and car-to-pedestrian collisions (≈ 0.0001 per insured vehicle year).

This study is the first real-world evaluation of the initial generation of VRU ADAS targeting traffic situations relevant for these technologies. ADAS for avoiding collisions with pedestrians and cyclists have a high traffic-safety potential; recent and future generations of these systems, cover more conflict situations and are thus expected to provide increasing safety benefits.

INTRODUCTION

Globally, pedestrians and cyclists represent 26% of all road traffic deaths [1]. There is a big variation in death rates across regions and countries, with low- and middle-income countries the worst affected. In EU countries, pedestrians and cyclists comprised around 21% and 8% of all road traffic deaths, respectively, in 2015 [2]; in the US the corresponding numbers were 16% and 2.2%, in 2016, [3]. In Sweden, in 2017, 15% of the road fatalities were pedestrians and 8% were cyclists [4, 5]. In many countries, roads still lack separate lanes for cyclists and adequate pedestrian crossings—and motor vehicle speeds are too high [1].

Infrastructure measures, such as the physical separation of motor-vehicle and VRU paths, have proven to be effective in preventing VRU crashes. The expansion of walking and cycling paths in Sweden is a good example: fatal pedestrian and cyclist crashes have decreased from one third of the total road-traffic fatalities in the 1970s to just over one fifth today [4]. Still, VRUs often share the road with motor vehicles, and crashes occur frequently—most commonly in urban areas where walking and cycling are common modes of transport [6].

For car-to-VRU collisions, the distribution of conflict situations in crash databases are used to identify frequent or severe situations to address with traffic safety measures. The majority of crashes are Straight Crossing Path (SCP) situations, i.e. the car is moving straight forward, and the car and the VRU are crossing each other's paths.

Situations in longitudinal traffic, when the car and the VRU are traveling in the same or opposite direction while sharing the same roadway are not as frequent, but often with more severe injuries for the VRU. Specific situations for car-to-pedestrians are collisons where the car is reversing hitting a pedestrian, and for car-to-cyclists; the cyclist riding into a car door that was being opened by the car driver or a passenger, hereafter called dooring [7-11].

As unprotected road users, pedestrians and cyclists are particularly vulnerable to severe or fatal injuries in case of a crash. One important way to reduce the consequences of a crash is to lower the impact speed [12-14]. To improve the situation where vulnerable road users and motor vehicles share the road, speed limits have been reduced in Swedish cities over the last decade (where appropriate) [15]. Additional speed-reducing measures, such as speed bumps and raised crosswalks and chicanes, have been implemented to achieve better speed compliance [16]. In the work with the Vision Zero initiative, a key indicator measuring the share of safe walking, bike, and moped passages was introduced [17, 18].

In the last decade, vehicle manufacturers have developed countermeasures to reduce the consequences of an impact with VRUs. These involve redesign of the bumper area [19], the hood, windshield, and pillar [20], and introduction of pedestrian airbags [21], and pop-up bonnets [22].

One of the most promising countermeasures presented by the automotive industry is advanced driver assistance systems (ADAS) specifically for pedestrian and cyclist situations. One example is the collision warning with full autobrake and pedestrian and cyclist detection implemented in Volvo car models [23]. Real-world evaluations have shown that autobrake systems are very effective in avoiding (as well as mitigating) car-to-car crashes in rear-end situations [24-33], and test institutes and predictive studies estimate that including pedestrian and cyclist detection will greatly reduce crashes with VRUs [34-38]. In December 2017, HLDI examined pedestrian-related collisions which showed a reduction in the frequency of bodily injury (BI) liability claims, as a result of analyzing an ADAS with a pedestrian detection feature. [39].

The aim of this study was to evaluate the first generation of driver support systems which are intended to detect VRUs, covering car-to-pedestrian- as well as car-to-cyclist collisions, by investigating real-world crashes collected from traffic situations relevant for these technologies.

DATA & METHOD

In this study we used insurance claims data from car-to-pedestrian collisions involving Volvo models with and without Pedestrian ADAS (collision warning with full autobrake and pedestrian detection). Also, car-to-cyclist collisions involving Volvo models with and without Cyclist ADAS (collision warning with full autobrake and cyclist detection) was studied.

To calculate the exposure, information covering all cars registered in Sweden with third-party liability insurance at If P&C insurance/Volvia was used. The analysis was performed using accident and exposure data for the years 2015-2017.

Data collection

Data including both car-to-pedestrian collisions and car-to-cyclist collisions in Sweden are continuously coded and collected in two databases. For cars with third-party liability insurance at If P&C insurance/Volvia, all crashes involving cyclists and pedestrians were coded using information from the claims. This means that a representative set of data, ranging from very low-severity crashes to fatal crashes, is available. These data include crashes sometimes not collected in, e.g. the national crash databases, because they are lower in severity or simply not included in the collection criteria; however, even these situations can result in injuries for VRUs. Two examples illustrate this point: the dooring situation, (defined as a single accident in police-reported accidents in Sweden) and the frequent situation; car reversing hitting a pedestrian, that is not considered at all in official statistics.

In most cases, information about the crash situation was available for both the pre-crash and crash events between car and pedestrian/cyclist. The pre-crash event was described by the conflict situation classification, if available, the driver's estimate of the car's speed just before the accident; and whether the driver's view was restricted. The crash event was described by the point of impact and the impact direction for both the pedestrian/cyclist and the car during the collision. This information was obtained from the claims form and descriptions by the driver and the pedestrian/cyclist. To more fully describe each situation, environmental conditions (light and weather conditions and road status), when (time of day) and where the collision occurred (urban or rural area), and demographics about the driver and the pedestrian/cyclist were recorded. Personal injuries were coded using the Abbreviated Injury Scale (AIS) [40].

Exposure data
Exposure data were calculated for the Volvo car models included in the study, by summing up the number of insured vehicle years (IVY): one car insured for one year is one insured vehicle year, two cars insured for half a year each is equal to one insured vehicle year, etc. Crashes involving cars with the optionally mounted VRU ADAS were identified and compared to crashes involving cars without the systems. For the Pedestrian ADAS detection system, the total exposure was 490,000 vehicle years and for the Cyclist ADAS detection system it was 420,000 vehicle years. For detailed information about the number of selected cases, see Tables 1 & 2.

System description: Pedestrian ADAS
The pedestrian detection technology (consisting of collision warning and autobrake system) was included in the third generation of Volvo Cars' collision avoidance system, available from 2010 (MY 2011) as an option in the Volvo models S/V60. From MY 2012 it has been available in the V/XC70 and S80 models, and from MY 2013 in the V40. Models introduced from 2015 on, starting with the new XC90, are equipped with the next generation of collision warning and autobrake system as standard. The system uses a combination of a long-range radar and a forward-sensing wide-angle camera that continuously monitors the area in front of the vehicle. For best performance, the pedestrian detection needs a clear view of the person's head, arms, shoulders, legs, and the upper and lower parts of the body—and the person should be moving normally; Figure 1. If large parts of the pedestrian's body are not visible, the system cannot detect it. In the first version of the system, representing all cases included in the study, the capacity for detecting a pedestrian in darkness was limited, but the version introduced in 2015 represents a great improvement. However, some contrast between the pedestrian's silhouette and the background is still needed for detection.

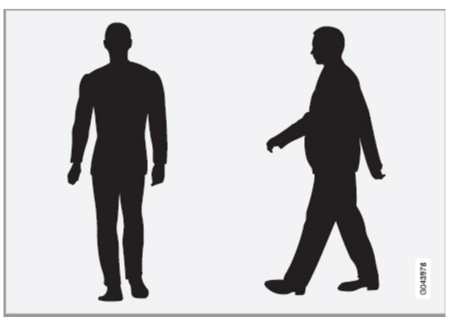

Figure 1. Examples of the clear body contours that the system regards as pedestrians, adapted from [41]

The pedestrian detection system will provide a warning and brake support in some of the situations when there is a credible risk of an accident. If the driver does not intervene after the warning, and the collision threat becomes imminent, intervention braking may automatically be applied to help slow down the car. Up to a speed of 80 km/h, the system may autobrake for a pedestrian, and up to approximately 35 km/h the collision may be avoided completely. In the most recent version, the system is able to reduce speed in up to 45 km/h in some car-to-pedestrian critical situations.

System description: Cyclist ADAS
Cyclist ADAS was an available option in Volvo's collision avoidance system starting in 2012 (MY 2013) in the S/V60, V/XC70, XC60, S80, and V40 models. Like the pedestrian ADAS, this system has been a standard feature in models introduced in 2015 and later, starting with the new XC90.

a) *b)* *c)*

Figure 2. Examples of clear body and bicycle outlines that the system regards as cyclists, adapted from [41-42]

For Cyclist ADAS, the technology is similar to the Pedestrian ADAS. To be able to recognize a cyclist, the system will optimally be able to detect clear, distinct body and bicycle outlines; Figure 2. The first version of the system was able to detect cyclists traveling in the same direction from behind; Figures 2.a & b. In the second generation of the system, introduced in 2015, cyclists can also be recognized from a side view; Figure 2c.

Crash data

Volvo car models V40, S/V/XC60, V/XC70, S80 and S/V/XC90 were selected from the car-to-pedestrian and car-to-cyclist crash databases, starting with the date Pedestrian ADAS and cyclist ADAS respectively were available for these models.

Car-to-pedestrian crash data The car-to-pedestrian crash data contain 12 Pedestrian ADAS cars and 37 non-Pedestrian ADAS cars, collected in Sweden between 2015 to 2017; Table 1.

Of the 12 car-to-pedestrian collisions in which the car was equipped with the Pedestrian ADAS system, six were SCP situations (the pedestrian was crossing the road in front of the car, going straight). The other cases represent a variety of situations: the car turned right as the pedestrian was crossing the road, a young boy was playing beside the road and rolled out onto the road as the car approached, the car was going straight and the pedestrian was standing still beside the road, and the pedestrian ran into the side of the car; in two cases, the car drove over the pedestrian's foot (one in a parking lot and one in a petrol station). In one case the car was reversing.
For cases with information of pre-crash factors, six occurred in daylight and four in darkness. In nine cases the weather was clear, nine cases happened in urban areas and two in non-urban areas. There were two seriously injured pedestrians, the remaining ten have moderate or minor injuries.

Of the 37 collisions with non-Pedestrian ADAS cars, 23 were SCP situations, in four cases the car was turning before the collision with a pedestrian crossing the road. In one case the car hit a pedestrian standing still beside the road. In two cases the car was moving forward in a parking lot when hitting the pedestrian, in one case the car skidded before hitting two pedestrians. One case occurred on a motorway in the night. In four cases the car was reversing.
Of the known pre-crash factors 19 of the cases occurred in daylight, 15 in darkness. It was clear weather in 24 of the cases, in two it was raining. The main part, 33 of the collisions, occurred in urban areas. Four of these pedestrian crashes were fatal, one pedestrian had a serious injury, in 11 of the cases the pedestrian had a moderate injury and the rest have only minor injuries.

Car-to-cyclist crash data The car-to-cyclist crash data contains 27 cars with Cyclist ADAS and 56 cars without the system (non-Cyclist ADAS) collected in Sweden between 2015 to 2017, Table2. Of the 27 cars with Cyclist ADAS, only four cars had the updated version of the system where cyclists can also be recognized from a side view.

Of the 27 collisions involving cars with the Cyclist ADAS system, there were one case where the car and the cyclist travelled in the same direction: the handlebar of the bicycle and the side of the car made contact. Of the remaining cases, 19 were SCP situations (the car was going straight when the cyclist crossed the road in front, from either the left or the right). Two of these cases occurred in a roundabout. In six cases, the car was turning right, and in one case the car was turning left, and collided with a cyclist crossing the road.

The majority of the cases occurred in urban areas, during daylight and in clear weather. None of the cyclists were seriously injured.

Of the 56 collisions with non-Cyclist ADAS cars, three cases were same direction situations. Of these three cases two occurred in a roundabout; in one case the car was overtaking the cyclist the handlebar of the bicycle touched the side of the car, in the other case the car was running into the cyclist, diagonally when the cyclist was leaving the roundabout. 31 of the collisions were SCP situations, 13 were situations where the car turned left or right before colliding with a cyclist crossing the road. In eight cases, the car was not moving forward, in three of these cases the car was reversing and five cases were dooring situations. The majority of these 56 crashes occurred in urban areas, during daylight and in clear weather without seriously injured cyclists.

Statistical methods

The rate of car-to-pedestrian collisions was compared per 10,000 IVYs for cars with and without the Pedestrian ADAS system.

The rate of car-to-pedestrian collisions for Pedestrian ADAS cars is defined as

$$\text{Rate}_{\text{Pedestrian ADAS}} = (\text{n}_{\text{Pedestrian ADAS}} / \text{IVY}_{\text{Pedestrian ADAS}}) \qquad (1)$$

where n is the number of car-to-pedestrian collisions. The number of claims can be considered using a Poisson distribution. Exact 95% Poisson confidence limits for the estimated rate were calculated as

$$\text{LCL} = \frac{\chi^2_{2\text{n},\ \alpha/2}}{2}\ , \qquad \text{UCL} = \frac{\chi^2_{2(\text{n}+1),\ 1-\alpha/2}}{2} \qquad (2)$$

The rate and confidence interval of pedestrian and car crashes for non-Pedestrian ADAS cars were defined comparably.

To evaluate the effectiveness of the Pedestrian ADAS technology, Poisson regression was used to compare the car-to-pedestrian collision rates per IVY for Pedestrian ADAS and non-Pedestrian ADAS cars. The calculations were performed with PROC GENMOD (SAS Institute) [42], using a model with a logarithmic link function. Regression models were constructed for the total number of pedestrian and car collisions. Rate ratios (RRs) were provided from the output, together with 95% confidence limits. The system's effectiveness (the reduction in crashes as a percentage) was calculated as $(1 - \text{RR}) * 100$.

RESULTS

Car-to-pedestrian collisions:

The crash database contained 12 car-to-pedestrian cases involving Pedestrian ADAS cars and 37 cases with cars without the system. Six of these cases where car-to-pedestrian straight crossing path (SCP) situations with Pedestrian ADAS cars, and 23 where cars in SCPs without the system; Table 1.

Table 1.
Number of car-to-pedestrian collisions and insured vehicle years for cars with and without the pedestrian detection system Pedestrian ADAS.

	Number of collisions all	Number of collisions SCP	Insured vehicle years
Pedestrian ADAS	12	6	142,627
non-Pedestrian ADAS	37	23	347,661

The crash rate for car-to-pedestrian collisions per 10,000 IVYs, all conflict situations included, was 0.84 (95% confidence interval [CI], 0.43, 1.47) for Pedestrian ADAS cars and 1.06 (95% CI, 0.75,1.47) for non-Pedestrian ADAS cars. The rate was 21% lower (nonsignificant) for the Pedestrian ADAS cars (RR = 0.79, 95% CI, 0.41–1.51).
When only SCPs were selected, the rate per 10,000 IVYs was 0.42 (95% CI, 0.15, 0.92) for Pedestrian ADAS cars and 0.66 (95% CI, 0.42, 0.99) for non- Pedestrian ADAS cars. The SCP crash rate was 36% lower (nonsignificant) for the Pedestrian ADAS cars (RR=0.64, 95% CI, 0.26–1.57).

Car-to-cyclist collisions:
For car models XC90, S/V90 and S/V60 (introduced in 2015 and after), the system is now standard mounted with the second generation of the system that is able to recognize cyclists in several conflict situations, see Figure 2. The crash data contain 27 car-to-cyclist collisions involving Cyclist ADAS cars, of which only four have the second generation of the system, and 56 collisions involving non-Cyclist ADAS cars; Table 2.

Table 2.
Number of car-to-cyclist collisions and insured vehicle years for cars with and without the cyclist detection system Cyclist ADAS.

	Number of collisions all	Number of collisions same-direction	Insured vehicle years
Cyclist ADAS	27	1	133,916
non-Cyclist ADAS	56	1	285,012

The rate for all car-to-cyclist collision situations per 10,000 IVYs was 1.98 (95% CI, 1.58, 2.46).

Given that the same-direction conflict situation, targeted by the first generation of the Cyclist ADAS, accounted for only 3 % of all car-to-cyclist crashes [10], no difference could be identified for this type of crash when cars with and without the Cyclist ADAS system were compared.

DISCUSSION

Predictions based on virtual simulations as well as physical testing in specific test scenarios have promised traffic safety improvements from VRU ADAS technologies [34-38]. The present study describes real-world follow-up results in car-to-pedestrian collisions, providing preliminary confirmation of these predictions.
These results, although not significant, indicate that cars equipped with Pedestrian ADAS system reduced car-to-pedestrian collisions by 21% when all types of conflict situations in the data were considered—and by 36% for the SCP situation specifically. This is in line with a predictive estimation of the system's performance made in 2010 that suggested that 30% of the pedestrian crashes could be avoided, and that fatal crashes when the pedestrian is struck by the front of a passenger car could be reduced by 24% [34]. A similar study predicted a reduction in fatally and severely injured pedestrians of 40% and 27%, respectively, for a conceptual AEB system [35].
The performance of Cyclist ADAS in car-to-cyclist collisions was not investigated, since the dataset available mainly covered the first generation of the system only targeting same-direction situations, (Figure 2a-b). This conflict situation was not frequent in the dataset analyzed, nonetheless, the Cyclist ADAS illustrates one small, but important, step towards car-to-cyclist crash avoidance functionalities. In the second generation of the Cyclist ADAS introduced in Volvo car models in 2015, cyclists can also be identified from a side view (Figure 2c). Since more than 40% of all car-to-cyclist collisions in Swedish data [10] are SCP situations, this second generation is expected to perform substantially better.
This study is based on insurance data, covering all levels of crash severity and including situations – that are not always covered in other crash databases with other selection criteria [8]. In general, results from performance estimations depend on the methodology that was applied; how the analysis is implemented, which situations are considered, and the representativeness of the input data. Thus, specific numbers need to be carefully interpreted. For example, in this study, only situations where the car was driving forward are relevant and expected to be reduced.

This is exemplified by the two results presented for Pedestrian ADAS. The overall car-to-pedestrian crash potential consider all types of conflict situations also including crashes where the car was reversing, and taking this total sample into account, 21 % of car-to pedestrian collisions were reduced. On the other hand, a specific evaluation of the SCP situation, one of the target situations of the system, reveals a greater effect (36%), from the Pedestrian ADAS.

Some limitations in this study should be mentioned. It was not possible to find any significant safety benefits attributable to the ADAS systems in this study. The number of cars in traffic equipped with this functionality was low in the first years after its introduction. Further, the accident rates of pedestrian and bicycle crashes with cars are relatively low in Sweden, so it takes time before there are enough data available to study. As a comparison, approximately 50 rear-end-frontal collisions occur per 10,000 IVYs—compared to one car-to-pedestrian and two car-to-cyclist collisions for the same exposure. This was obvious when the collision warning and autobrake systems were evaluated in 2016; there was only one crash for the cars equipped with the pedestrian detection feature, and no crashes for the cars equipped with cyclist detection [32]. The possibility of achieving reliable performance estimations will increase, since the systems are now standard features in all new Volvo models. Given the higher frequency of VRU crashes in other regions of the world [1], it is suggested that research on the effectiveness of advanced driver assistance systems also be performed in other countries.

This study did not evaluate a mitigation effect, i.e. when the system was activated and the speed (and thus the crash severity) was reduced, but the crash was not completely avoided. In car-to-VRU crashes even slight reductions in impact speeds have a large effect on the injury outcome for pedestrians and cyclists [12], so it is therefore suggested that crash mitigation be included in future studies.

In this study, we found a clear indication that the first generation of Pedestrian ADAS is effective in reducing car-to-VRU crashes, and it was suggested that more recent generations of both Pedestrian- and Cyclist ADAS will be even more efficient in terms of traffic safety improvements for VRUs. Other countermeasures to reduce or mitigate car-to-VRU injuries have been implemented, including: infrastructure measures [15, 44], consumer rating tests on vehicles [36, 37], protective gear for cyclists [45], and motor-vehicle measures [19-23]. All of these initiatives should be considered in order to maximize a long-term decrease in VRU injury rates.

CONCLUSIONS

To our knowledge, this is the first study to analyze real-world crash data in relevant situations to evaluate ADAS systems targeting car-to-pedestrian and –cyclist collisions. Car-to pedestrian collisions were reduced by 21% when all conflict situations were considered, and by 36% in the specific straight-crossing path conflict situation, for cars equipped with Pedestrian ADAS. For Cyclist ADAS, the target situation in the first generation of the system only cover a low share of car-to-cyclist collisions, and no performance estimation was made. Our results, albeit nonsignificant, indicate that as more data become available, further improvements are foreseen in crash reduction and mitigation for the vulnerable road users that share the road with motor vehicles.

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SPEEDING IN CRASHES IN THE UNITED STATES OF AMERICA: A PILOT STUDY USING EVENT DATA RECORDER INFORMATION FROM NASS-CDS

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ABSTRACT

The prevalence of speeding in crashes is only currently reported for fatal crashes in the United States of America (USA) using police reports, and the prevalence reported (27%) is well below that found in a national study that measured travel speeds (65%). The aim of this study was to explore how event data recorder (EDR) data from the National Automotive Sampling System – Crashworthiness Data System (NASS-CDS) database could be used to estimate the prevalence of speeding in crashes in the USA. EDR files collected as part of the NASS-CDS in 2015 were examined to determine the presence and extent of speeding, provided they met certain criteria. AIS coded injury data was also extracted when available to examine speeding by injury severity. 335 EDR files were identified as meeting the criteria. 188 of these had complete AIS coded injury information. From this sample, it was found 61% were speeding, but this reduced to 44% if NASS-CDS weightings were applied. Speeding by more than 10 mph was found in 26% of crashes (16% weighted). Speeding was found to increase with increasing injury severity: 76% of MAIS 3+ crashes involved speeding, and 52% involved speeding by more than 10 mph. EDR data was found to be a useful source of travel speed data that may be used to examine speeding in the USA. It indicates that speeding is a larger problem in crashes than suggested by the current method that uses police reports. Expanding the sample size by using more years of data and calculating the change in impact speed and associated change in injury severity would allow for more robust estimates of the prevalence of speeding and its contribution to road trauma in the USA.

INTRODUCTION

Speed is considered to be a major factor in the frequency and severity of road crashes [1,2]. Speed limits are set with the intention of controlling the maximum speed at which vehicles travel. However, drivers may still travel above the speed limit, termed speeding. A recent large-scale speed survey conducted in the United States of America (USA) by the National Highway Traffic Safety Administration (NHTSA) showed that 64.8% of vehicles were speeding, 40% speeding by more than 5 mph and 18.3% were speeding by more than 10 mph [3].

In the USA the prevalence of speeding in crashes is currently only estimated for fatal crashes. NHTSA defines a crash as speeding related if "any driver in the crash was charged with a speeding-related offense or if a police officer indicated that racing, driving too fast for conditions, or exceeding the posted speed limit was a contributing factor in the crash" [4]. This definition includes what might be termed "inappropriate speed for the conditions" as well as traveling above the speed limit. Even so, the estimate produced by this definition is only 27%, far lower than the percentage of drivers that are speeding or travelling at more than 5 mph above the speed limit in the speed survey [3].

The presence of speeding by a vehicle involved in a crash is often difficult to determine. Determining the travel speed of a vehicle prior to a crash is a specialised discipline known as crash reconstruction which is beyond the scope of most crash reports prepared by police, perhaps with the exception of some fatal crashes. Traditional crash reconstruction methods rely on pre-impact tyre marks to calculate speed loss prior to impact and often produce an underestimate of travel speed as they cannot determine speed loss prior to the start of the tyre mark. This issue is further exacerbated by the advent of highly effective anti-lock braking systems on vehicles.

The advent of event data recorders (EDRs) provides a new opportunity to accurately ascertain the travel speed of vehicles involved in crashes and provide more accurate estimates of the prevalence of speeding in crashes of all severities. EDRs store a range of data from a vehicle's sensors in the event of a crash. In many cases this includes pre-crash travel speed for 2.5 to 5 seconds prior to the crash, typically recorded at 2 Hz. This data has been shown to be highly accurate for travel speed [5].

This paper details a pilot study that examined how EDR data from the National Automotive Sampling System – Crashworthiness Data System (NASS-CDS) database could be used to estimate the prevalence of speeding in crashes.

METHOD

As part of a separate study, the EDR files collected in NASS-CDS from vehicles crashed in the USA in 2015 were examined to identify EDR files that fulfilled the following criteria;

- From a striking vehicle
- From a vehicle that was not maneuvering (e.g turning)
- Injury severity for at least one vehicle was known
- Crash did not involve a heavy vehicle or motorcycle
- Crash was not a side-swipe or animal only impact
- EDR file had recorded crash data
- EDR file contained pre-impact speed
- Speed limit known

Each EDR file was individually checked to match the crash event data stored in the EDR file to the crash sampled in NASS-CDS by a person trained and experienced in interpreting EDR files. The travel speed was defined as the highest speed that the vehicle was recorded to be traveling in the pre-crash time period recorded on the EDR file. This travel speed was compared against the posted speed limit for that vehicle stated in the NASS-CDS database to determine speeding. Information on injury severity according to the maximum abbreviated injury score (MAIS) was also extracted from the NASS-CDS database, when available (injury information is only available for cars less than ten years old)

NASS-CDS sampling has a stratified, multiphase, unequal selection probability design that deliberately oversamples crashes with a higher injury severity. The NASS-CDS database provides case weights that can be used to account for the unequal selection probability. The weights of the sample crashes varied from 4.6 to 15,112. This high degree of variation in the weights means that, when considering small groups of crashes, some care must be taken to ensure that the result is not simply an artefact of the weighting. For example, the crash with the highest weight accounted for 36% of the total moderate injury weights, and 31% of the total serious injury weights, as opposed to 7% of the total sample. No consensus has been reached on how best to deal with this issue. The method suggested by Samaha, Prasad and Nix [6] of attenuating the weights to the 95% percentile value within an injury severity category was applied the data for this study. Weighted, weighted with attenuation, and unweighted results are shown for comparison.

RESULTS

1077 EDR files were collected from 970 crashes as part of NASS-CDS in 2015 and a total of 335 crashes met the criteria. A detailed breakdown of cases excluded is shown in Table 1.

Table 1.
Cases excluded by criterion

Criterion	Number excluded
Non-striking vehicle	244
Vehicle maneuvering	30
Injury severity unknown	210
Heavy vehicle or motorcycle involved	45
Sideswipe or animal strike	56
EDR file contained no data	20
EDR file did not contain speed data	27
Speed limit unknown	3
Total cases excluded	635

Table 2 shows the percentage of vehicles speeding in the 335 crashes. The percentage reduces when the data is weighted according to the weights provided in the NASS-CDS database. Attenuating the weights to the 95th percentile increase the percentages, but they remain closer to the weighted values than the unweighted.

Table 2.
Prevalence of speeding by level of speeding and weighting from 2015 NASS-CDS data

Speeding level	Unweighted		Weighted		Weighted - Attenuated	
	Number	Percentage	Number	Percentage	Number	Percentage
Total cases	335	-	219,124	-	177,243	-
Speeding	205	61.2	95,516	43.6	92,712	52.3
Speeding >8km/h (5mph)	131	39.1	51,333	23.4	50,159	28.3
Speeding >16km/h (10mph)	85	25.4	34,132	15.6	32,958	18.6

The percentage of vehicles speeding by crash injury severity is shown in Table 3. Only 188 of the 335 crashes had injury information available for all vehicles involved in the crash. When considering the unweighted results, the percentage of crashes involving speeding increases with increasing injury severity across all levels of speeding. However, the weighted results (with weighting attenuated) show a decrease in percentage of vehicles speeding for MAIS 2 crashes. The difference in percentage of crashes involving speeding between crash injury severity levels appears to increase at higher levels of speeding.

Table 3.
Prevalence of speeding by level of speeding and weighting from 2015 NASS-CDS data

Speeding level	MAIS 0,1				MAIS 2				MAIS 3+			
	Unweighted		Att. Weight		Unweighted		Att. Weight		Unweighted		Att. Weight	
	No.	%	No.	%	No.	%	No.	%	No.	%	No.	%
Total	128	-	68,185	-	35	-	8,741	-	25	-	1,697	
Speeding	77	60.2	40,220	59.0	24	68.6	2,745	31.4	19	76.0	1,068	62.9
Speeding >8km/h	52	40.6	26,145	38.3	17	48.6	2,083	23.8	16	64.0	845	49.8
Speeding >16km/h	33	25.8	17,589	25.8	12	34.3	1,418	16.2	13	52.0	736	43.3

DISCUSSION

The unweighted results for speeding (61%) are similar to the levels of speeding found in the US national speed survey conducted by NHTSA but are well above the current estimate of speeding in fatal crashes (27%). Once the results are weighted the percentage of speeding is less than found in the US national speed survey, but still well above the estimated level of speeding in fatal crashes. The exception to this finding is the results for speeding by 10 mph are closer to the NHTSA speeding survey result when they are weighted.

It would be expected that speeding would be more prevalent in higher injury severity cases as increases in speed are known to increase the risk of serious and fatal crashes more than for less severe crashes [1]. The findings of this study are therefore as expected in that regard. There were too few fatal cases to consider them separately in the analysis, however, fatal crashes alone would be expected to have even higher levels of speeding than MAIS 3+ crashes. The results therefore suggest that the current estimate of speeding in fatal crashes is a gross underestimate. This is despite having a broader definition that includes inappropriate speed in the estimate in addition to speeding. The current NHTSA estimate may only represent cases of speeding much higher than 10 mph as high levels of speeding may be more easily identified by police.

The vehicles in the sample are biased towards newer vehicles, as this was required for both injury information, and travel speed to be present in the EDR file. It is unknown if the age of the vehicle has an influence on speeding, though it may be thought that older vehicles are more likely to be driven by younger drivers [7] who may be more prone to speeding. Young drivers have been found to be more likely to be "speeders" according to a national survey conducted in the USA [8]. If this is the case the results are an underestimate of speeding in the general population.

The sample does not include heavy vehicles or motorcycles. The NHTSA travel speed survey [3] found that heavy vehicles have higher median speeds but lower 85% percentile speeds than passenger vehicles. Motorcycles are not identified separately in the NHTSA travel speed survey. Speeding, as identified by NHTSA for fatal crashes [4], is more common amongst motorcycles than passenger vehicles, but less common amongst heavy vehicles. While motorcycles represent only a small proportion of the vehicle fleet they are over-represented in serious crashes [9]. The limiting of the dataset to crashes involving only passenger vehicles may have resulted in a slight underestimate in terms of the general population, though it is also quite possible that this made no real difference to the result.

A major limitation of this study is the sample size when breaking down the sample for further analysis. This makes using the NASS-CDS weights to correct for the sampling method difficult, as a small number of crashes can become overly influential on the weighted result. Attempts to correct for this by attenuating the results to the 95th percentile value within the injury severity category still yielded the odd result of MAIS2 crashes having a lower percentage of speeding than MAIS0 and MAIS1, and MAIS3+ crashes, as the 6 crashes with the highest weights were all not speeding in a sample of only 35 crashes. Future work could incorporate more years of the NASS-CDS data to increase the sample size and allow it to be analysed in more detail. The soon to be released Crash Investigation Sampling System (CISS), the successor to NASS-CDS, will provide EDR equipment to all field crash technicians [10] and therefore may provide more EDR data per year of data collection for future studies of this kind.

A further limitation is that the selection criteria were designed for a separate study, and this resulted in the exclusion of some cases that may have been relevant to speeding. One of the selection criteria was that the vehicle had to be a striking vehicle, but the struck vehicle in some crashes may also choose to travel faster than the speed limit (e.g. when it is travelling straight through an intersection). A revised set of selection criteria specific to this type of analysis would increase the number of cases included per year of NASS-CDS data.

Traveling above the speed limit is known to increase both the risk of being involved in a crash and the severity of the crash [1,2]. However, it should not be assumed that the elimination of speeding would result in a reduction in crashes that is equivalent to the percentage of vehicles speeding. Doecke and Ponte [11] conducted a preliminary study that estimated the contribution of speeding to road trauma by using EDR data from NASS-CDS to calculate the new impact speed had the vehicle not been speeding. They applied risk curves to this new impact speed to determine the new injury risk and calculate the overall reductions that could be achieved by eliminating speeding. They found that 22% of crashes could be avoided altogether, MAIS 3+ injuries could be reduced by 62% and MAIS

1 and MAIS 2 crashes could be reduced by 27%. These results were based on only 59 crashes from 2013 therefore their results should be viewed as preliminary. Future work in this area should consider applying the method of Doecke and Ponte (2017) to a large sample of NASS-CDS EDR data in order to robustly estimate the contribution of speeding to road trauma in the USA.

A recent National Transportation Safety Board report [12] highlighted that the key solutions to the problem of speeding in the USA are automated speed enforcement (ASE) and the vehicle technology intelligent speed adaptation (ISA), that are not currently implemented on a wide scale. This study, albeit a pilot study, adds further evidence of the large scale of the problem of speeding in the USA and the road safety benefits that could be gained by wide scale implementation of ASE and ISA.

CONCLUSIONS

EDR data is a useful source of travel speed data that may be used to examine speeding in the USA. It indicates that speeding is a larger problem in fatal crashes than suggested by the current method that uses police reports. Expanding the sample size by using more years of data and calculating the change in impact speed and associated change in injury severity would allow for more robust estimates of the prevalence of speeding and its contribution to road trauma in the USA.

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THE EFFECT OF P-AEB SYSTEM PARAMETERS ON THE EFFECTIVENESS FOR REAL WORLD PEDESTRIAN ACCIDENTS

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ABSTRACT

The objective of this ACEA funded study was to determine the effect of different pedestrian autonomous emergency braking (P-AEB) systems on the collision speeds of real world pedestrian accidents originating from three different accident databases. The precrash phases of real world passenger car to pedestrian frontal accidents from the in-depth accident databases were investigated using different pre-crash simulation tools. Collision parameters were compared between the original real-world cases and cases with treatment conditions. For treatment simulations, the car was equipped with a virtual generic P-AEB system, triggered at a time to collision (TTC)≤ 1 s. The range of the generic sensor was 80 m and the opening angle was varied between 60°, 90° and 120°. For the braking system, two different brake gradients (24.5 m/s³ and 35 m/s³) were modelled with different decelerations of 0.8 g and 1.1 g. Accidents from the Austrian in-depth accident database CEDATU (n=50), the German GIDAS (n=1084) and Swedish V_PAD (n=68) were used for the baseline. The effect of using different data samples was compared to the effect of assuming different generic AEB system parameters. The best performing P-AEB system (120°, innovative brake system) avoided 42% of the CEDATU cases, while the baseline P-AEB system (60°, standard brake system) avoided 18%. The best performing AEB System was able to avoid 79.4% of the V_PAD sample. The baseline P-AEB avoided in V_PAD at least 66.2% compared to GIDAS with 39.5%. The lower the mean collision speed of the sample, the higher was the benefit of the P-AEB system, as a higher percentage of cases can be avoided. The study shows that system parameters and the selection of accidents can greatly affect the outcome in prospective traffic safety analyses. As a significant reduction of collision speeds was seen in all three data sources, the study highlights the need for a combined vehicle safety assessment instead of a separate evaluation of active and passive pedestrian safety measures.

INTRODUCTION

Pedestrians accounted for 21% of the total road fatalities in the European Union in 2016 [1]. Safety measures addressing pedestrians have not been as effective as those for car occupants. While the total number of road fatalities decreased by 41% in the period from 2007 and 2016, it was only reduced by 36% for pedestrians [1]. It is expected that active safety systems, such as pedestrian autonomous emergency braking (P-AEB) systems will help to avoid or mitigate pedestrian accidents. Studies agree, however, that all accidents cannot be avoided, which is the reason why passive safety systems will be still needed in the future [2–8]. In the Euro NCAP VRU assessment active and passive safety measures are evaluated separately, i.e. in a non-integrative way. However, active safety measures influence the boundary conditions of accidents which were not avoided by the active safety measure. The question is raised of what targets for passive safety measures are relevant for vehicles with P-AEB systems in the future.

The present study was conducted in the framework of the project ProPose, which is funded by ACEA (European Automobile Manufacturers' Association) and addresses the following questions:

1. How many real-world accidents can be avoided with P-AEB systems?
2. Is there a need to consider an update of the speed range addressed by passive safety measures in the future?
3. How does the sensor opening angle and brake characteristic affect the effectiveness of the P-AEB system?

The effect on collision speed for different crash data samples was analyzed in order to suggest input to future pedestrian crash test setups, relevant for the design of passive safety measures. In contrast to other studies, the analyses were examined by comparing results based on three different accident databases.

METHOD

The effectiveness of the conceptual P-AEB systems was determined by means of comparing baseline- (the crash situations without the AEB) with treatment (the same situations but with a concptual P-AEB system) virtual simulations.
Collision parameters of the original real-world cases (w/o P-AEB) were compared to those with a conceptual P-AEB system. The method used in this study is referred to as 'virtual pre-crash simulation'. In the last couple of years this type of investigation gained importance for the evaluation of effectiveness of active safety systems [9–14].
To analyse the effectiveness of P-AEB systems it is crucial that the velocity-time-history is known for the entire duration of the pre-crash phase, where the P-AEB deploys.

Input Data

In this study, the pre-crash phase of real-world passenger car to pedestrian frontal collision accidents from three different in-depth accident databases (Table 1) were investigated using different pre-crash simulation tools. Within the accident databases, the reconstructed accidents including the pre-crash phase are available. In CEDATU (Central Database for In-Depth Accident Study) [15,16] accidents are reconstructed with the software PC Crash on the basis of police-, medical-, witness and court reports, photos and photogrammetric analysis of the accident side. In V_PAD [17] (Volvo Cars Pedestrian Accident Database), the information considered by the crash investigator at Volvo's Traffic Accident Research Team is compiled and the pre-crash phase is digitized in order to provide vehicle paths in relation to vehicle velocities and to the surroundings in a numerical time history data (THd) format. The GIDAS (German In-Depth Accident Study) accidents are recorded on scene and therefore often provide additional information [18]. Apart from regional differences, the three databases are also differing in terms of their case selection criteria: In CEDATU Austrian accidents with at least one injured road user are included, for which access to the court file is given [16]. In GIDAS accidents are selected according to a statistical sampling process [18] from the area around Hannover and Dresden. The V_PAD sample [17] consists of Swedish pedestrian accidents reported to the insurance company Volvia (IF P&C Insurances), where all new Volvo passenger cars in Sweden are insured for at least three years. The different inclusion criteria for the databases are clearly reflected in injury distributions and speed statistics, see Table 1.

Table 1: Comparison of applied data sources, simulation tools and variations

Source	CEDATU	GIDAS	V_PAD
Region	Austria	Hannover, Dresden	Sweden
Number of accidents for simulation	50	1084	68 SCP cases
cases with MAIS 4+ (AIS98)	50 %	7 %	3 %
cases with MAIS 3 (AIS98)	14 %	9 %	10 %
cases with MAIS 2 (AIS98)	24 %	33 %	40 %
cases with MAIS 1 (AIS98)	6 %	45 %	41 %
cases with unspec. MAIS 3+ (AIS98)	6 %	6 %	4 %
Analysed Scenarios	All	All	SCP
Mean initial speed [km/h]	50 (SD=22.9)	35.5 (SD=16.8)	31.5 (SD=17.1)
Mean collision speed [km/h]	47.2 (SD=20.4)	30.7 (SD=14.6)	23.6 (SD=16.3)
Median collision speed [km/h]	45	29.1	20
Simulation tool	X-Rate	rateEFFECT	VCART
Variations	Sensor 1-3; Brake 1-4	Sensor 1, Brake 1	Sensor 1-3; Brake 1-4

Only vehicle-to-pedestrian accidents which comply with the following filter criteria are considered in this study:

- the vehicle is a car or van, mass up to 3.5t,
- the vehicle is moving forward,
- the pedestrian was upright (not laying) prior to the impact,
- the pedestrian was struck by a single vehicle,
- only one pedestrian was involved in the accident,
- the vehicle was not skidding before the crash (but braking vehicles were included),

- Additional filter criterion for CEDATU and GIDAS: the pedestrian was impacted by the front of the vehicle,
- Additional Filter Criteria for V_PAD: the crossing path of the pedestrian was straight (SCP according to Figure 6 in the Appendix were considered).

The conflict situations (according to the classification introduced by Lindman et al. [17], which is explained in detail in Figure 6 in the Appendix) covered in the CEDATU and GIDAS sample, are shown in Figure 1: In the majority (80%) of the CEDATU cases, the pedestrian was crossing the road while the cars were driving straight (SCP). In 60% of the SCP accidents the pedestrian was entering the street straight from the left (far-side) and in 22,5% (9 cases) straight from the right side (near-side). In 20% of the CEDATU cases the pedestrian was either walking in the same direction (SD), oncoming direction (OD) of the, or the car was turning to the left (LT) prior to the impact. In the GIDAS dataset, 84% of the pedestrian were crossing the road while the cars were driving straight (SCP). I the remaining 9% of the GIDAS sample, the pedestrian was walking in the same direction (SD), oncoming direction (OD) of the car or the car was turning left (LT) or to the right (RT) prior impact. For 5%, another conflict situation occurred. In the V_PAD dataset, only conflict situations with a straight crossing pedestrian (SCP) were included. In 68% of the CEDATU and 69% of the GIDAS cases, the accident occurred on dry roads compared to V_PAD, where only 33.8% occurred on dry roads.

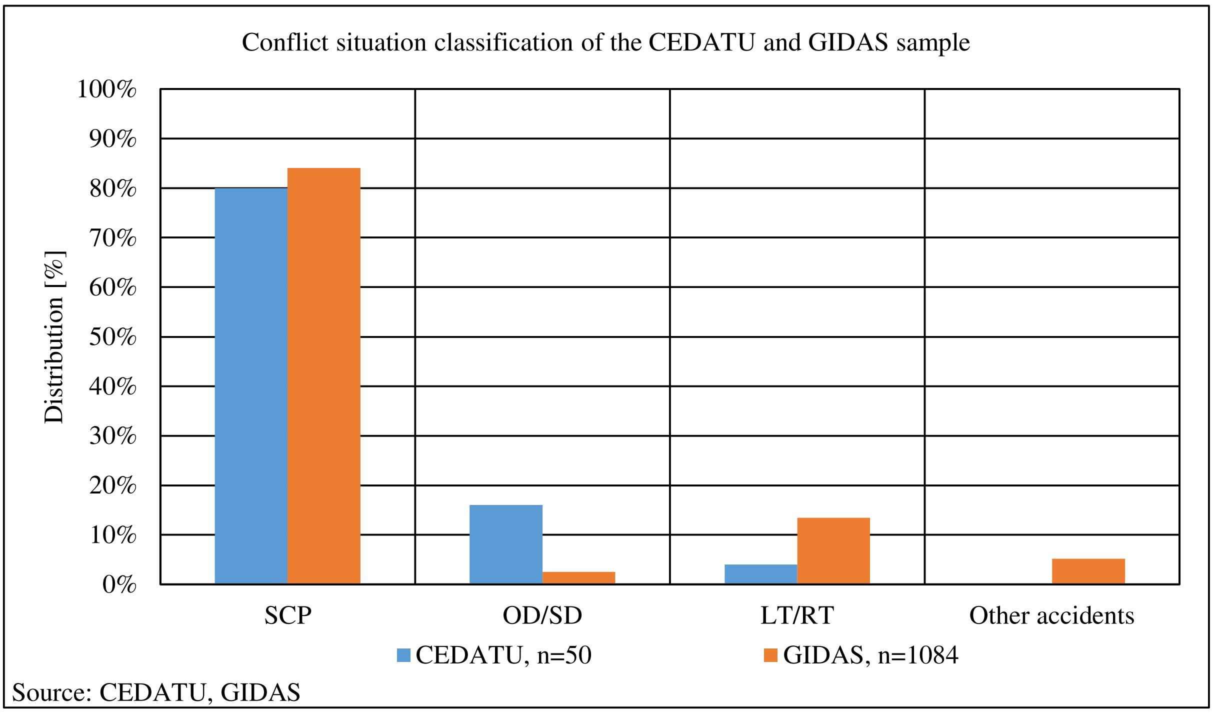

Figure 1. Conflict situations covered in the CEDATU and GIDAS sample. For the V_PAD sample, only SCP crashes were considered.

Virtual pre-crash simulation

The pre-crash phases of reconstructed real-world accidents were rerun within a virtual forward simulation, where the vehicle follows the trajectory and the velocity profile of the reconstructed case until the system reacts. The baseline simulations were compared to treatment simulations, where the vehicles are virtually equipped with an ideal, conceptual P-AEB System having a generic sensor and various braking strategies.

The virtual forward pre-crash simulations in this study were made using three different simulation tools: X-RATE, rateEFFECT and VCaRT: In general, each of them operates on a time-step basis. At each time-step, the tool updates its information (speed, position, rotation, etc.) on dynamic objects by querying the dynamics simulation module. Based on that information, the sensor vision module determines which objects in the environment are visible. The sensor information is then forwarded to the function logic module which represents the P-AEB systems that are simulated by the individual tools. When the function logic module decides to intervene by e.g. braking, appropriate deceleration values are forwarded to the dynamics module for simulation of the next time step. The simulation terminates as soon as the stop criteria are fulfilled (i.e. first collision is detected or maximum simulation time reached).

X-RATE (Extended Effectiveness Rating of Advanced Assistance Systems) is developed by the Vehicle Safety Institute at TU Graz to simulate a variation of different sensor parameters and different active safety systems. It has already been used successfully for several research questions (e.g. pedestrian collision avoidance systems [19], collision mitigation for motorcycles at junctions [20], collision mitigation at intersections [21]) or in combination with traffic flow simulation [22]). X-RATE is developed in MATLAB and operates in conjunction with PC-Crash as driving dynamics simulation core.
rateEFFECT is a tool developed and used by Volkswagen Group to analyse the performance of advanced driver assistance or safety systems in traffic scenarios and to evaluate the effectiveness of active safety systems. The functionality is very similar to X-RATE as the vehicle dynamics and the scenery is based on PC Crash, too. Via a system editor it is possible to define own active systems with predefined or self-developed function blocks. The system configuration generally consists of sensors, algorithms, driver models and actuators. [23,24] The effectiveness assessment is an important procedure during the process of function development and is used for internal and external research questions, latest for the accident analysis done for the effectiveness evaluation of the General Safety Regulation for the European Commission [12–14].
VCaRT (Volvo Cars Research pre-crash simulation Tool) is a MATLAB tool to evaluate the potential of conceptual and ideal crash avoidance/mitigation ADAS. The tool main parts are simulation control, vehicle surrounding, virtual vehicle and collision control. The simulation control synchronizes the execution of the other parts, which can be configured depending on the test to be performed. Elements in the vehicle surrounding are 3-dimensional representations of the objects. The vehicle representation is based on a point-mass-model combined with actuator models that constrains the response on function logic requests. Examples of parameters that can be varied in the sensor model are field of view, sensor position and classification time.

Analysis of results

In order to analyse the potential safety effect of the P-AEB systems, the collision speed was used. It was defined as the speed of the vehicle at the first time step when the pedestrian and the vehicle geometries were intersecting. The mean and median collision velocities as well as the standard deviations (SD) were analysed from the different data sets separately. The mean of the relative reduction ($\overline{\Delta v_{c\_rel}}$) of the collision speed was calculated according to Equation (1) as 1 minus the mean value of the case-wise ratio of the collision speed in the treatment simulations ($v_{c-treatment_i}$) and the baseline simulation ($v_{c-baseline_i}$), with n being the number of analysed cases.

$$\overline{v_{c\_red\_rel}} = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{v_{c-treatment_i}}{v_{c-baseline_i}} \qquad \text{Equation (1)}$$

Conceptual P-AEB system

The generic sensor of the virtual P-AEB system was positioned 1.8 m behind the vehicle front. The range of the sensor model was set to 80 m. The opening angle of the sensor model was varied between 60° (Sensor 1), 90° (Sensor 2) and 120° (Sensor 3). The sensor vision was implemented by considering vision rays, also described in [25] and checks visibility of objects every 15 ms. The vision rays are emitted horizontally with a resolution of 0.1°, as shown in Figure 2. Intersections of the vision rays and the pedestrian are detected at each time step. If the pedestrian is fully within the sensor area, this is classified and the Time to Collision (TTC) is calculated.
The TTC is calculated by deriving a relative speed vector between the car and the pedestrian at each time step. The algorithm estimates how long it would take until a detected point, moving with the relative speed, contacts the ego-vehicle (car). The minimum time for all detected points is the estimated TTC for this time-step.
The P-AEB is triggered, when the pedestrian is classified (i.e. visible and 100% in the sensor area) for at least 150 ms (acquisition time) and the calculated TTC is ≤ 1 s. The car and pedestrian follow the original trajectory and the acceleration profiles remain unchanged until the AEB takes over.
After getting the AEB trigger signal, a 0.2 s actuator delay is assumed (=reaction time of the brake system).

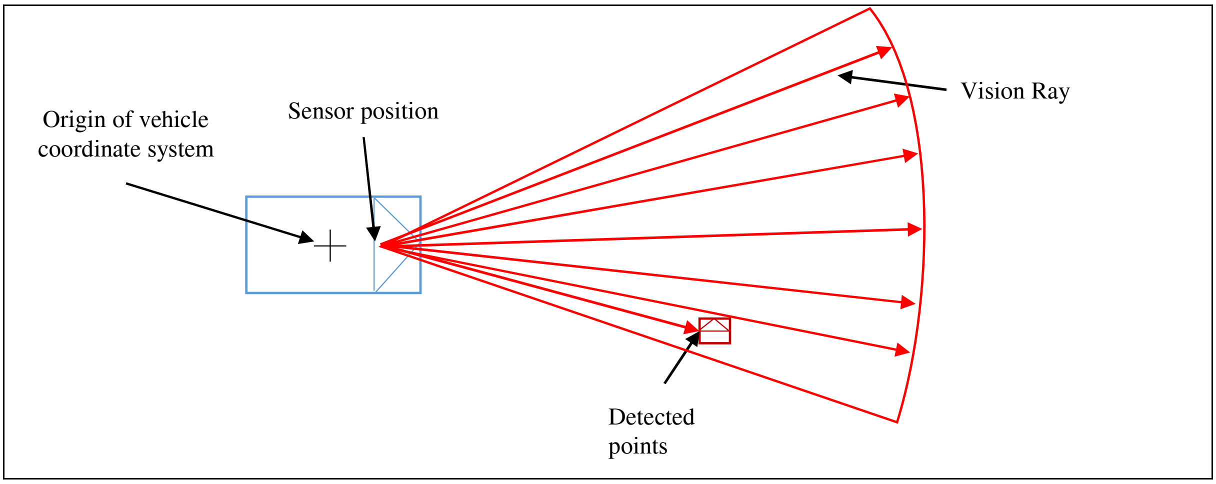

Figure 2. Top view of the sensor vision based on [25]

As brakes are activated, the maximum realisable acceleration is build up. The build-up time depends on the brake gradient of the system (see Equation (2). The results for the build-up times are shown in Table 9 in the appendix.

$$\textit{build-up time} = \frac{deceleration}{brake\ gradient} \qquad \text{Equation (2)}$$

The maximum deceleration depends on the friction coefficient which in turn depends on the road conditions. Different brake systems were evaluated (Table 2), which differed in terms of braking gradient and maximum realisable deceleration. In total four variations were investigated.

Table 2.
Definition of the braking systems for treatment simulations

	Braking system	Brake gradient	Max. realisable deceleration
Brake 1	Standard	24.5	0.8*g
Brake 2	Standard	24.5	1.1*g
Brake 3	Innovative	35	0.8*g
Brake 4	Innovative	35	1.1*g

The braking profiles of the different braking strategies are shown in Figure 3. After the actuator delay, the deceleration increases with the defined brake gradients to the maximally feasible deceleration.
Brake 1 and Sensor 1 as well as the applied strategy are in accordance with a previous studies [12–14].

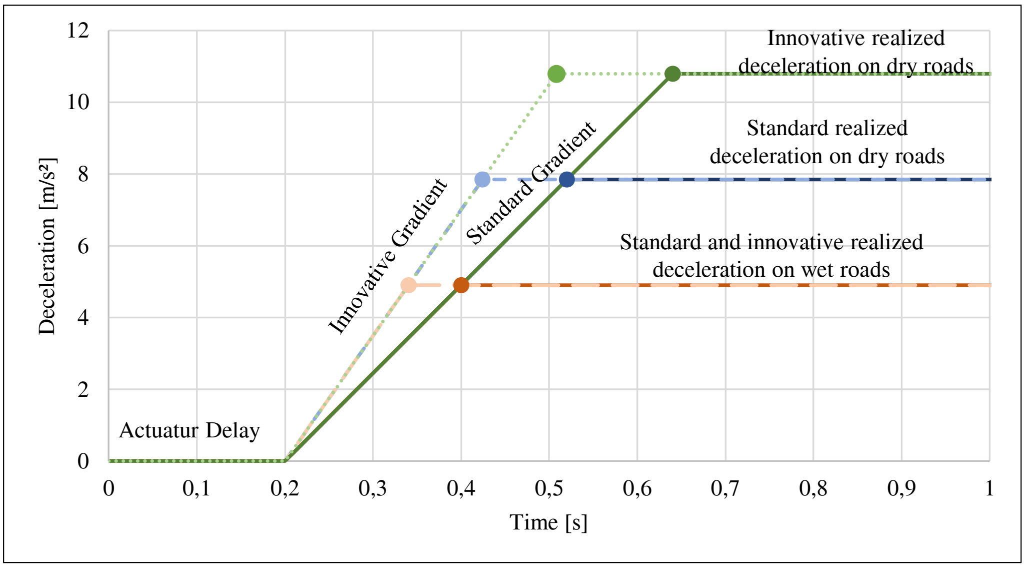

Figure 3. Braking Profile

RESULTS

In total, twelve treatment simulations of every baseline simulation were performed for the CEDATU and V_PAD sample. In GIDAS only one treatment simulation per baseline simulation (with Sensor 1 and Brake 1) was performed.
The results are presented by means of the data sample in this section. Collision speeds and the share of avoided cases of the different treatment simulations are compared to the baseline sample. For avoided accidents the collision speed was set to 0 km/h, resulting in a relative reduction of 100%. Mean and Median values were analysed per braking system for each sensor as well as overall braking systems.

CEDATU Cases

The mean collision speed of the original baseline CEDATU cases was 47.2 km/h (SD=20.4 km/h) and the median 45 km/h. The mean collision speed over all simulated P-AEB strategies was reduced by 55% to 24.9 km/h (SD=22 km/h). The individual results of the treatment simulations are shown in Table 3, depending on the sensor-opening angle and the braking system. The highest reduction of the collision speed $\overline{v_{c\_red}}$ (including avoided accidents as accidents with 0 km/h) was observed with Sensor 3 and Brake 4. The baseline collision speed of 47.2 km/h (SD=20.4 km/h) was reduced by 67.1% to 19.2 km/h (SD=22.7 km/h and the median from 45 km/h to 6.7 km/h. Sensor 3 and Brake 4 avoided 21 accidents (42%). The lowest change of the collision speed was observed with Sensor 1 and Brake 1. The reduction was 17.8 km/h (45.5%) and 9 accidents (18%) were avoided. A comparison of Sensor 1 and 2 shows that the difference of the mean collision speed due to the increased sensor angles was 0.1 km/h. A difference of the collision speed of about 0.3 km/h was observed between Sensor 1 and Sensor 3. Sensor 3 avoided one additional accident compared to Sensor 1 or 2. A comparison of Brake 1, 2 and 3 shows that a higher maximum deceleration results in a lower collision speed than a larger brake gradient.
With Brake 1 and Sensor 1 or 2, nine accidents were avoided (18%). When increasing the maximum deceleration to 1.1 g (Brake 2), five additional collisions were avoided (in total 28% avoided accidents). By increasing the brake gradient to 35 m/s³ (Brake 3), two additional accidents were avoided compared to brake 1. Combined with the higher maximum deceleration (Brake 4), a total number of 20 (40%) accidents were avoided.

Table 3.
Results of the CEDATU treatment simulations depending on the sensor opening angle and braking strategy including avoided accidents as accidents with 0 km/h

Sensor strategy	Braking strategy	Median v_c [km/h]	Mean $\overline{v_c}$ [km/h]	Mean reduction $\overline{v_{c\_red}}$ [km/h]	Mean rel. reduction $\overline{v_{c\_red\_rel}}$ [%]	Avoided cases
Baseline		45	47.2 (SD=20.4)	-	-	-
Sensor 1	Brake 1	27.6	29.4 (SD=22.5)	17.8	45.5%	9 (18%)
	Brake 2	19.5	23.8 (SD=22.6)	23.4	56.4%	14 (28%)
	Brake 3	25.1	27.6 (SD=22.5)	19.6	50.0%	11 (22%)
	Brake 4	8.7	19.6 (SD=22.6)	27.6	64.7%	20 (40%)
	Overall	24.2	25.1 (SD=22.9)	22.1	54.1%	
Sensor 2	Brake 1	27.6	29.3 (SD=22.6)	17.9	45.9%	9 (18%)
	Brake 2	19.4	23.7 (SD=22.6)	23.5	56.8%	14 (28%)
	Brake 3	25.0	27.5 (SD=22.6)	19.7	50.2%	11 (22%)
	Brake 4	8.7	19.5 (SD=22.6)	27.7	65.1%	20 (40%)
	Overall	23.0	25.0 (SD=22.9)	22.2	54.5%	
Sensor 3	Brake 1	27.6	29.1 (SD=22.7)	18.1	47.9%	10 (20%)
	Brake 2	19.4	23.5 (SD=22.7)	23.7	58.8%	15 (30%)
	Brake 3	25	27.3 (SD=22.8)	19.9	52.2%	12 (24%)
	Brake 4	6.7	19.2 (SD=22.7)	28.0	67.1%	21 (42%)
	Overall	23.0	24.8 (SD=23.0)	22.4	56.5%	

In Table 4 the results of the CEDATU sample were separated between cases where the pedestrians were coming from the left (far side) or right side (near side).
The mean collision speed of the 24 far side cases was 45.8 km/h (SD=16.9 km/h). The mean collision speed of the treatment simulations of all P-AEB systems was 23.7 km/h (SD=20.5 km/h), with a reduction of 55.7%. Due to the best braking strategy (Brake 4) the collision speed was reduced by 66.8% to 17.5 km/h (SD=19.8 km/h) compared to the least effective braking strategy (Brake 1), for which the mean collision speed was reduced to 28.2 km/h (47.2%). In the simulations with Brake 4, twelve accidents were avoided, while six accidents were avoided with Brake 1. For the far side scenario, no influence of the sensor angle was observed.
The sample comprises nine accidents from the nearside scenario with a baseline mean collision speed of 30 km/h (SD=13.1 km/h). The collision speed was reduced to 11.2 km/h (SD=12.3 km/h) within the simulations with Sensor 1 or Sensor 2, which is a reduction of 61.9%. The simulations with Sensor 3 achieved a collision speed of 10 km/h (SD=12.8 km/), this was a reduction of 73%. With Sensor 1 or 2, at least 3 accidents were avoided (33%). Sensor 3 and braking system 4 was the most effective system as 5 accidents were avoided (55%) and the lowest mean collision speed for treatment simulations (7.2 km/h, SD=11.8 km/h) was observed.

Table 4.
CEDATU treatment simulations for far side and nearside SCP traffic simulation scenarios including avoided accidents as accidents with 0 km/h

		Farside situations (n=24)			Nearside situations (n=9)		
Sensor strategy	Braking strategy	Mean $\overline{v_c}$ [km/h]	$\overline{v_{c\_red}}$ [km/h] ($\overline{v_{c\_red\_rel}}$)	Avoided cases	Mean $\overline{v_c}$ [km/h]	$\overline{v_{c\_red}}$ [km/h] ($\overline{v_{c\_red\_rel}}$)	Avoided cases
Baseline		45.8 (SD=16.9)	-	-	30.0 (SD=13.1)	-	-
Sensor 1	Brake 1	28.2 (SD=20.5)	17.5 (47.3%)	6 (25%)	13.0 (SD=12.7)	16.9 (56.4%)	3 (33%)
	Brake 2	22.4 (SD=20.2)	23.4 (58.6%)	8 (33%)	12.1 (SD=11.9)	17.9 (58.7%)	3 (33%)
	Brake 3	26.8 (SD=20.1)	18.9 (50.1%)	6 (25%)	11.4 (SD=12.4)	18.6 (62.6%)	3 (33%)
	Brake 4	17.5 (SD=19.8)	28.2(66.9%)	12 (50%)	8.4 (SD=11.6)	21.6 (69.9%)	4 (44.4%)
	Overall	23.7 (SD=20.5)	22.0 (55.7%)	-	11.2 (SD=12.3)	18.7 (61.9%)	--
Sensor 2	Brake 1	28.2 (SD=20.5)	17.5 (47.3%)	6 (25%)	13.0 (SD=12.7)	16.9 (56.4%)	3 (33%)
	Brake 2	22.4 (SD=20.2)	23.4 (58.6%)	8 (33%)	12.1 (SD=11.9)	17.9 (58.7%)	3 (33%)
	Brake 3	26.8 (SD=20.1)	18.9 (50.1%)	6 (25%)	11.4 (SD=12.4)	18.6 62.6%)	3 (33%)
	Brake 4	17.5 (SD=19.8)	28.2(66.9%)	12 (50%)	8.4 (SD=11.6)	21.6 (69.9%)	4 (44.4%)
	Overall	23.7 (SD=20.5)	22.0 (55.7%)	-	11.2 (SD=12.3)	18.7 (61.9%)	-
Sensor 3	Brake 1	28.2 (SD=20.5)	17.5 (47.3%)	6 (25%)	11.8 (SD=13.4)	18.1 (67.5%)	4 (44.4%)
	Brake 2	22.4 (SD=20.2)	23.4 (58.6%)	8 (33%)	10.9 (SD=12.5)	19.1 (69.8%)	4 (44.4%)
	Brake 3	26.8 (SD=20.1)	18.9 (50.1%)	6 (25%)	10.2 (SD=12.9)	19.8 (73.7%)	4 (44.4%)
	Brake 4	17.5 (SD=19.8)	28.2(66.9%)	12 (50%)	7.2 (SD=11.8)	22.7 (81.0%)	5 (55.5%)
	Overall	23.7 (SD=20.5)	22.0 (55.7%)	-	10.0 (SD=12.8)	19.9 (73.0%)	-

An influence of the opening angle was observed in two simulated accident cases without sight obstructions at junctions (conflict situation LT/SD and SCP). The relative trajectory of the pedestrian to the vehicle is shown in Figure 4 with black lines. For the first accident (SCP), only the P-AEB with Sensor 3 was able to avoid the accident. In the second case (LT/SD), the AEB was triggered with Sensor 2 and 3 earlier. The System was able to reduce the collision speed by about 23.4% from 25 km/h to 19.4 km/h with the best system (Sensor 3 and Brake 4). In Figure 4, the relative position of the pedestrian to the vehicle is shown for 2 other CEDATU cases as grey line. These two cases with sight obstructions were detected for all sensor angles at the same time.
In another 5 accidents with sight obstructions, the pedestrian was classified at the same time and no influence of the opening angle was observed.

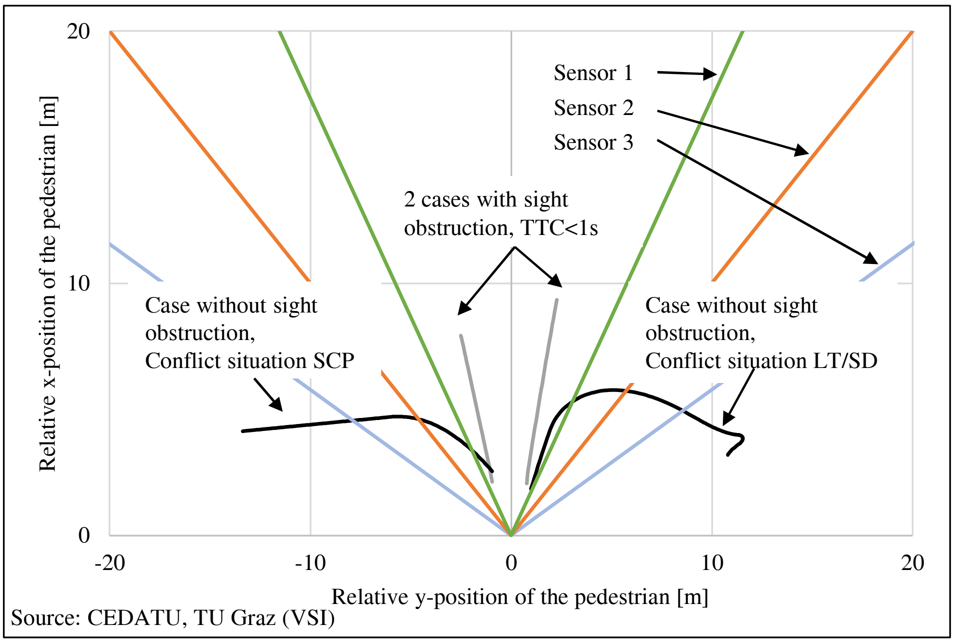

Figure 4. Trajectories of the pedestrian relative to the vehicle of CEDATU simulations for four selected cases

GIDAS Cases

The mean collision speed of the original GIDAS cases was 30.7 km/h (SD=14.6). Due to treatment simulations with Sensor 1 and Brake 1 (Table 5), the collision speed was reduced by 17.1 km/h to 13.6 km/h (SD=14.7), which equals a relative reduction ($\overline{v_{c\_red\_rel}}$) of 57.7%. This system avoided 39.6% of 1078 cases.

Table 5.
Results of the GIDAS treatment simulations depending on the sensor opening angle and braking strategies including avoided accidents as accidents with 0 km/h

Sensor strategy	Braking strategy	Median v_c [km/h]	Mean $\overline{v_c}$ [km/h]	Mean reduction $\overline{v_{c\_red}}$ [km/h]	Mean rel. reduction $\overline{v_{c\_red\_rel}}$ [%]	Avoided cases
Baseline		29.1	30.7 (SD=14.6)	-	-	-
Sensor 1	Brake 1	11.0	13.6 (SD=14.7)	17.1	57.7%	429 (39.6%)

V_PAD Cases

The mean collision speed of the original V_PAD cases was 23.6 km/h (SD=16.3 km/h) and the median 20 km/h. The mean collision speed for all simulated P-AEB strategies was reduced by 70.2% to 7 km/h (SD=22 km/h).
The treatment simulation results are shown in Table 6, depending on the sensor opening angle and the braking system. The highest change of collision speed $\overline{v_{c\_red}}$ (including avoided accidents with 0 km/h) was achieved with Sensor 3 and Brake 4. The baseline collision speed of 23.6 km/h (SD=16.3 km/h) was reduced to 5.8 km/h (SD=12.4 km/h). This represents a reduction of 17.8 km/h ($\overline{v_{c\_red\_rel}}$ =86.6%). The lowest reduction of the collision speed ($\overline{v_{c\_red\_rel}}$ =79%) was achieved with Sensor 1 and Brake 1. The effect of the different sensors was very small. The mean collision speeds differed by only 0.1-0.2 km/h for all brakes. The results of Sensor 2 and 3 were equal for all brakes. The mean collision speed of Sensor 1 over all braking systems was 7.1 km/h

(SD=13.2 km/h). All braking systems with Sensor 2 and Sensor 3 were able to reduce the collision speed to 7 km/h (SD=13.3 km/h).
A comparison of the braking systems shows that Brake 4 leads to the lowest collision speed for all three simulated sensors. With Brake 2 and 3, differences in standard deviation and number of avoided accidents were observed.
In the simulations with Sensor 1 and Brake 1 at least 45 (66.2%) accidents were avoided, while the number of avoided cases with Sensor 2 and 3 was at least 47 (69.1%). The best system (Sensor 3, Brake 4) avoided 54 accidents (79.4%).

Table 6.
Results of the V_PAD treatment simulations depending on the sensor opening angle and braking strategy including avoided accidents as accidents with 0 km/h

Sensor strategy	Braking strategy	Median v_c [km/h]	Mean $\overline{v_c}$ [km/h]	Mean reduction $\overline{v_{c\_red}}$ [km/h]	Mean rel. reduction $\overline{v_{c\_red\_rel}}$ [%]	Avoided cases
Baseline		20	23.6 (SD=16.3)	-		-
Sensor 1	Brake 1	0	8.2 (SD=13.9)	15.4	79.0%	45 (66.2%)
	Brake 2	0	7.2 (SD=13.3)	16.4	81.1%	48 (70.6%)
	Brake 3	0	7.2 (SD=13.1)	16.4	81.4%	49 (72.1%)
	Brake 4	0	6.0 (SD=12.4)	17.7	83.7%	52 (76.5%)
	Overall	0	7.1 (SD=13.2)	16.5	81.3%	-
Sensor 2	Brake 1	0	8.1 (SD=14.0)	15.6	81.9%	47 (69.1%)
	Brake 2	0	7.0 (SD=13.3)	16.6	84.0%	50 (73.5%)
	Brake 3	0	7.0 (SD=13.2)	16.6	84.3%	51 (75.0%)
	Brake 4	0	5.8 (SD=12.4)	17.8	86.6%	54 (79.4%)
	Overall	0	7.0 (SD=13.3)	16.6	84.2%	-
Sensor 3	Brake 1	0	8.1 (SD=14.0)	15.6	81.9%	47 (69.1%)
	Brake 2	0	7.0 (SD=13.3)	16.6	84.0%	50 (73.5%)
	Brake 3	0	7.0 (SD=13.2)	16.6	84.3%	51 (75.0%)
	Brake 4	0	5.8 (SD=12.4)	17.8	86.6%	54 (79.4%)
	Overall	0	7.0 (SD=13.3)	16.6	84.2%	-

In Table 7 the results of the V_PAD sample were separated in far side and near side scenarios. The mean collision speed of the 32 far side cases was 26.8 km/h (SD=17.8 km/h). The collision speed was reduced to 9.7 km/h (SD=15.3 km/h) with simulations of Sensor 1. The mean relative reduction ($\overline{v_{c\_red\_rel}}$) was 74%. The simulations with Sensor 2 and 3 achieved a reduction of 80.3 % to a collision speed of 9.4 km/h (SD=15.4 km/h). With Sensor 1, at least 19 accidents (59.4%) were avoided. The most effective System (Sensor 3 and Brake 4) avoided 23 (71.9%) of the 32 far side scenarios and reduced the collision speed about 18.6 km/h (82.6%) to 9.4 km/h (SD=15.4 km/h)
The V_PAD sample comprises 36 nearside scenarios with a baseline collision speed of 20.9 km/h (SD=14 km/h). The collision speed was reduced for all 3 sensors by about 87.7% to 4.8 km/h (SD=10.6 km/h). Brake 1 avoided 26 (72.2%), Brake 2 28 (77.7%) and Brake 3 29 (80.5%) accidents. The best system with Brake 4 avoided 31 of the 36 near side cases (86.1%). No influence of the sensor opening angle for the nearside scenario was observed.

Table 7.
V_PAD treatment simulations for farside and nearside SCP traffic simulation scenarios including avoided accidents as accidents with 0 km/h

		Farside scenario (n=32)			Nearside scenario (n=36)		
Sensor strategy	Braking strategy	Mean $\overline{v_c}$ [km/h]	$\overline{v_{c\_red}}$ [km/h] ($\overline{v_{c\_red\_rel}}$)	Avoided cases	Mean $\overline{v_c}$ [km/h]	$\overline{v_{c\_red}}$ [km/h] ($\overline{v_{c\_red\_rel}}$)	Avoided cases
Baseline		26.8 (SD=17.8)	-	-	20.9 (SD=14.0)	-	-
Sensor 1	Brake 1	10.9 (SD=15.9)	15.8 (71.7%)	19 (59.4%)	5.8 (SD=11.3)	15.1 (85.5%)	26 (72.2%)
	Brake 2	9.9 (SD=15.5)	16.8 (73.4%)	20 (62.5%)	4.8 (SD=10.3)	16.1 (87.9%)	28 (77.7%)
	Brake 3	9.5 (SD=15.0)	17.3 (74.7%)	20 (62.5%)	5.1 (SD=10.8)	15.7 (87.3%)	29 (80.5%)
	Brake 4	8.5 (SD=14.5)	18.3 (76.4%)	21 (65.6%)	3.7 (SD=9.7)	17.1 (90.2%)	31 (86.1%)
	Overall	9.7 (SD=15.3)	17.0 (74.0%)	-	4.8 (SD=10.6)	16.0 (87.7%)	-
Sensor 2	Brake 1	10.6 (SD=16.1	16.1 (77.9%)	21 (65.5%)	5.8 (SD=11.3)	15.1 (85.5%)	26 (72.2%)
	Brake 2	9.6 (SD=15.7)	17.1 (79.7%)	22 (68.8%)	4.8 (SD=10.3)	16.1 (87.9%)	28 (77.7%)
	Brake 3	9.2 (SD=15.1)	17.6 (80.9%)	22 (68.8%)	5.1 (SD=10.8)	15.7 (87.3%)	29 (80.5%)
	Brake 4	8.2 (SD=14.6)	18.6 (82.6%)	23 (71.9%)	3.7 (SD=9.7)	17.1 (90.2%)	31 (86.1%)
	Overall	9.4 (SD=15.4)	17.3 (80.3%)	-	4.8 (SD=10.6)	16.0 (87.7%)	-
Sensor 3	Brake 1	10.6 (SD=16.1	16.1 (77.9%)	21 (65.5%)	5.8 (SD=11.3)	15.1 (85.5%)	26 (72.2%)
	Brake 2	9.6 (SD=15.7)	17.1 (79.7%)	22 (68.8%)	4.8 (SD=10.3)	16.1 (87.9%)	28 (77.7%)
	Brake 3	9.2 (SD=15.1)	17.6 (80.9%)	22 (68.8%)	5.1 (SD=10.8)	15.7 (87.3%)	29 (80.5%)
	Brake 4	8.2 (SD=14.6)	18.6 (82.6%)	23 (71.9%)	3.7 (SD=9.7)	17.1 (90.2%)	31 (86.1%)
	Overall	9.4 (SD=15.4)	17.3 (80.3%)	-	4.8 (SD=10.6)	16.0 (87.7%)	-

Summary of most and the least effective system

In Table 8, the mean reduction of the least effective system (Sensor 1, Brake 1) and the most effective System (Sensor 3, Brake 4) including avoided accidents as accidents with 0 km/h collision speed is shown. The results show a similar reduction of the collision speed for Sensor 1 and Brake 1 for all three databases. In the GIDAS sample, the speed was reduced by 17.1 km/h (57.7%) compared to 17.8 km/h (45.5%) in the CEDATU cases and 15.4 km/h (79%) in the V_PAD cases. With the most effective system (Sensor 3, Brake 4), a higher reduction of the collision speed was observed compared to the least effective System. In CEDATU, a reduction of 28 km/h (67.1%) was observed and in V_PAD, 17.8 km/h (86.6%).

Table 8.
Mean reduction of the collision speed through treatment simulations including avoided accidents as accidents with 0 km/h

	Sensor 1, Brake 1		Sensor 3, Brake 4	
Database	Mean reduction $\overline{v_{c\_red}}$ [km/h]	Mean rel. reduction $\overline{v_{c\_red\_rel}}$ [%]	Mean reduction $\overline{v_{c\_red}}$ [km/h]	Mean rel. reduction $\overline{v_{c\_red\_rel}}$ [%]
CEDATU	17.8	45.5%	28	67.1%
GIDAS	17.1	57.7%	-	-
V_PAD	15.4	79.0%	17.8	86.6%

DISCUSSION

Effect of different data sources

Accident scenarios in different countries can highly differ [26] for various reasons (e.g. different speed limits, country specific regulations, etc.). Thus, it is valuable to include different regions for such kind of investigation. For the present study, three databases were available.

The three different data samples differed in terms of the collision velocities of the accidents. The mean speed in the CEDATU sample was highest with 47.2 km/h, followed by GIDAS with 30.7 km/h and V_PAD with 23.6 km/h. The greater severity of the CEDATU accidents is also obvious from the analysis of the injury severities: In the CEDATU sample, 50% of the pedestrians suffered an injury of severity greater than AIS 4 +. In the GIDAS sample only 7% and the V_PAD sample only 3% of the pedestrians sustained AIS 4+ injuries.

Even if the relative speed reduction is similar in simulations based on the three different data sources, the mean speeds for remaining crashes is lower in V_PAD. The V_PAD sample is based on insurance claim reports, and is thus including a wide range of crash situations. Compared to VRU cases in the police reported sample in STRADA, only 50% of crashes reported to the insurance company were covered by police reports [27]. This is a probable reason why the mean collision speed in this data sample is lower than in the other two data samples. Also, the baseline sample from V_PAD only included SCP crashes that are associated with lower collision speeds than e.g. situations in longitudinal traffic. CEDATU and GIDAS include more severe accident cases and therefore, results based on CEDATU and GIDAS are reflecting higher collision speeds. Differences in initial speed are caused by the original focus of CEDATU on accidents resulting in fatalities (cases before 2008) and different share of conflict situations between the CEDATU and GIDAS datasets.

For all three data sources, information of crashes were collected retrospectively. The collision speeds and trajectories of the baseline simulations are calculated based on accident sketches. However, in GIDAS an accident team is investigating the accident on the spot whereby in CEDATU and V_PAD the data are investigated based on various kinds of reports. In order to compensate for uncertainties in the pre-crash data, robustness analysis of parameters should be performed (e.g. variation of pedestrian- and car speed). This is usually done for baselines from V_PAD, but was not performed in the current study.

Although it was tried to perform analysis as similar as possible, the applied simulation tools were not harmonised. Those differences are discussed within the P.E.A.R.S. initiative [11], which is working on the definition of a harmonised assessment process for effectiveness evaluations.

The results show a similar reduction of the collision speed for all three data sources with the least effective system (Sensor 1 and Brake 1).

Speed range for passive safety measures

To calculate the overall effectiveness, the avoided cases are assigned a collision speed of 0 km/h. Else the effectiveness evaluation would rate systems poorer as they are, because only severe cases remain.

When defining requirements for the passive safety measures, though, it makes no sense to consider avoided cases. Therefore, those were excluded for the definition of requirements to future passive safety measures that is discussed in the following section.

It is remarkable that even for the severe CEDATU sample the least effective P-AEB system (Sensor 1, Brake 1) is able to reduce the mean collision speed to less than 40 km/h, which is the impact speed in current passive safety systems. 63.4% of the unavoided cases would be covered by current pedestrian safety testing. In the V_PAD simulations with the least effective system, 87% of the simulated were below 40 km/h.

The speed distribution (shaded area) and the cumulative speed distribution (lines) of the cases are shown in Figure 5. The baseline speeds include all cases, the treatment simulation only unavoided cases. The analysis show that if it is intended to cover the same ratio of accidents with passive safety measures as today (with vehicles without P-AEB system), the speed considered for the evaluation of passive safety measures can be reduced by at least 34%. With the impact speed at 40 km/h [ref procedure], it would be possible to address a larger proportion of accidents than today. Looking at the results based on the V_PAD sample (although considering only SCP situations) more than 90% of the remaining accidents had speeds below this.

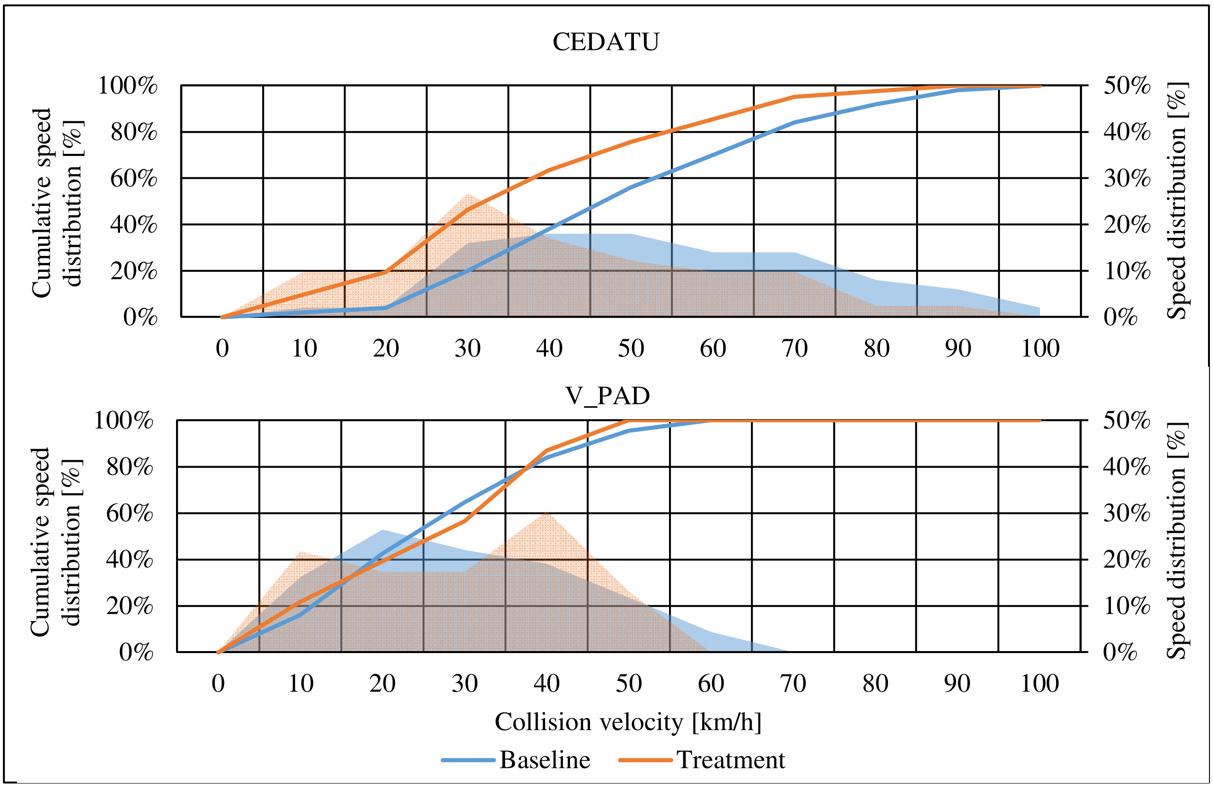

Figure 5. Distribution of the cumulative collision speed for crashes in baseline and unavoided crashes in treatment condition (baseline cases in the treatment not considered)

Effect of opening angle

A similar effect of the sensor opening angle was noticed in treatment simulations of the V_PAD and CEDATU cases. Increasing the sensor angle did affect the results only marginally. Within CEDATU, a sensor opening angle of 120° additionally avoided one accident more (+2%) compared to 60° and 90°. For V_PAD, a sensor opening angle of 90° and 120° avoided 2 additional accidents (+2.9%) compared to 60°.

Effect of braking characteristics

A higher brake gradient (Brake 3 versus Brake 1) leads to two additional (+4%) avoided cases in CEDATU and four additional (+5.8%) in the V_PAD sample. Increasing the maximum realisable deceleration (Brake 1 vs 2 and 3) has a greater effect on the CEDATU cases than on the V_PAD sample.

The effect of the different braking systems depends to a great extent on the sample composition. In the CEDATU sample, 68% of the cases were on dry road, 69% in GIDAS and 33.8% in V_PAD. A comparison of Brake 2 and 3 in V_PAD showed no differences in mean collision speed, while 5.6 km/h in CEDATU.

For real sensors, proper classification and collision detection of moving objects such as pedestrians is a particular challenge. With the ideal generic sensors, in the performed simulations, the pedestrian was classified only when it was 100% in the sensor field of view. Collision detection was based on deriving a relative speed vector between the car and the pedestrian and exact detected positions, while real sensor output is noisy and contains measurement error. The algorithm of the real safety system therefore operates under the assumption that the data is noisy, which leads to different implementations than with an ideal sensor. Furthermore, environmental influences (rain, fog) also negatively affect the visibility of objects, which has not been accounted for in the ideal sensor. Overall, the effects from ideal P-AEB systems that were evaluated in this study can differ from real P-AEB systems.

CONCLUSIONS

Virtual precrash simulations of different ideal and conceptual P-AEB systems using real-world pedestrian cases from three different accident databases as baseline, showed that the lower the mean baseline collision speed in the data sample, the more accidents were avoided. The maximum deceleration was the most influential P_AEB system parameter on the share of avoided cases and on the collision speed of the remaining cases. With the best system and the least severe data sample, 20% of the accidents/crashes still remained. A drastic reduction of collision speed (min 34%) was observed in all three data samples and this even with the most conservative P-AEB system parameters. This clearly highlights the need for a combined vehicle safety assessment instead of a separate evaluation of active and passive pedestrian safety measures.

ACKNOWLEDGEMENT

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APPENDIX

Table 9.
Calculated Build - Up Times

Build-up times	Brake gradient	
Realized Deceleration	24.5 m/s³	35 m/s³
$0.5*g = 4.91$ m/s²	0.2 s	0.14 s
$0.8*g = 7.85$ m/s²	0.32 s	0.22 s
$1.1*g = 10.79$ m/s²	0.44 s	0.31 s

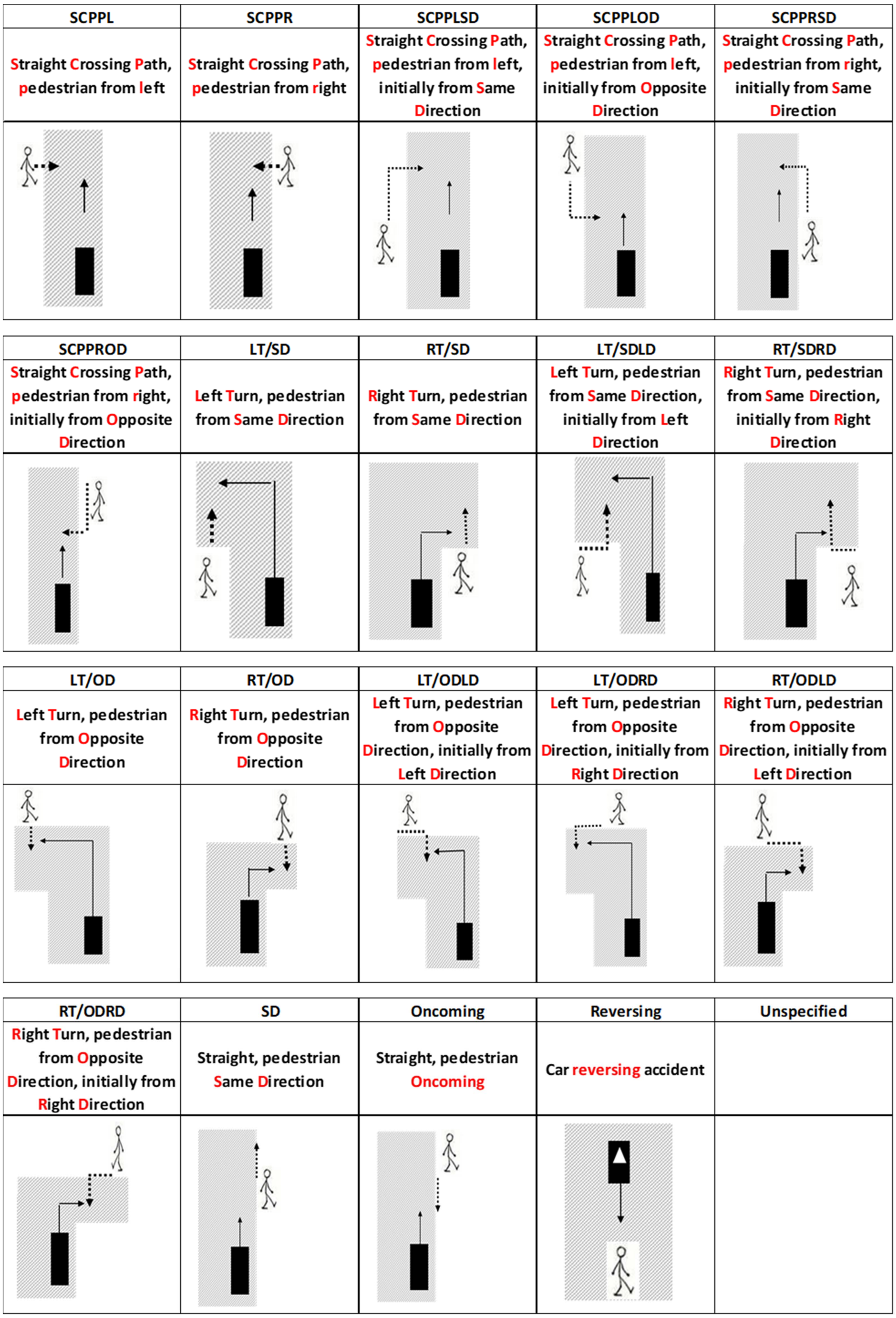

Figure 6: Definition of conflict situations according to Lindman et al. [17]

THE L3PILOT COMMON DATA FORMAT – ENABLING EFFICIENT AUTOMATED DRIVING DATA ANALYSIS

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ABSTRACT

Analyzing road-test data is important for developing automated vehicles. L3Pilot is a European pilot project on level 3 automation, including 34 partners among manufacturers, suppliers and research institutions. Targeting around 100 cars and 1000 test subjects, the project will generate large amounts of data. We present a data format, allowing efficient data collection, handling and analysis by multiple organizations.

A project of the scope of L3Pilot involves various challenges. Data come from a multitude of heterogeneous sources and are processed by a variety of tools. Recorded data span all data types generated in various vehicular sensors/systems and are enriched with external data sources. Videos supplement time-series data as external files. Derived measures and performance indicators – required to answer research questions about effectiveness of automated driving – are processed by analysis partners and included for each test session.

As a file format, we chose HDF5, which offers a data model and software libraries for storing and managing data. HDF5 is designed for flexible and efficient I/O and for high volume and complex data. The usage of different computing environments for specific tasks is facilitated by the portability that comes with the format. Portability is also important for exploiting the rising potential within artificial intelligence (e.g. automatic scene detection and video annotation).

Based on lessons learned from past field tests, we defined a general frame for the common data format that is aligned with the data processing steps of FESTA "V" evaluation methodology. The definitions include representation of the source signals and a hierarchical structure for including multiple datasets that are gradually supplemented (post-processed or annotated) during the various analysis steps. By using the HDF5 format, analysis partners have the freedom to exploit their familiar tools: MATLAB, Java, Python, R, etc. First comparisons between time-series data in previous projects (e.g. AdaptIVe) and the proposed data format show a reduction in storage size of around 80 %, without losses in performance. Much of that is due to efficient internal compression and structuring of data. Considering the amount of objective data involved in automated driving, this leads to a great benefit, in terms of usability.

This paper presents a compact, portable, and extensible format aimed at handling extremely large amounts of field test data collected in automated driving pilots. As a harmonized format between tens of organizations performing tests in the L3Pilot project, the proposed format has the potential to promote data sharing as well as development of common tools and gain popularity for use in other projects. The format is designed to allow efficient storing of data and its iterative processing with analysis and evaluation tools. The format also considers the requirements of AI tools supporting neural network training and use.

INTRODUCTION

Automated Driving (AD) technology has matured to a level motivating large-scale road tests which can answer key open questions before market introduction. These newly-attained levels of maturity will ensure an appropriate assessment of the impact of AD. Of interest is what is happening both inside and outside of the vehicles. Also ensuring vehicle safety is of utmost importance as well as evaluating societal impacts. As a further point, the evaluation of emerging business models is of interest.

A point that has proven to be the crux in many previous projects is the data exchange between partners, as well as the evaluation. This led to devising a data format common to the whole project, thereby easing the exchange of data and the further development of evaluation processes and tools based on the data.

First, we will present the organization of data in previous projects and present the current project, L3Pilot [1]. After that, we will show how the process for deriving the requirements for the data format came together, followed by a few formats shortlisted for storage of the data. We will then describe the format itself and afterwards discuss it and its limitations.

PREVIOUS PROJECTS AND EFFORTS

Over the years, numerous projects have paved the way for advanced driver assistance systems (ADAS) and AD. Each of those projects had a slightly different approach to data acquisition, handling and evaluation. This section shortly picks out a few of these projects and gives some details on the used methods.

In 2008, a big European project was started with euroFOT [2]. It identified and coordinated an in-the-field testing of new intelligent vehicle systems with the potential for improving the quality of European road traffic. During the project, the effectiveness of various lateral and longitudinal control functions and active safety functions on public roads was assessed. Data collection and analysis was organized from test sites. Each test site was using similar (Matlab based), but still with differences, data formats and individual analysis tools [3].

With AdaptIVe [4] in 2014, the focus moved from ADAS to AD. In the three and a half years of the project, AD functions for scenarios such as parking and motorway driving were developed and demonstrated. Raw data for the evaluation was delivered by the vehicle owners. At the evaluation partner, the needed signals (cf. [5], Annex 3) were extracted and converted to an internal evaluation format, a mixture of CSV and MATLAB.

From past EU Field Operational Test (FOT) projects, at least TeleFOT [6] and DRIVE C2X [7] used fixed formats when gathering data from several test sites to a central data storage. These projects assessed, in respective order, in-vehicle navigation systems and short-range vehicle communication prototypes.

In 2017, the L3Pilot project was kicked off. L3Pilot will test automated driving functions (ADFs) in 100 cars with 1,000 test subjects across 10 different countries in Europe. The tested functions will be mainly of SAE automation level 3, some of them of level 4 [8]. Together, European automotive industry, suppliers and researchers will pave the way for large-scale field operational tests on public roads creating a harmonized Europe-wide testing environment. The overall objective of L3Pilot is to test and study the viability of AD as a safe and efficient means of transportation, explore and promote new service concepts to provide inclusive mobility.

SIGNAL DERIVATION / METHOD / REQUIREMENTS

L3Pilot follows the FESTA V-process methodology [9] of setting up and implementing tests with the four main pillars and adapting the methodology to suit L3Pilot needs (cf. Figure 1). The four pillars in L3Pilot are: Prepare, Drive, Evaluate and address legal and cyber-security aspects.

This paper focuses on the Prepare pillar with additional focus on the early phase of the Evaluate pillar. The Drive pillar is handled by the vehicle owners. As can be seen in the figure, the first step in L3Pilot is the definition of automation functions and use cases, with a major attention on motorways. In a further step, the research questions for this project are derived from the specified use cases. Accompanying the research questions are various hypotheses that this project will investigate. In order to do this, different data are needed. One part will be subjective data, i.e. data that originate from questionnaires and user evaluation. Particularly interesting from a data processing point of view, and therefore for a data format, are the data recorded in the vehicles. To specify what data to record, performance indicators and derived measures are defined, which are used to answer the research questions and confirm the hypotheses. Derived measures, in this context, are quantities that are directly calculated from source signal time-series data. These can be vehicular signals or information about the environment delivered by car sensors. Performance indicators, on the other hand, are no longer time-series data. They take different forms depending on the indicators. They can be single values giving a certain value or the average in a recording or in a specific scenario. However, they can also be histograms over some value in multiple occurrences of a driving scenario. The set of signals needed for the calculation of these measures results in a list of required signals, that are to be recorded during each session in the pilot vehicles. The full process following the FESTA-V up to the data can be found in [10].

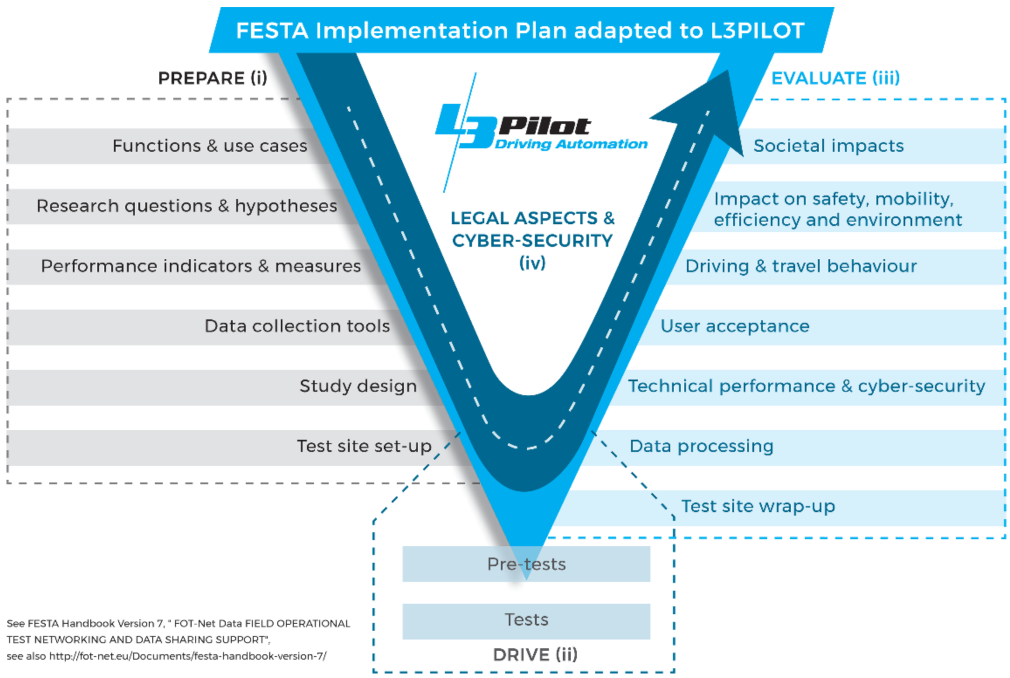

Figure 1. The FESTA implementation Plan adapted to L3Pilot

With the needed signals defined, the focus shifts towards the actual data. As stated before, different data are aggregated during the project. The three main sources are subjective data, objective data and video feeds. The data important for the L3Pilot Common Data Format (CDF) are the objective data. These include original vehicle signals and derived measures calculated from the source signals. In a project of the size of L3Pilot, there is not one platform running all the pilot vehicles and systems. One can think of platforms such as ADTF [11] or ROS [12] to just name two. Therefore, a simple export of the data collected in the car is not a viable option, since the export files of the different platforms are seldom compatible.
After the successful conversion, the Evaluate pillar starts with the data processing at the evaluation partner. Complementing the vehicle data will be data that originate from other, external, sources such as weather or map providers. Another factor is that multiple partners will be doing different analysis on the data, using different tools. One of the main programs used for post-processing and data analysis by the partners in this field is MATLAB. Additionally, in the previous years, Machine Learning has proven to be an important factor for the automatic detection of scenarios and video annotation. Therefore, a support of Python by the data format is of utmost importance. Considering statistical analysis of factors, some partners will also rely on R, SPSS or others. This leads to a requirement for a wide support of tools, platforms and programming languages.
Considering the aim of 1000 drivers in 100 cars, the amount of data recorded and transferred between vehicle owners and evaluation partners in terms of actual file sizes is another factor that should not be neglected. This leads to another criterion, the portability of files and results. For portability, memory efficiency is of course important.
Considering all these requirements, the common data format task force decided that a single file-based data format should be used in L3Pilot, to support an easy exchange of data between different partners. In order to reduce the amount of data that is transferred, compression was noted as another key feature to improve the process.
Within the L3Pilot project, it is agreed upon, that vehicle owners convert their datasets into the presented CDF. This enables the evaluation partners to use common tools to analyze the data, no matter which vehicle owner they work with.

CONSIDERED FILE FORMATS

As stated in the previous section, the decision upon a file-based format was taken quite early in the project. Therefore, going forward in the decision process, only file-based formats were considered. Solutions for big data storage were not further considered, although they can play an important role in the data management within an institution. As a first step towards the CDF, various file formats were evaluated and discussed. In various previous projects, that are partially listed in the section above, many different file formats were used. All of them have their own advantages and disadvantages. These differ strongly depending on the intended use of the formats. During the decision process for the CDF, many of them were evaluated and the pros and cons were compared. The

following formats were the ones taken into closer account during the decision process, as the task force already had experience with them, or they were deemed as promising.
A format that is commonly used among researchers in this field is the MATLAB file format [13]. The newest iteration is v7.3 that was introduced with MATLAB R2006b, however, the default version for files is v7. In it, data is stored in a binary format. It is a proprietary format, that is supported by MATLAB across all platforms that MATLAB supports. All datatypes included in MATLAB are supported and can be loaded and saved, while also supporting compression of data. One limitation is its strong link to MATLAB, however, for many research projects this was not an issue, since MATLAB is commonly used. This offers the opportunity to re-use existing tools from other or previous projects. The MATLAB file format was used in euroFOT [3] and internally during the evaluation in AdaptIVe [5].
A commonly used file format for exchange of numerical data is Comma-Separated Values (CSV). In it, values are simply stored as text, separated by commas (or any other type of delimiter), thus the name. Time-series are represented by new lines for each element. It is easy to use, doesn't need any updates and can be read and written by almost any program. However, there are also drawbacks to this format. CSV doesn't support the use of metadata. Therefore, value formats and e.g. minimum and maximum values of a column must be defined in a separate supporting document. One of the main advantages of CSV, the textual basis, is also one of its disadvantages, because it doesn't directly provide any compression and therefore takes up a lot of memory for long recordings. CSV was partially used for data transfers during the AdaptIVe project.
The Hierarchical Data Format (HDF) [14] exists in different versions. The current version is HDF5 revision 1.10.4 (as of January 2019). HDF was developed with portability in mind. It is supported by various languages such as C/C++, Fortran, Java, MATLAB and Python. Due to its support by a wide selection of programming languages, it can be used in the various available operating systems. It can therefore be easily implemented into different scripts and programs. HDF supports the storing of a wide array of datatypes including doubles, integers and strings. Additional datatypes can easily be added. To support portability, HDF has features for data compression. Different compression algorithms can be applied in order to save storage space. Metadata is stored in attributes in HDF files. This supports portability and simplifies the management of many files. Starting from version 7.3, the MATLAB file standard is based upon HDF5, thereby becoming compatible with HDF5 tools. As a disadvantage, for readability, HDF5 uses a binary format. An easy peek into the data without using the access libraries is therefore not possible. However, several data viewers exist. Editing the data can be another issue, depending on the viewers' capabilities. Another disadvantage is, that there is one inner core module on which almost all implementations of HDF5 rely upon. An error in this module would be devastating.
During L3Pilot, the main drawback of HDF5 was the somewhat limited documentation of programming examples. Another shortcoming and even a related bug were later found in Java libraries, as the main data viewer provided by HDF Group, HDFView, could not, at that time, display an array of compound datatypes used in the L3Pilot CDF. This was fixed by the HDF Group upon a report by the team.

L3PILOT COMMON DATA FORMAT

Considering the previously stated requirements, a file format was selected. The selection came upon HDF5. This allows us to define different datasets for the needed signals.
Since HDF5 supports a wide array of programming languages, the vehicle owners can use their preferred language and platform to convert their data recorded in their proprietary format. On the evaluation side, the corresponding partner should be able to use existing or preferred tools with small modifications. This allows for an efficient use of resources, as more time can be committed to developing and implementing new features.
HDF5 offers two ways of organizing data: datasets and groups [15]. Groups can contain zero or more HDF5 objects and can be accessed together using the group name. They can be hierarchically organized and have circular references. Datasets are where the data is stored. They are a collection of data elements, or raw data, and metadata that stores a description of the data elements, data layout, and all other information necessary to read, write and interpret the stored data. These data values can be of various datatypes. Already defined are datatypes such as double, integer, etc. However, the library also offers the opportunity to define new datatypes, if needed. Included in the datasets as well are the metadata, which include attributes. These attributes can be used to describe the contained data, thus allowing a verbal description of the data and, e.g., providing the unit of a logged signal. These attributes are independent and can be read and written without loading the complete HDF file. Datasets can be on the root level or belong to one or more groups. One advantage of datasets and groups is that each of them can be loaded individually without loading the complete file.
Derived through various iterations from the use cases and research questions, various logged signals are available on vehicle owner side. In order to allow for an efficient and quick access to the data, the signals are coarsely grouped according to their origin. For this purpose, datasets and groups are used by the CDF. All vehicle signals are organized in datasets on the top level of the file ("/") (cf. Table 1). The "egoVehicle" dataset contains all signals originating directly from the ego vehicle itself. This would be signals such as the ABS status or the speed

of the vehicle. All information about the lane markings, e.g. the distance to the lane markings and their type, is contained in the “laneLines” dataset. Dynamic objects and their properties such as speed and distance are saved in the “objects” dataset. Information from a global navigation satellite system (GNSS), e.g. GPS or Galileo, is stored in the “positioning” dataset. The previously discussed derived measures and performance indicators are calculated at the evaluation partners, and then stored in the “derivedMeasures” and “performanceIndicators” datasets.

In order to gain more information about the recorded trips, external data can be useful. Two important external data sources that were identified for the L3Pilot project are weather and map information. Weather information can be provided by various weather services and contains information about temperature, precipitation and cloud coverage. Map data provides information about the number of lanes, speed limits or intersections. These data are saved in the datasets “map” and “weather”. These are located hierarchically under the “/externalData” group.

Some data cannot, or only with major difficulties, be derived from vehicle signals. One of these signals is, for example the secondary task performed by the driver during different situations. These kinds of signals are added by annotations through human experts, or students supervised by experts, watching the time-synced video feed of the recording. These annotations are normally added at the evaluation partner and not supplied by the vehicle owner. Annotations are located hierarchically under the “/annotations” group. For each annotation a subgroup is added with the name of the annotation. In this example it is “/sceondaryTask”. It includes two datasets “comments” and “enum”. In “comments” all comments that are additionally made by the annotator are stored, i.e. if there is an extraordinary reason for this annotation. The dataset “enum” contains the annotation as numerical value so that it can easily be reused in subsequent scripts and calculations. For the example of the secondary task, this would contain the annotated secondary task masked as an enum and the file time referencing it to the recording. Groups are used here, in order to have the possibility to flexibly extend the annotations.

Table 1.
All datasets according to the L3Pilot Common Data Format and the associated groups.

Group	*Dataset*	*Description*
/	egoVehicle	Signals directly concerning the ego vehicle
	laneLines	Information on the lane markings
	objects	A list of (dynamic) objects
	positioning	Information from the positioning system (local or GNSS)
	derivedMeasures	Contains all the derived measures
	performanceIndicators	Contains all the performance indicators
/externalData	weather	Contains information about the weather
	map	Contains map information
/annotation	-	Group containing various annotations
/annotation/secondaryTask	comments	Comments on the annotation by the annotator
	enum	The annotation values

Considering the memory usage and a memory efficient storage of the recorded data, the datatypes of all signals are carefully selected. For this purpose, the desired and expected precision of all signals is reviewed. Many signals such as vehicle speeds or accelerations come in high precisions, with many digits to the right of the decimal point. For these signals, the “double” datatype is used, which allows for a high precision. Other signals such as the ID of an object, the speed limit or the number of lanes are not needed with high precision. Therefore, these values are saved as integers. Another common signal in recorded data is the status of a system. In general, it takes very few distinct values that are known beforehand. These status signals are saved as “enums” in the CDF. HDF5 allows the definition of arbitrary enums. For the CDF, they are based upon “uint8” and take few distinct values. Table 2 summarizes the commonly used datatypes.

Table 2.
Different used datatypes in the Common Data Format, their sizes and examples

Datatype	*Size in byte*	*Exemplary value*	*Exemplary N/A value*
Double	8	3.14159265359…	NaN
int64	8	1545572564000	-1
int32	4	42	-1
enum (uint8)	1	ON (1)	N/A (-1)

In a project of the size of L3Pilot and with the wide variety of vehicle owners and sensor setups, not all the signals will always be available or will fit the same format. For the CDF this means, that some signals will not be available in some recordings. For missing values, "N/A" values are defined, i.e. values that are used when the signal is not provided. This makes it easier for programs and scripts to run on the data anyway. For floating point numbers, "not a numer" (NaN) [16] is used. Since NaN is not defined for integer types, values that are not expected to appear are used here, e.g. "-1".

All signals in the CDF are synchronized between the datasets. In order to achieve this, a frequency of 10 Hz was selected for the project. For reference, each dataset contains two different time signals. The first is the "FileTime" which simply counts up in discrete 10 Hz steps from the beginning of the recording. This can be used for easy reference in the file itself. The second time signal is the "posix" time in milliseconds, named "UTCTime" in the file. This allows references to external data sources such as weather or traffic services. The posix time is the time in seconds, milliseconds or nanoseconds (depending on the application) since 00:00:00 on 1 January 1970 in UTC. It doesn't include any leap seconds and therefore differs from the atomic time used in GNSS systems by currently 37 seconds (as of January 2019) [17].

Since not all signals are always recorded with the requested frequency of 10 Hz, interpolation methods are defined per signal. For continuously available signals, a simple linear interpolation is defined for most cases. However, since a linear interpolation is not applicable for status signals with few distinct values, a zero-order-hold (ZOH) interpolation is defined for these signals. Thereby each signal is held for one sample interval and then changes. In addition, a maximum time of loss is defined per signal. This is to prevent unreasonable behavior in signals when data loss was too long. For high precision variables this might be very close to zero seconds, for other signals (e.g. GNSS) this could be up to 10 seconds.

Another step towards memory efficient storage is the utilization of the HDF5 built-in compression. One common algorithm here is the "DEFLATE" compression [18]. This algorithm is not restricted by patents. Many different implementations for almost all common programing languages are available. The algorithm works especially well on data that does not change often. In that case, it will only save the value for the first occurrence and save the next value only if it changes. This saves a lot of memory especially for Boolean values and other mostly static variables.

In order to support faster I/O and memory efficient computing, HDF has a feature called chunking. Here, data is not saved in one continuous block in the file, but in so called chunks. These chunks are specified when creating the file according to the data that is to be stored. When reading the file, only one chunk at a time is loaded into the memory. This is especially useful, when handling large amounts of data. For the implementations in the L3Pilot project, the chunk size is selected in a way to get chunks of about 1 MB. Chunks are applied to the respective datasets. Since the size of a single timestep is known due to the mandated format and signals, the chunk size can be set accordingly.

DISCUSSION

For a preliminary assessment, memory consumption was measured for data coming from 32 hours of motorway data recorded in a previous project. The mean duration of one trip from this project is roughly 52 minutes. For that purpose, the raw data size was calculated from the known sizes of the datatypes and the length of the recordings. This is given in Table 3 as "Raw data, calculated" and taken as the reference for all other file sizes. This would lead to an average data file size of 84.54 MB for a recording length of 52 minutes. Using HDF5 for storing the data and activating the compression. the average reduction in file size is around 89 %. This results in an average file size of 9.63 MB. In terms of absolute memory, we can now save the recordings with only around 395 MB instead of the ~3.5 GB that would have been needed without the compression.

Table 3.
Comparison of file sizes for a selection of different file formats.

Format	*Mean file size*	*Relative*
Raw data, calculated	84.54 MB	100 %
HDF5, compression, DEFLATE	9.63 MB	11.17 %
csv	54.91 MB	64.94 %
mat file, v7	8.86 MB	10.48 %
mat file, v7.3	9.29 MB	10.98 %

For benchmarking, a few comparisons to other formats are done. The first one is CSV. All data that is written to the HDF5 files is taken and written to a csv file using the MATLAB function *dlmwrite*. This simply writes a matrix to a csv file. This results in an average file size of 54.91 MB. Compared to the raw calculated data size, this is only ~65 %, which can be explained by the fact, that data is written as ASCII characters, which only uses

one byte per character. Even though some numbers take up multiple characters, the overall number is still smaller than having double datatypes with eight bytes.
As another comparison, the MATALB mat file format is considered. Here the commonly used version 7 is compared as well as the newer version 7.3 which is however not enabled by default. v7.3 is built upon HDF5 and can therefore also be read using HDF5 tools. As can be seen from the table, v7 offers the best compression in the sense of the smallest average file size. With v7.3, the file size slightly increases which MATLAB also notes in its documentation, which can happen due to overhead in the description of the file contents.
Overall it can be seen, that the proposed format offers a good performance in terms of memory. It does not quite reach the memory efficiency of the long-matured MATLAB mat file format; however, it is not dependent on a proprietary program and can be accessed using multiple languages and programs.
The binary nature of the format, which is one of its advantages, because it allows compression, is also one of its disadvantages. The binary format leads to the restriction that the data can only be accessed using the appropriate tools and programming APIs. This also hides the structure of the data from peeks and from an easy overview of contained signals without using additional tools. This is however not seen as a drawback in the L3Pilot project, since the structure of the data is known beforehand by all partners.

CONCLUSIONS

In this paper we present the CDF approach we decided to implement to manage the heterogeneous data sources in the L3Pilot project. The intention of the format is to make the process of data exchange and evaluation more flexible and efficient. The paper showed the methodology used to define the signals needed for the evaluation in the project and presented the considerations that went into the decisions on the file format.
A preliminary test showed that the L3Pilot CDF using HDF5 is more efficient than some previously used formats, such as csv. On the other hand, it performs almost as well in terms of memory efficiency as the MATLAB proprietary format, while being independent of the software used. The portability is already by now exemplified by various tools built using the format but in different environments: Windows or Linux, and using Python, R or Matlab.
In the next months, the format will be extensively used and tested in the piloting phase of the L3Pilot project and will constantly evolve and mature, leading to a proven format that could be applied to many other projects of similar scale and type. Various analysis tools will be developed and adapted to support the format.

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