Effectiveness of Intersection Advanced Driver Assistance Systems in Preventing Crashes and Injuries in Left Turn Across Path / Opposite Direction Crashes in the United States

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ABSTRACT (ACADEMIC)

Intersection crashes represent one-fifth of all police reported traffic crashes and one-sixth of all fatal crashes in the United States each year. Active safety systems have the potential to reduce crashes and injuries across all crash modes by partially or fully controlling the vehicle in the event that a crash is imminent. The objective of this thesis was to evaluate crash and injury reduction in a future United States fleet equipped with intersection advanced driver assistance systems (I-ADAS). In order to evaluate this, injury risk modeling was performed. The dataset used to evaluate injury risk was the National Automotive Sampling System / Crashworthiness Data System (NASS/CDS). An injured occupant was defined as vehicle occupant who experienced an injury of maximum Abbreviated Injury Scale (AIS) of 2 or greater, or who were fatally injured. This was referred to as MAIS2+F injury. Cases were selected in which front-row occupants of late-model vehicles were exposed to a frontal, near-, or far-side crash.

Logistic regression was used to develop an injury model with occupant, vehicle, and crash parameters as predictor variables. For the frontal and near-side impact models, New Car Assessment Program (NCAP) test results were used as a predictor variable. This work quantitatively described the injury risk for a wide variety of crash modes, informing effectiveness estimates.

This work reconstructed 501 vehicle-to-vehicle left turn across path / opposite direction (LTAP/OD) crashes in the United States which had been originally investigated in NMVCCS. The performance of thirty different I-ADAS system variations was evaluated for each crash. These

variations were the combinations of five Time to Collision (TTC) activation thresholds, three latency times, and two different intervention types (automated braking and driver warning). In addition, two sightline assumptions were modeled for each crash: one where the turning vehicle was visible long before the intersection, and one where the turning vehicle was only visible after entering the intersection. For resimulated crashes which were not avoided by I-ADAS, a new crash delta-v was computed for each vehicle. The probability of MAIS2+F injury to each front row occupant was computed.

Depending on the system design, sightline assumption, I-ADAS variation, and fleet penetration, an I-ADAS system that automatically applies emergency braking could avoid 18%-84% of all LTAP/OD crashes. An I-ADAS system which applies emergency braking could prevent 44%-94% of front row occupants from receiving MAIS2+F injuries. I-ADAS crash and injured person reduction effectiveness was higher when both vehicles were equipped with I-ADAS. This study presented the simulated effectiveness of a hypothetical intersection active safety system on real crashes which occurred in the United States, showing strong potential for these systems to reduce crashes and injuries.

However, this crash and injury reduction effectiveness made the idealized assumption of full installation in all vehicles of a future fleet. In order to evaluate I-ADAS effectiveness in the United States fleet the proportion of new vehicles with I-ADAS was modeled using Highway Loss Data Institute (HLDI) fleet penetration predictions. The number of potential LTAP/OD conflicts was modeled as increasing year over year due to a predicted increase in Vehicle Miles Traveled (VMT). Finally, the combined effect of these changes was used to predict the number of LTAP/OD crashes each year from 2019 to 2060. In 2060, we predicted 70,439 NMVCCS-type LTAP/OD crashes would occur. The predicted number of MAIS2+F injured front row occupants in 2060 was

3,836. This analysis shows that even in the long-term fleet penetration of Intersection Active Safety Systems, many injuries will continue to occur. This underscores the importance of maintaining passive safety performance in future vehicles.

Effectiveness of Intersection Advanced Driver Assistance Systems in Preventing Crashes and Injuries in Left Turn Across Path / Opposite Direction Crashes in the United States

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GENERAL AUDIENCE ABSTRACT

Future vehicles will have electronic systems that can avoid crashes in some cases where a human driver is unable, unaware, or reacts insufficiently to avoid the crash without assistance. The objective of this work was to determine, on a national scale, how many crashes and injuries could be avoided due to Intersection Advanced Driver Assistance Systems (I-ADAS), a hypothetical version of one of these up-and-coming systems. This work focused on crashes where one car is turning left at an intersection and the other car is driving through the intersection and not turning. The I-ADAS system has sensors which continuously search for other vehicles. When the I-ADAS system determines that a crash may happen, it applies the brakes or otherwise alerts the driver to apply the brakes. Rather than conduct actual crash tests, this was simulated on a computer for a large number of variations of the I-ADAS system. The basis for the simulations was real crashes that happened from 2005 to 2007 across the United States. The variations that were simulated changed the time at which the I-ADAS system triggered the brakes (or alert) and the simulated amount of computer time required for the I-ADAS system to make a choice. In some turning crashes, the car cannot see the other vehicle because of obstructions, such as a line of people waiting to turn left across the road. Because of this, simulations were conducted both with and without the visual obstruction. For comparison, we performed a simulation of the original crash as it happened in real life. Finally, since there are two cars in each crash, there are simulations when either car has the I-ADAS system or when both cars have the I-ADAS system. Each simulation either ends in a crash or not, and these are tallied up for each system variation. The number of

crashes avoided compared to the number of simulations run is crash effectiveness. Crash effectiveness ranged from 1% to 84% based on the system variation. For each crash that occurred, there is another simulation of the time immediately after impact to determine how severe the impact was. This is used to determine how many injuries are avoided, because often the crashes which still happened were made less severe by the I-ADAS system.

In order to determine how many injuries can be avoided by making the crash less severe, the first chapter focuses on injury modeling. This analysis was based on crashes from 2008 to 2015 which were severe enough that one of the vehicles was towed. This was then filtered down by only looking at crashes where the front or sides were damaged. Then, we compared the outcome (injury as reported by the hospital) to the circumstances (crash severity, age, gender, seat belt use, and others) to develop an estimate for how each of these crash circumstances affected the injury experienced by each driver and front row passenger. A second goal for this chapter was to evaluate whether federal government crash ratings, commonly referred to as "star ratings", are related to whether the driver and passengers are injured or not. In frontal crashes (where a vehicle hits something going forwards), the star rating does not seem to be related to the injury outcome. In near-side crashes (the side next to the occupant is hit), a higher star rating is better. For frontal crashes, the government test is more extreme than all but a few crashes observed in real life, and this might be why the injury outcomes measured in this study are not related to frontal star rating.

Finally, these crash and injury effectiveness values will only ever be achieved if every car has an I-ADAS system. The objective of the third chapter was to evaluate how the crash and injury effectiveness numbers change each year as new cars are purchased and older cars are scrapped. Early on, few cars will have I-ADAS and crashes and injuries will likely still occur at roughly the rate they would without the system. This means that crashes and injuries will continue to increase each year because the United States drives more miles each year. Eventually, as consumers buy new cars and replace older ones, left turn intersection crashes and injuries are predicted to be reduced. Long into the future (around 2050), the increase in crashes caused by miles driven each year outpaces the gains due to new cars with the I-ADAS system, since almost all of the old cars without I-ADAS have been removed from the fleet. In 2025, there will be 173,075 crashes and 15,949 injured persons that could be affected by the I-ADAS system. By 2060, many vehicles will have I-ADAS and there will be 70,439 crashes and 3,836 injuries remaining. Real cars will not have a system identical to the hypothetical I-ADAS system studied here, but systems like it have the potential to significantly reduce crashes and injuries.

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LIST OF ABBREVIATIONS

I-ADAS: Intersection Advanced Driver Assistance System
LTAP/OD: Left Turn Across Path / Opposite Direction
LTAP/LD: Left Turn Across Path / Lateral Direction
LTIP: Left Turn Into Path
RTIP: Right Turn Into Path
SCP: Straight Crossing Path
NMVCCS: National Motor Vehicle Crash Causation Survey
NASS: National Automotive Sampling System
CDS: Crashworthiness Data System
NCAP: New Car Assessment Program
NHTSA: National Highway Traffic Safety Administration
DOF: Direction of Force
AIS: Abbreviated Injury Scale
GAD: General Area of Damage
SHL: Specific Horizontal Location / Specific Longitudinal Location
MY: Model Year
CISS: Crash Investigation Sampling System

1. INTRODUCTION

Intersection crashes represent one-fifth of all police reported traffic crashes and one-sixth of all fatal crashes in the United States each year (K. D. Kusano and Gabler, 2014). Active safety systems have the potential to reduce crashes and injuries across all crash modes by partially or fully controlling the vehicle in the event that a crash is imminent. Intersection Advanced Driver Assistance Systems (I-ADAS) are active safety systems with the potential to reduce the number of intersection crashes and resulting injuries. Two-vehicle intersection crashes can be grouped into five crash modes: Left Turn Across Path / Opposite Direction (LTAP/OD), Left Turn Across Path / Lateral Direction (LTAP/LD), Left Turn Into Path (LTIP), Right Turn Into Path (RTIP), and Straight Crossing Path (SCP). This work considers the effect of I-ADAS on LTAP/OD crashes. A diagram of these crash modes is given in Figure 1.

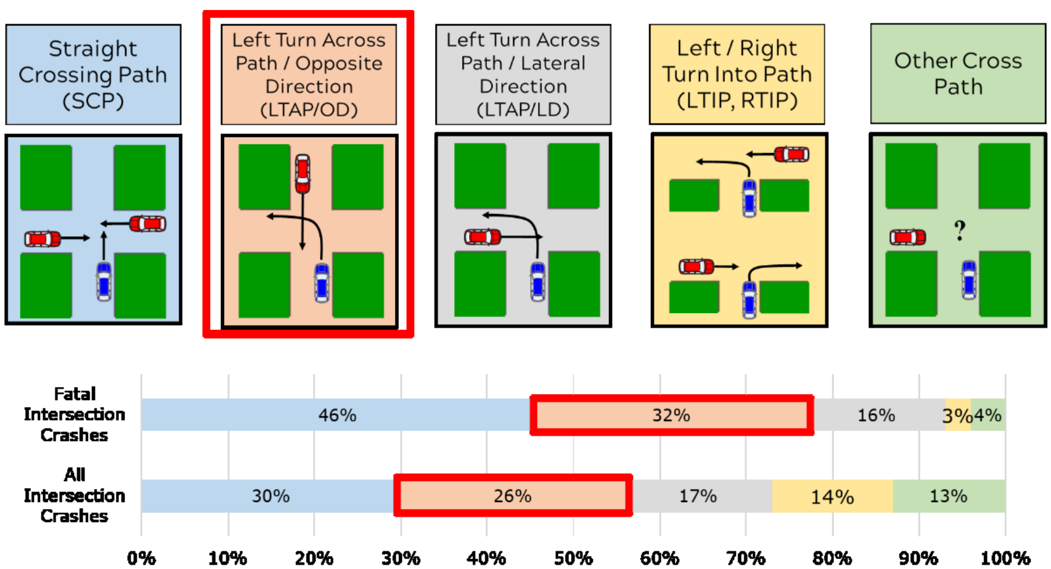

Figure 1. Types of two-vehicle intersection crashes. LTAP/OD crashes are the subject of this thesis.

The proposed I-ADAS system for passenger vehicles evaluated in this study consisted of a system which scans for potential collision partners in the presence of an intersection. If the I-ADAS vehicle detects that a collision is imminent with another vehicle, the I-ADAS vehicle triggers a warning to the driver or automatically begins braking to avoid the crash. The I-ADAS system is able to prevent crashes or modify crash outcomes when activated. Scanlon and Gabler and demonstrated the ability of the system to avoid crashes and injuries (Scanlon, 2017; Scanlon et al., 2017) in SCP crashes.

The objective of this thesis was to evaluate crash and injury reduction in a future United States fleet equipped with intersection advanced driver assistance systems (I-ADAS). We assumed that the average vehicle in this future fleet will have better passive safety than vehicles in the current fleet as older vehicles are replaced with newer ones. Many vehicles in the U.S. fleet currently have excellent passive safety, as measured by their performance in New Car Assessment Program (NCAP) testing. While the I-ADAS system is similar to previously published systems, this work greatly expands the injury models used to estimate injury benefits and project absolute (not proportional) benefits in the United States to 2060.

Literature Review

In 2015, passenger vehicles were exposed to 1.061 million side impacts and 2.572 million frontal impacts in the United States (NHTSA, 2017, p. 91). To reduce the risk of injury in these crashes, automakers have incorporated highly effective injury countermeasures including strengthened side structures, energy absorbing door padding, side and frontal airbags, and seatbelt pretensioners and load limiters. In 2015 there were 3,215 fatal side impact crashes and 6,360 vehicles with fatalities in frontal impact crashes, suggesting that the risk in side and frontal impacts has not been eliminated. However, many of those fatalities were in older vehicles without the latest countermeasures and, while tragic, provide limited guidance on the residual side crash problem of a future fleet.

Previous work has investigated the relationship between New Car Assessment Program (NCAP) performance and real-world outcomes. The NCAP program rates cars on a scale of five stars. Star ratings are derived from frontal, side, and pole impact crash tests and represent the risk of injury in a crash. A higher star rating indicates a lower risk of injury. Segui-Gomez et al. (2010) evaluated the relationship between EuroNCAP performance and fatal to severe injury outcomes for frontal crashes and found no statistically significant relationship. However, Kullgren et al. (2010) found a significant link between EuroNCAP score and fatality risk across all crash modes. This thesis considered United States vehicles and U.S. NCAP. Kahane (1994) found that in head-on collisions between vehicles of similar mass, drivers of vehicles with a poor NCAP score had a 20%-25% higher fatality risk. This study considered an older population of vehicles and made no claims about the injury reduction, only fatality reduction.

Scanlon et. al. (2017) investigated the crash and injury benefits of a hypothetical I-ADAS in Straight Crossing Path (SCP) crashes using the same I-ADAS system. Sander computed intersection AEB benefits using a different system design (Sander, 2017) with effectiveness estimates developed using the German In-Depth Accident Study (GIDAS) crash dataset. Vehicle-to-Vehicle or Vehicle-to-Infrastructure (V2V or V2I) technologies have also been explored as a potential method for avoiding intersection crashes. These technologies are advantageous because they do not require line-of-sight, which is a strong limitation of the method provided here. The primary disadvantage of V2V and V2I technologies is that effectiveness is limited by the degree to which vehicles are equipped with this technology (Boran et al., 2012). This work considers only the benefits of a hypothetical vehicle-based I-ADAS system.

Improvements to Previous Work

The model used in this work was derived from a model developed by John Scanlon (Scanlon, 2017). A significant number of improvements were made to the core modeling strategy which were independent of the crash mode which was analyzed (SCP, LTAP/LD, or LTAP/OD). I-ADAS performance in LTAP/OD crash situations had not been previously published and was completed as a part of this work.

As part of the core modeling strategy, the injury modeling in this work was re-written and was greatly enhanced. The injury models considered a larger number of predictor variables of crash outcomes. Statistical significance was evaluated using a p-value metric with more statistical power, allowing more predictor variables to be included in the models. The injury models for frontal and near-side impact consider the effect of NCAP ratings, and a method of "joining" the NCAP ratings with crash data was developed. These injury models were re-written in R from original SAS code. This made the models easier to use in future projects.

The updates to the core modeling strategy included a large number of small improvements and bugfixes to the set of programs which compute the results. The updates to the codebase improved the correctness of the model, especially in situations where multiple small impact events occurred, such as in sideslap crash configurations. More data output was added to the model to analyze the effectiveness of a potential automated emergency steering (AES) system (Bareiss and Gabler, 2019). Runtime performance of the model was also improved.

2. APPROACH

Data Sources

NASS/CDS

This study used cases from the National Automotive Safety System / Crashworthiness Data System, or NASS/CDS (Zhang and Chen, 2013). NASS/CDS conducted in-depth crash investigations of approximately 5,000 crashes per year from 1979 to 2015. Information about the occupants, vehicles, and the crash environment were included along with a scene diagram to allow detailed crash analysis. Crashes where one or more passenger vehicles were towed due to damage were eligible for inclusion in NASS/CDS. NASS/CDS used a stratified survey design to oversample severe crashes. Sampling weights are provided for each case to allow computation of nationally representative conclusions. NASS/CDS contains detailed injury information compiled by medical doctors and emergency responders using the standardized Abbreviated Injury Scale (AIS). The 2008 update of the AIS scale was used to determine injury severity (Gennarelli, 2008). The AIS scale is a six-point scale which ranges from AIS=1 for a minor injury to AIS=6 for an untreatable injury.

In 2017, NASS/CDS was replaced by the Crash Investigation Sampling System (CISS). Case details for CISS 2017 were released in September 2019. Due to the difference in sampling scheme used for CISS, direct comparisons cannot be made between CISS and NASS/CDS and data from CISS was not included in this work.

NMVCCS

This work uses cases from the National Motor Vehicle Crash Causation Survey (NMVCCS). NMVCCS was a study conducted by NHTSA from 2005 to 2007 to collect detailed information shortly after a crash in order to determine the likely reasons why a crash occurred. NMVCCS collected much of the same information as NASS/CDS and used the same sampling infrastructure to enable the generation of nationally relevant conclusions from the dataset. NMVCCS differs from NASS/CDS in several important ways. NMVCCS includes detailed scene diagrams collected before vehicles were moved from their final rest locations. In contrast, scene information in NASS/CDS is typically collected two weeks after the crash. After this delay, any evidence of the vehicle's impact point, trajectory, and final rest position will likely be missing. Additionally, a crash was eligible for NMVCCS if emergency responders were called to the scene of the crash, a more severe selection criterion than that used for NASS/CDS. However, NMVCCS contains neither detailed injury information from hospital records nor any crash reconstruction of delta-v.

NCAP Ratings

This study used crash test ratings from the United States National Highway Traffic Safety Administration (NHTSA) New Car Assessment Program (NCAP) tests (NHTSA and Department of Transportation, 2008). U.S. NCAP is a consumer information program intended to provide vehicle safety information when buying a new car. U.S. NCAP evaluates vehicle safety on a scale from one to five stars, five stars representing the safest vehicle (lowest risk of injury). NCAP rating is a consumer information program intended to use market forces to encourage safety improvements. NCAP tests are not required by Federal Motor Vehicle Safety Standards. The vehicle safety rating is based on the results of three crash tests: frontal barrier, vehicle-to-vehicle side, and vehicle-to-pole side impact. The vehicle-to-vehicle side impact test is a near-side impact for the vehicle occupants. No current NCAP test evaluates far-side impact performance.

Vehicle-to-Vehicle Side Test

The vehicle-to-vehicle side crash test impacts a moving deformable barrier (MDB) into the test vehicle at 38.5 mph with the MDB wheels crabbed at an angle of 27° with respect to the longitudinal axis of the MDB and the lateral axis of the test vehicle. Two anthropomorphic test devices (ATDs), sometimes referred to as crash test dummies, are seated on the stuck side of the subject vehicle. An ES-2re ATD is seated in the driver seat and a SID-IIs ATD is seated in the rear passenger seat. For the front seat ATD, the probability of injury at the Abbreviated Injury Scale 3 or greater level (AIS3+) is computed for the head, chest, abdomen, and pelvis using injury risk curves which are a function of HIC_{36}, rib deflection, abdominal force, and pelvis force, respectively. For the rear seat ATD, the probability of AIS3+ injury is evaluated for the head and pelvis using injury risk curves derived from HIC_{36} and pelvic force, respectively. A joint measure of risk is computed for the front seat ATD in Equation 1 (P_{joint} from NHTSA-2006-26555, page 40044).

$$P_{joint} = 1 - (1 - P_{head}) \times (1 - P_{chest}) \times (1 - P_{abdomen}) \times \left(1 - P_{pelvis}\right) \qquad (1)$$

NHTSA uses this joint measure of AIS3+ risk to the front row ATD in the side impact test to assign the NCAP rating. P_{joint} values of 5%, 10%, and 15%, are the thresholds for five-star, four-star, and three-star vehicles, respectively. This work used this joint measure of AIS3+ injury risk in a side crash test as an indicator of occupant protection performance in real-world near-side impact crashes. Near-side impact refers to an impact on the same side of the vehicle as the seating position of the occupant.

The NCAP MDB side crash test was updated in 2011 to use the more biofidelic ATDs and associated injury risk curves described above. The earlier NCAP MDB side crash test used the SID dummy with very different measurement capabilities and injury risk curves than the ES-2re and SID-IIs ATDs. Because of this, the results of the pre-2011 and post-2011 NCAP MDB tests cannot be compared. This study is based exclusively on the newer post-2011 NCAP test results.

Frontal Barrier Test

In the frontal barrier test, the test vehicle is towed into a fixed rigid barrier at 56 km/h (35 mph). Two ATDs are placed in the vehicle. A Hybrid III 50th percentile male ATD is seated in the driver seat and a Hybrid III 5th percentile female ATD is seated in the passenger seat. Both ATDs are belted. For each ATD, the probability of injury at the AIS 3 level or greater (AIS3+) is computed for the head, neck, and chest, and the probability of AIS2+ injury is computed for the femur. A joint measure of risk is computed for each ATD using the equation for P_{joint} from NHTSA-2006-26555 (page 40043):

$$P_{joint} = 1 - (1 - P_{head}) \times (1 - P_{neck}) \times (1 - P_{chest}) \times \left(1 - P_{femur}\right) \quad (2)$$

NHTSA uses this joint measure of risk to the front row ATDs to assign a star rating for both front row occupants. P_{joint} values of 5%, 10%, and 15% are the thresholds for five-star, four-star, and three-star vehicles, respectively. This work used the P_{joint} value directly as an indicator of occupant protection performance in real-world frontal impact crashes.

3. INJURY RISK CURVES FOR BEST PERFORMING VEHICLES

Introduction

The objective of this chapter was to estimate the risk of injury to occupants of vehicle in frontal, near-, and far-side impacts. Many vehicles in the U.S. fleet currently have excellent passive safety, as measured by their performance in NCAP testing. We seek to understand the relationship between injury outcomes and passive safety performance measured by NCAP testing to predict injury outcomes in a future fleet. A secondary objective was to evaluate the relationship between NCAP test performance and injury outcomes.

Methods

Dataset Selection

This study used crashes from NASS/CDS case years 2007-2015. The following selection criteria were used to limit the cases analyzed:

- Frontal, near- and far-side impacts were selected. Near side impacts were those in which an occupant was located on the same side of the vehicle as the impact. The impacted side of the vehicle was determined by the general area of damage (GAD) in NASS/CDS. All directions of force (DOF) were considered.
- Only front row occupants of age of 12 or older were considered. This limited the study to "adult size" occupants.
- The crash must have involved exactly two passenger vehicles. Passenger vehicles were defined by the BODYTYPE variable in NASS/CDS. This selects crashes that only had vehicles which were eligible to receive NCAP ratings.

- Only single-event crashes were considered. The injury models developed in this study were intended to model the impacts in I-ADAS simulations, which are single event crashes.
- Cases with a national weighting factor RATWGT greater than 5,000 were excluded to limit skewing of the results, following the methodology by Kononen et al (2011).
- The struck vehicle must have had an NCAP star rating assigned starting in MY 2011. This restriction did not apply to the far side impact model. The NCAP rating system was changed for MY 2011 vehicles. Not all vehicles were rated in the NCAP program. Low volume and luxury vehicles typically were not rated in the NCAP program; these vehicles were given the rating of "Not Rated". Additionally, not all vehicles in NASS/CDS had enough identifying information to uniquely identify an NCAP rating from the NCAP database. Vehicles which were the same generation as those tested starting in MY 2011 were included. For example, the MY 2011 Toyota Corolla was the tenth generation of the vehicle, and that generation was first available in MY 2009. Toyota Corollas from MY 2009 to MY 2010 were included in the dataset, using the NCAP rating from the MY 2011 version of the vehicle. The earliest model year vehicles included in the dataset were MY 2007.
- Cases were excluded in which data was missing for either injury severity or any of the predictor variables in the model.
- Ejection cases and pole impact cases were not considered.

NASS/CDS sampled 20,218 frontal impact occupants and 9,956 side impact vehicle occupants from 2007 to 2015. After applying the selection criteria above, the dataset contained 1,000 frontal impact occupants, 143 near-side impact occupants, and 211 far-side impact occupants. However, for one NASS/CDS sampling stratum in the near-side dataset, only one occupant was selected. This occupant was excluded from the study in order to perform logistic regression modeling. The final occupant dataset for near-side impact included 142 occupants. Detailed information about the dataset for each crash mode is presented in Table 1, Table 2, and Table 3 for frontal, near-, and far-side impact, respectively.

Injury in this study was defined as MAIS2+F injury, which represents an injury from moderate to untreatable level across any body region. In addition, occupants with injury of unknown severity (AIS=7) but were fatally injured were included.

Table 1. Dataset properties for the frontal impact model.

	Number of Occupants	**%**	**Weighted Number of Occupants**	**%**
All Vehicles				
All Vehicles	1,000	100%	367,429	100%
MAIS2+F				
MAIS 0,1	839	84%	337,027	92%
MAIS 2+F	161	16%	30,402	8%
Gender				
Female	554	55%	211,155	57%
Male	446	45%	156,275	43%

	Number of Occupants	%	Weighted Number of Occupants	%
Belt Status				
Belted	833	83%	311,521	85%
Unbelted	167	17%	55,908	15%
Age Group				
12-20	154	15%	62,593	17%
21-29	234	23%	96,510	26%
30-64	491	49%	183,805	50%
65+	121	12%	24,521	7%
Frontal Overlap				
Distributed	534	53%	187,855	51%
Moderate Overlap	298	30%	114,793	31%
Small Overlap	168	17%	64,781	18%
Seating Position				
Left Front Seat	774	77%	290,998	79%
Right Front Seat	226	23%	76,431	21%
Direction of Force				
11 o'clock – 1 o'clock	868	87%	327,725	89%
2 o'clock – 4 o'clock	16	2%	2,924	1%
8 o'clock – 10 o'clock	24	2%	10,522	3%

	Number of Occupants	%	Weighted Number of Occupants	%
N/A	92	9%	26,258	7%
Crash Compatibility				
Car struck Car	474	47%	174,026	47%
Car struck LTV	262	26%	103,736	28%
LTV struck Car	179	18%	54,668	15%
LTV struck LTV	85	8%	35,000	10%
Other Vehicle General Area of Damage (GAD)				
Side	508	51%	179,403	49%
Front	315	32%	98,388	27%
Rear	177	18%	89,639	24%

Table 2. Dataset properties for the near-side impact model.

	Number of Occupants	%	Weighted Number of Occupants	%
All Vehicles				
All Vehicles	142	100%	63,410	100%
Injury Level				
AIS 0,1	125	88%	61,907	98%
AIS 2+	17	12%	1,502	2%

	Number of Occupants	%	Weighted Number of Occupants	%
Gender				
Female	82	58%	36,901	58%
Male	60	42%	26,509	42%
Belt Status				
Belted	128	90%	53,063	84%
Unbelted	14	10%	10,346	16%
Thorax Airbag				
Not Present	8	6%	5,158	8%
Present and Not Deployed	54	38%	23,618	37%
Present and Deployed	80	56%	34,634	55%
Curtain Airbag				
Not Present	3	2%	1,699	3%
Present and Not Deployed	50	35%	24,101	38%
Present and Deployed	89	63%	37,610	59%

	Number of Occupants	%	Weighted Number of Occupants	%
Age Group				
12-20	22	15%	8,943	14%
21-29	33	23%	14,852	23%
30-64	58	41%	22,826	36%
65+	29	20%	16,790	26%
First Impact Specific Longitudinal Location				
Side Front and Occupant Compartment	49	35%	20,041	32%
Side Front	26	18%	11,810	19%
Side Occupant Compartment	24	17%	11,743	19%
Side Rear and Occupant Compartment	22	15%	8,375	13%
Side Rear	10	7%	6,268	10%
Distributed	6	4%	3,562	6%
Unknown	5	4%	1,611	3%

	Number of Occupants	%	Weighted Number of Occupants	%
Seating Position				
Left Front Seat	112	79%	47,454	75%
Right Front Seat	30	21%	15,956	25%
Crash Compatibility				
Car struck Car	74	52%	37,653	59%
LTV struck Car	37	26%	11,810	19%
Car struck LTV	22	15%	11,175	18%
LTV struck LTV	9	6%	2,773	4%

Table 3. Dataset properties for the far-side impact model.

	Number of Occupants	%	Weighted Number of Occupants	%
All Vehicles				
All Vehicles	211	100%	92,694	100%
Injury Level				
MAIS 0,1	195	92%	90,907	98%
MAIS 2+F	16	8%	1,787	2%

	Number of Occupants	%	Weighted Number of Occupants	%
Gender				
Female	110	52%	57,832	62%
Male	101	48%	34,862	38%
Belt Status				
Belted	187	89%	85,625	92%
Unbelted	24	11%	7,069	8%
Thorax Airbag				
Present and Not Deployed	206	98%	91,853	99%
Present and Deployed	5	2%	841	1%
Curtain Airbag				
Present and Not Deployed	174	82%	78,544	85%
Present and Deployed	37	18%	14,150	15%
Age Group				
12-20	43	20%	19,601	21%

	Number of Occupants	%	Weighted Number of Occupants	%
21-29	35	17%	17,725	19%
30-64	101	48%	45,384	49%
65+	32	15%	9,984	11%
First Impact Specific Horizontal Location (SHL)				
Side Front and Occupant Compartment	61	29%	25,135	27%
Side Rear and Occupant Compartment	43	20%	22,019	24%
Side Front	40	19%	20,412	22%
Side Occupant Compartment	36	17%	15,776	17%
Distributed	14	7%	4,509	5%
Unknown	10	5%	3,215	3%
Side Rear	7	3%	1,628	2%
Seating Position				
Left Front Seat	165	78%	74,974	81%

	Number of Occupants	%	Weighted Number of Occupants	%
Right Front Seat	46	22%	17,721	19%
Crash Compatibility				
Car struck Car	107	51%	48,977	53%
LTV struck Car	59	28%	20,821	22%
Car struck LTV	31	15%	17,107	18%
LTV struck LTV	14	7%	5,789	6%

NCAP Rating

One of the parameters used in the frontal and near-side injury models was the probability of MAIS3+ injury to the driver in the NCAP frontal test or MDB test for the frontal and near-side injury models, respectively. For each NASS/CDS case, this required matching the corresponding NCAP test result to each vehicle. Assigning the correct NCAP test result to each NASS/CDS vehicle was non-trivial because NASS/CDS vehicles and NCAP vehicles do not share the same vehicle identifier. In NASS/CDS, vehicles were identified by VIN and make/model/model year. In NCAP, vehicles were identified by make/series/model year, where "series" was the model, door configuration, and drive configuration.

A matching procedure was developed to select the correct test result for each NASS/CDS vehicle. First, the make, model, model year, door configuration, and drive configuration were determined for each vehicle in this sample using the NHTSA Product Information Catalog Vehicle

Listing (vPIC) web Application Programming Interface (API) (NHTSA, 2016). The NHTSA vPIC API is not comprehensive and does not provide all information for all vehicles. For example, 23% of vehicles did not have door configuration information available from the vPIC API.

Second, the make, model, and model year information was used to query the NHTSA Safercar database (NHTSA, 2018) for the correct NCAP variant. This was an approximate process because the model/door/drive encoding used by the vPIC API was different from the encoding used by the Safercar Database. For example, a Chevrolet Silverado has a model name of "Silverado" in NASS/CDS but a model name of "Silverado 1500" in the Safercar database, and trim line information was not available for all vehicles in NASS/CDS. For vehicles with multiple NCAP tests, e.g. when the manufacturer requested a re-test, the latest test result was used. For some NASS/CDS vehicles, not enough information was available to determine the NCAP variant associated with that vehicle, but all NCAP variants associated with the vehicle used the same test results. For example, drive type information may not be available for a vehicle, but each drive variation for that vehicle may use the same Side MDB test, so selecting the correct variation is unnecessary.

For each Safercar test result associated with each NASS/CDS vehicle, the results of the test were used to compute the risk to the driver, using the appropriate equation for P_{joint} in Federal Docket No. NHTSA-2006-26555 (NHTSA and Department of Transportation, 2008). A diagram explaining this functionality is given in Figure 2. Some vehicles in NASS/CDS did not have enough information to obtain a matching NCAP MDB test using this process. In most cases, this was because the NASS/CDS vehicle had been redesigned prior to MY 2011 when the most up-to-date NCAP testing began. Because of this, no test results were available. For the remaining vehicles, this was because the vehicle was not rated by NHTSA. Low volume and luxury vehicles were not typically rated in the NCAP program.

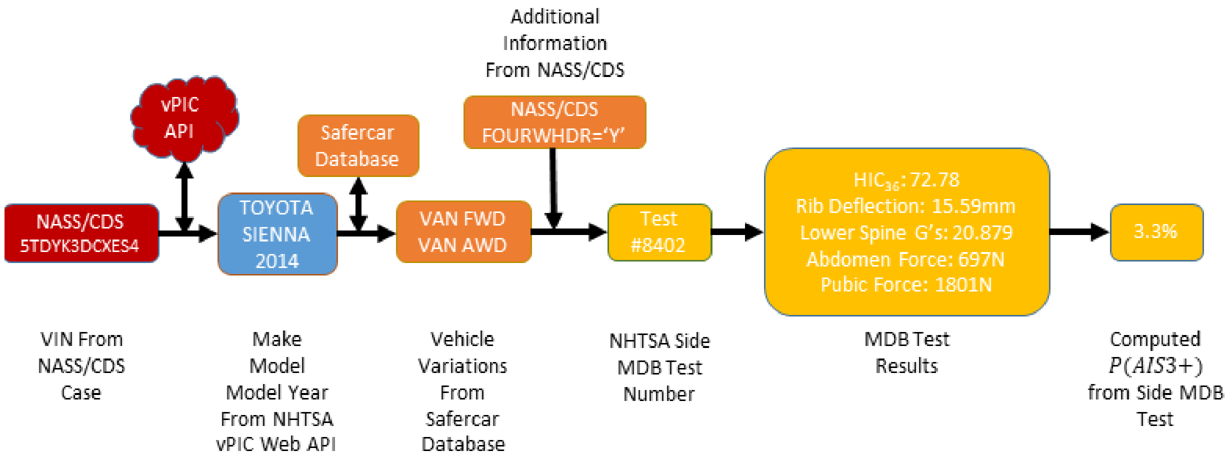

Figure 2. Procedure for identifying the NCAP MDB test injury risk for vehicles in NASS/CDS. The same procedure is used for the frontal barrier test.

Injury Risk Modeling

Three logistic regression models were developed to predict the probability of MAIS2+F injury to front row occupants in frontal, near-, and far-side impacts. Modeling was performed using the survey package in R (Lumley, 2019) in order to account for the complex NASS/CDS sampling scheme (Zhang and Chen, 2013). The predictor variables listed below were used for each of the models. Each variable was not present in each model. A table of which predictor variable was used in each model is given in Table 4.

- **Delta-V**. Delta-V has been shown to be an important metric of crash severity across many crash modes (Fildes et al., 2007; Gabler et al., 2005a; Kononen et al., 2011; K. Kusano and Gabler, 2014; Kusano and Gabler, 2013, 2012; Tsoi and Gabler, 2015). The limits of delta-v estimation are also well-established (Gabler et al., 2004, 2003; Hampton and Gabler, 2010, 2009; Johnson and Gabler, 2014, 2012; Niehoff and Gabler, 2006). Our model used resultant delta-v. Delta-V describes the change in velocity of the vehicle over the entire crash.
- **Belt Use**. Viano and Parenteau (2010) and Prasad et al (2015) showed that belt use was related to injury outcomes in side impacts.
- **Age and Gender**. Occupant demographics such as age and gender have been shown to be related to occupant injury risk (Beck et al., 2007; Gabler et al., 2005b; Langford and Koppel, 2006; McCoy et al., 1989; Mock et al., 2002; Tatem and Gabler, 2019, 2017; Yau, 2004). In this study, occupant ages were divided into two groups: 13-64 and 65 and older.
- **NCAP Risk**. This value was the probability that an AIS3+ injury would be experienced by the front seat ATD in the NCAP MDB or frontal test assigned to each occupant in the *NCAP Matching* section above. While the ATD was typically positioned in the driver seat, we applied this predictor variable to NASS/CDS occupants in the left front and right front seats. This predictor variable was not used in the far-side impact model because NCAP tests not conducted for the far-side impact crash mode in the United States as of October

2019. Euro NCAP, the European equivalent to the United States NCAP program, has proposed a far-side impact test but it has not been implemented.

- **Crash Compatibility.** The difference in size between both collision partners has been shown to affect crash outcomes (Gabler and Hollowell 1998). Two vehicle sizes were considered: passenger vehicles, and light trucks and vans (LTV). Crash compatibility was modeled using a categorical variable with four categories: LTV struck LTV, LTV struck car, car struck LTV, and car struck car. Car struck car was the reference category. Crash compatibility was not considered as a predictor variable for the side impact models because not enough cases were available.
- **Frontal Overlap.** Work by the Insurance Institute for Highway Safety (IIHS) found that some vehicles exhibited structural weakness when exposed to frontal impacts in which only a portion of the front of the vehicle impacts another vehicle, referred to as a small overlap crash (Sherwood, Nolan et al. 2009). Frontal overlap was modeled using a categorical variable with three categories based on the SAE J224 specific horizontal location (SHL) encoded in NASS/CDS: full engagement (D), moderate overlap (Y or Z), or small overlap (L or R). The SAE J224 codes are given in Figure 3. Full engagement was the reference category. Frontal overlap was only considered as a predictor variable for the frontal impact model.
- **BMI.** Body mass index has been shown to be related to injury outcomes in crashes (Mock, Grossman et al. 2002). BMI was modeled as a continuous variable with units kg/m^2.
- **Struck vehicle impact location**. We hypothesized that impact location on the struck vehicle affects injury outcomes. Struck vehicle impact location was modeled as a

categorical variable, depending on whether the struck vehicle general area of damage (GAD) was the front, rear, or side. Front was the reference category. This variable was only considered for the frontal impact model.

- **Occupant seating position.** We hypothesized that occupant seating position was related to injury outcomes. Occupant seating position was modeled as a categorical variable, stating whether the occupant was seating in the driver seat or the passenger seat.

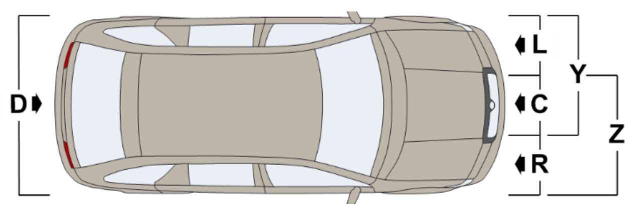

Figure 3. SAE J224 Specific Horizontal Location (SHL) Coding Convention.

Table 4. Predictor variables used for each injury model.

Predictor Variable	**Frontal Model**	**Near-Side Model**	**Far-Side Model**
Delta-V	✓	✓	✓
Belt Status	✓	✓	✓
Gender	✓	✓	✓
Age	✓	✓	✓
NCAP Risk	✓	✓	✗

Crash Compatibility	✓	✗	✗
Frontal Overlap	✓	✗	✗
BMI	✓	✓	✓
Struck Vehicle Damage Location	✓	✗	✗
Seating Position	✓	✓	✓

Results

Full Model

The final injury risk models are given below. Equation 3 gives the logit injury risk function. Equations 4, 5, and 6 give the logits for each injury model. Table 5 gives the weights for each injury model.

$$P[MAIS2{+}F] = \frac{1}{1 + e^{-logit}} \tag{3}$$

$$\begin{gathered} logit_{frontal} = \beta_0 \cdot \Delta v + \beta_2 \cdot isbelt + \beta_3 \cdot ismale + \beta_4 \cdot senior + \\ \beta_5 \cdot P_{Frontal}(AIS3{+}) + \beta_6 \cdot compat_{CT} + \beta_7 \cdot compat_{TC} + \\ \beta_8 \cdot compat_{TT} + \beta_9 \cdot overlap_{Mod} + \beta_{10} \cdot overlap_{small} + \\ \beta_{11} \cdot bmi + \beta_{12} \cdot target_{rear} + \beta_{13} \cdot target_{side} + \beta_{14} \cdot driver \end{gathered} \tag{4}$$

$$\begin{gathered} logit_{near} = \beta_0 + \beta_1 \cdot \Delta v + \beta_2 \cdot isbelt + \beta_3 \cdot ismale + \beta_4 \cdot senior + \\ \beta_5 \cdot P_{MDB}(AIS3\,+) + \beta_6 \cdot bmi + \beta_7 \cdot driver \end{gathered} \tag{5}$$

$$\begin{gathered} logit_{far} = \beta_0 + \beta_1 \cdot \Delta v + \beta_2 \cdot isbelt + \beta_3 \cdot ismale + \beta_4 \cdot senior + \\ \beta_5 \cdot bmi + \beta_6 \cdot driver \end{gathered} \tag{6}$$

Table 5. Injury model parameters for frontal, near-, and far-side impact.

Predictor Variable	**Parameter**	**Coefficient**	**Lower Bound**	**Upper Bound**	**P-Value**
		Frontal Model			
—	β_0, Intercept	-6.300	-8.397	-4.204	<0.001**
Delta-V	β_1, Delta-V (kph)	0.085	0.051	0.119	<0.001**
Belt Use	β_2, Belted	-0.796	-1.558	-0.034	0.042**
Gender	β_3, Gender = male	-0.905	-1.556	-0.254	0.007**
Age	β_4, Age ≥ 65	1.076	0.109	2.043	0.031**
NCAP Risk	β_5, $P_{Frontal}(AIS3+)$	-3.474	-12.923	5.976	0.472
Crash Compatibility	β_6, Car struck LTV	1.183	0.297	2.070	0.010**
	β_7, LTV struck car	0.293	-0.610	1.195	0.526
	β_8, LTV struck LTV	-1.818	-1.818	0.772	0.430
Frontal Overlap	β_9, Moderate overlap	-0.194	-1.212	0.824	0.709
	β_{10}, Small overlap	-0.601	-2.076	0.875	0.426
Body Mass Index	β_{11}, BMI (kg/m^2)	0.091	0.040	0.142	<0.001**
Struck Vehicle Impact Location	β_{12}, Struck rear	-1.708	-2.856	-0.560	0.004**
	β_{13}, Struck side	-0.265	-1.006	0.477	0.485
Seating Position	β_{14}, Driver Seat	0.564	-0.583	1.710	0.337
		Near-Side Model			
—	β_0, Intercept	-19.489	-31.621	-7.356	0.003**
Delta-V	β_1, Delta-V (kph)	0.177	0.057	0.297	0.006**
Belt Use	β_2, Belted	0.021	-1.635	1.677	0.980
Gender	β_3, Gender = male	2.597	0.848	4.347	0.005**

Age	β4, Age ≥ 65	-3.035	-4.908	-1.163	0.002**
NCAP Risk	β5, $P_{MDB}(AIS3+)$	12.004	4.312	19.696	0.003**
Body Mass Index	β6, BMI (kg/m^2)	0.089	0.010	0.168	0.032**
Seating Position	β7, Driver Seat	0.771	0.040	1.503	0.044**
Far-Side Model					
—	β0, Intercept	5.257	-6.928	17.442	0.400
Delta-V	β1, Delta-V (kph)	0.100	0.038	0.163	0.002**
Belt Use	β2, Belted	-2.747	-4.741	-0.753	0.009**
Gender	β3, Gender = male	0.108	-1.430	1.646	0.891
Age	β4, Age ≥ 65	0.444	-1.446	2.334	0.647
Body Mass Index	β5, BMI (kg/m^2)	0.035	-0.043	0.113	0.380
Seating Position	β6, Driver Seat	-0.878	-1.885	0.129	0.092

Reduced Model

Some predictor variables were not statistically significant predictors of injury risk in the dataset. A simplified model was then developed with included only significant predictors of injury risk. Table 6 contains the coefficients of the simplified models.

Table 6. Simplified model injury risk parameters for frontal, near-, and far-side impact.

Predictor Variable	**Parameter**	**Coefficient**	**Lower Bound**	**Upper Bound**	**P-Value**
Frontal Model					
—	β0, Intercept	-6.516	-8.206	-4.825	<0.001**
Delta-V	β1, Delta-V (kph)	0.090	0.053	0.128	<0.001**

Belt Use	β_2, Belted	-0.769	-1.545	0.008	0.054
Gender	β_3, Gender = male	-0.891	-1.544	-0.238	0.008**
Age	β_4, Age ≥ 65	1.070	0.106	2.034	0.031**
Crash Compatibility	β_6, Car struck LTV	1.222	0.500	1.943	0.001**
Body Mass Index	β_{11}, BMI (kg/m^2)	0.084	0.042	0.125	<0.001**
Struck Vehicle Impact Location	β_{12}, Struck rear	-1.455	-2.437	-0.472	0.004**
Near-Side Model					
—	β_0, Intercept	-20.726	-33.017	-8.436	0.002**
Delta-V	β_1, Delta-V (kph)	0.194	0.072	0.315	0.003**
Gender	β_3, Gender = male	-3.550	-5.742	-1.358	0.002**
Age	β_4, Age ≥ 65	2.693	0.961	4.424	0.004**
NCAP Risk	β_5, $P_{MDB}(AIS3+)$	12.578	4.801	20.355	0.002**
Body Mass Index	β_6, BMI (kg/m^2)	0.083	0.010	0.156	0.030**
Seating Position	β_7, Driver Seat	0.765	0.011	1.519	0.052
Far-Side Model					
—	β_0, Intercept	-4.332	-5.868	-2.796	<0.001**
Delta-V	β_1, Delta-V (kph)	0.124	0.052	0.196	0.001**
Belt Use	β_2, Belted	-2.573	-4.665	-0.480	0.018**

Discussion

Mechanisms for injury risk varied from crash mode to crash mode. The only statistically significant predictor of injury risk across all three crash modes in this study was delta-v. Belt use was a significant predictor of injury risk in frontal and far-side impacts, but not in near-side impacts. This may be due to the reduced sample size of the near-side impact dataset. The size of the dataset sample was limited by the relatively recent introduction of the updated NCAP MDB side test and the small number of vehicle in NASS/CDS to which these upgraded test results applied. Cases without NCAP test values from this new test were excluded.

Limitations

This study had a number of limitations. The primary limitation was the small number of cases available for analysis. In the frontal and near-side impact models, this was due to the restriction to vehicles that had ratings from the post-2011 NCAP frontal and side crash tests, respectively. A direct comparison between pre- and post-2011 NCAP dummy performance could not be made. Second, our hypothesis was that occupant protection at the MAIS2+F level in real-world crashes would be correlated with the risk of MAIS3+ injury as estimated in NCAP tests. The near-side impact model found such a correlation, but this finding does not provide insights into the mechanisms which led to this correlation. Third, previous research has shown a statistically significant relationship between near-side impact injury outcomes and belt status (Prasad et al., 2015; Viano and Parenteau, 2010) which was not shown in this study. We expect in larger dataset of crash occupants that these predictor variables may show statistical significance. NASS/CDS data collection ended in 2015, and no more data is available from that study. The replacement program, the Crash Investigative Sampling System (CISS), could serve as an effective data source for an update to this work. CISS 2017 was released in September 2019 and no cases from CISS were included in this study.

4. CRASH AND INJURY PREVENTION ESTIMATES FOR INTERSECTION DRIVER ASSISTANCE SYSTEMS IN LEFT TURN ACROSS PATH / OPPOSITE DIRECTION CRASHES IN THE UNITED STATES

Introduction

Intersection Advanced Driver Assistance Systems (I-ADAS), sometimes referred to as left-turn assist, are a promising design feature to help prevent or reduce the severity of some of these Left Turn Across Path / Opposite Direction (LTAP/OD) crashes. A diagram depicting an LTAP/OD crash is shown in Figure 4.

The objective of this chapter was to estimate the number of LTAP/OD crashes and injuries that could be prevented in the United States if vehicles were equipped with an Intersection Advanced Driver Assistance System (I-ADAS) with the same capabilities as the hypothetical system analyzed in this study. Results are presented for the case where only one vehicle in a conflict was equipped with I-ADAS and for the case where both vehicles were equipped with I-ADAS.

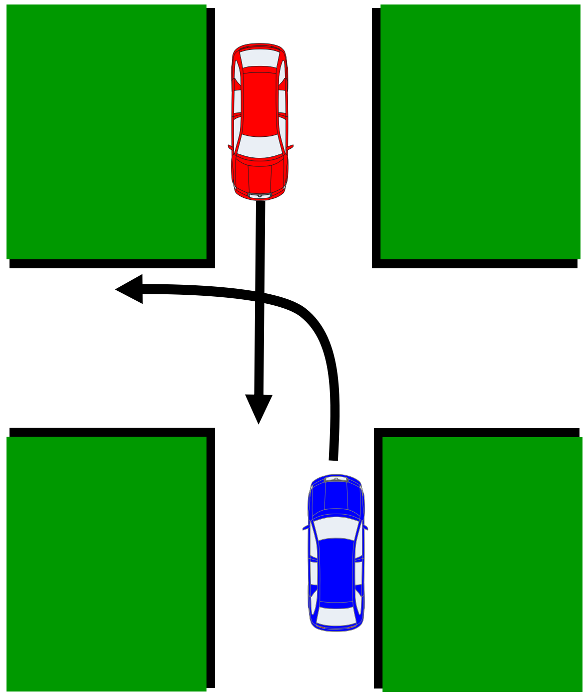

Figure 4. A diagram of the LTAP/OD crash mode. The red car (from above) is the traveling through vehicle and the blue car (from below) is the turning vehicle.

Methods

Data Source

The study was based on the analysis of 501 crashes investigated as a part of NMVCCS. A detailed summary of the included cases can be found in Table 7. Cases were excluded if necessary information, such as pre-crash movement, speed limit, stop location, vehicle dimensions, vehicle rest positions, or occupant demographics, was not available. Intersection crashes in which a rollover occurred were not considered. Crashes with three or more vehicles impacted were not considered.

Table 7. Case Inclusion Criteria for NMVCCS LTAP/OD Cases. Weighted count refers to the total case weight (RATWGT variable in NMVCCS) for each row.

Group		**Count**	**Weighted Count**
All LTAP/OD Crashes in NMVCCS		667	231,412
Valid LTAP/OD after Manual Inspection		665	231,189
Missing Case Information	**Unknown pre-crash Movement**	9	6,529
	Missing Diagram/Photograph/Speed Limit	8	1,647
	Stop Location not provided in Diagram	7	2,360
PC-Crash Exclusion	**Rollover**	41	13,080
	3 or more Moving Vehicles Impacted	10	2,092
	Missing Vehicle in CVS database	29	7,232
	Scene Diagram Not Correctly Scaled	29	5,237
Injury Benefits	**Unknown occupant age/gender**	31	16,049
Final Dataset for LTAP/OD Reconstruction		**501**	**176,963**

Crash Reconstruction

The purpose of crash reconstruction was to determine the location and speed as a function of time for each vehicle involved in the crash. The methods for path and speed reconstruction have been described previously (J. M. Scanlon et al., 2016; John M. Scanlon et al., 2016; Scanlon et al., 2017). In summary, we assumed each vehicle followed the path indicated on the scene diagram drawn by the NMVCCS crash scene investigator. Speed reconstruction for each vehicle occurred in three phases: the pre-intersection phase, the intersection phase, and the evasive action phase. The pre-intersection phase covered the vehicle deceleration prior to crossing the intersection boundary. The intersection phase covered the vehicle acceleration while entering the intersection. The evasive action phase covered any evasive action before the crash. The moment of impact was reconstructed as part of the evasive action phase. These phases are shown in Figure 5.

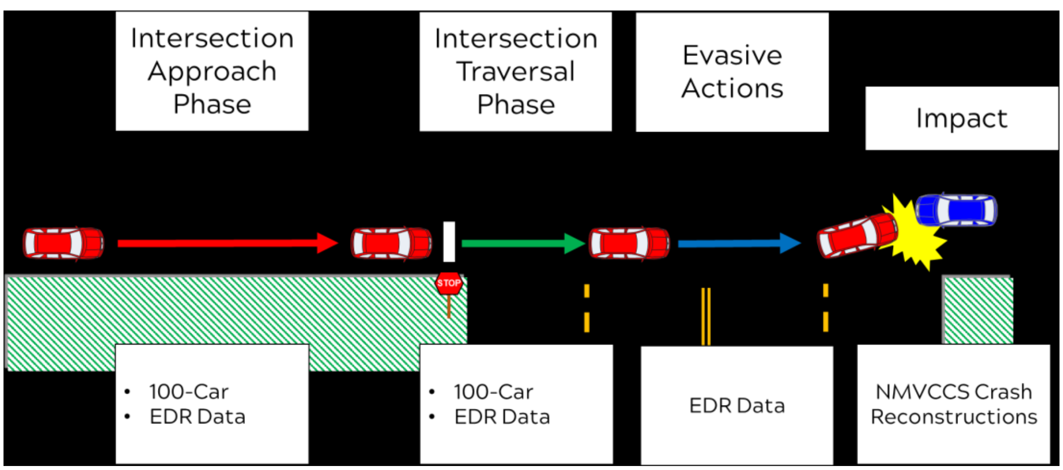

Figure 5. Phases of vehicle movement as part of the reconstruction methodology.

The pre-intersection phase modeled three possible pre-intersection movements: stopped, rolling stop, or traveling through. The model was selected based on the PREMOVE variable in

NMVCCS and the crash narrative. The stopped model assumed the vehicle was stopped at the intersection boundary and required no information prior to the vehicle stopping. The rolling stop model included a deceleration model developed previously from the 100-Car Naturalistic Driving Study using the methodology of Noble et al. (2016). The traveling through model assumed that no deceleration occurred prior to entering the intersection.

The intersection phase of speed reconstruction was dependent on the pre-intersection movement. The rolling stop and completely stopped vehicles used an acceleration model developed from Event Data Recorder (EDR) data (Scanlon et al., 2018, 2015; Tsoi et al., 2014, 2013), where vehicles accelerate from the intersection boundary to the point of impact. Traveling through vehicles did not have any simulated acceleration during this phase. During the evasive action phase, the speed of the vehicle simulated from the intersection phase was compared to the impact speed determined from a PC-Crash (Datentechnik, 2013) simulation of the NMVCCS crash. A logistic regression model developed from EDR data was used to determine the probability that the vehicle performed evasive braking based on the intersection phase impact speed and the PC-Crash impact speed. In some cases the speed of the vehicle at impact from the intersection phase was higher than the impact speed simulated using PC-Crash. We assumed this difference was caused by the vehicle performing some evasive braking prior to the crash. Two variations of each crash were simulated using I-ADAS: one with evasive braking and one without. The weight of each crash was split for each variation, weighted by the probability that evasive braking occurred. In cases where the probability of evasive braking or no evasive braking was extremely likely (probability of 99% or greater), the unlikely scenario was not simulated. Additionally, for cases where the impact speed was below 15 mph for traveling through drivers, we always assumed evasive braking had occurred. Evasive braking assumed a jerk value of $-11m/s^3$ with a peak deceleration of 0.3g, 0.4g, or 0.8g dependent on icy, wet, or dry surface conditions noted by the NMVCCS crash investigator. When evasive braking did not occur, the beginning of the intersection phase was moved backwards along the vehicle path until the simulated impact speed matched the reconstructed impact speed.

I-ADAS Simulation

The hypothetical I-ADAS system design modeled in this work has been described previously for Straight Crossing Path (SCP) crashes by Scanlon et. al. (2017). The vehicle detection sensor was located on the front center of the vehicle and had a 100m range with a 90° sensing cone centered forward (45° on each side). This sensor configuration differed from what was used in the SCP study. We assumed sensors in this system continuously scanned for potential collision partners. In LTAP/OD crashes, both vehicles approached the intersection from opposing directions, which means in many situations it was possible to see an oncoming vehicle long before it entered the intersection. In addition, a real sensor with a nominal 100m range may be able to see vehicles farther away in the straight line conditions present in many LTAP/OD crash situations. This conservative sightline assumption causes the simulation method to understate system benefits in some cases. However, this was not always the case: sometimes, a line of cars in the opposing left turn lane could obstruct the view of the traveling through vehicle from the turning vehicle.

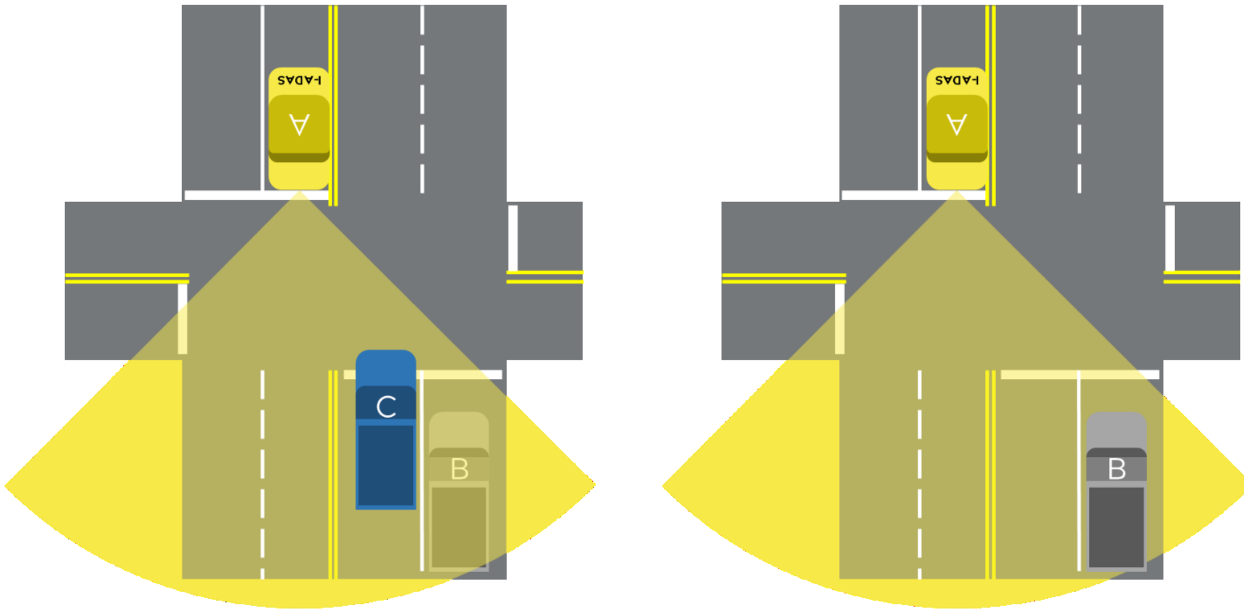

Figure 6. I-ADAS sightline assumption. In the left diagram, the vehicle C is blocking the view of vehicle B from the I-ADAS sensor. This is referred to as the worst-case sightline assumption. In the right diagram, no block vehicle is present. This is referred to as the best-case sightline assumption.

We simulated two sightline assumptions, referred to as the worst-case and best-case sightline assumptions. In the best-case sightline assumption, the earliest detection opportunity for both vehicles was when the left turning vehicle began to turn left (left its initial travel lane) and had a clear line of sight to the potential collision partner. In the worst-case sightline assumption, the I-ADAS vehicle was not able to detect the potential collision partner if the clear line of sight extended through the left turn lane, simulating the case where a line of cars blocked the left turn lane. In cases where no left turn lane was present, the worst-case sightline assumption case did not have a line of cars, and the simulation was identical to the best-case sightline assumption with identical I-ADAS performance. After detection, the I-ADAS system waited for a simulated computational latency time. Three computational latency times were simulated: 0ms, 125ms and

250ms. The 0ms (instantaneous) case represents an optimistic limiting case. After this computational latency time, the time to collision (TTC) was continuously monitored. Time to Collision is defined in Equation 7, where v is speed of the I-ADAS vehicle, a is acceleration of the I-ADAS vehicle, and d is the distance to the intersection point of the paths of the I-ADAS vehicle and the target vehicle.

$$TTC = \frac{-v + \sqrt{v^2 - 2da}}{a} \tag{7}$$

This definition of TTC is sometimes referred to as enhanced TTC, or eTTC (Chen et al., 2016). If the TTC dropped below a configurable threshold, two system designs were simulated: either a warning was issued, or automated braking was activated. The TTC thresholds simulated were 1.0 to 3.0 seconds in 0.5 second increments. The warning based system was simulated to apply braking at $-11m/s^3$ after a perception-reaction time (Nygård, 1998). Three perception-reaction time values of 0.69s, 0.93s, and 3.2s were used. Reaction times were developed previously using a simulator study (Chen et al., 2011, 2015), and these values are the 17th percentile, 50th percentile, and 83rd percentile reaction times, respectively. We assumed drivers were alert and always responded. The automated braking system was simulated to apply braking at $-35m/s^3$ without delay. Brake application continued until full braking was reached. Full braking was -0.3g, -0.4g, or -0.8g (Franck et al., 2009) depending on whether the original crash had icy, wet, or dry conditions, respectively, as noted by the NMVCCS crash scene investigator.

A total of 30 I-ADAS variations (five TTC thresholds, three system latencies, and two system designs) were simulated for each original crash. Each of the 15 warning-based I-ADAS variations was simulated three times for each perception-reaction time. These 75 I-ADAS-reaction time variations were simulated under the worst-case and best-case sightline assumptions. These 150 I-ADAS-reaction time variations were simulated for either vehicle equipped with I-ADAS in each case, and additionally for the case where both vehicles were equipped with I-ADAS. These 450 I-ADAS-reaction-time-sightline-equipped variations were simulated for up to four evasive maneuver conditions in the original case. In addition, each original NMVCCS case was re-simulated without I-ADAS as a baseline for evaluating injury. A total of 447,122 simulations were conducted.

Impact Simulation

Simulated I-ADAS crashes had three possible outcomes: unmodified, modified, and avoided. Unmodified cases had no I-ADAS braking in either vehicle and the outcome was identical to the original NMVCCS case. Modified cases had I-ADAS braking which changed the characteristics of the crash but did not avoid the crash. Avoided cases had I-ADAS braking which prevented the crash from occurring. For unmodified and modified cases, injury risk was modeled. Injury risk modeling was described in the previous chapter. Injury risk was modeled to be a function of impact location, delta-v, vehicle parameters, and occupant parameters. Delta-V was computed for each vehicle in each I-ADAS simulation using PC-Crash. Simulations were performed by placing each vehicle in PC-Crash in their respective positions and orientations at the moment of contact. Each vehicle was assigned its respective velocity at impact, and the simulation was run for 300ms. Total delta-v was computed over this time frame. Because the intent of this study was to predict injury effectiveness for a future fleet, all vehicles were assumed to be equipped with frontal and side airbags and have passive safety performance equivalent to vehicles rated five stars under the NHTSA New Car Assessment Program (NCAP) rating system. Injury benefits were computed for all front-row occupants age 12 or older in each vehicle as noted in each NMVCCS case.

Results

Results are given for the crash avoidance and injury reduction benefits of I-ADAS. Additional results for an I-ADAS system with an alternate sensor configuration are given in the appendix.

Crash Avoidance Benefits

The first goal of this chapter was to predict the potential crash avoidance benefits of I-ADAS in LTAP/OD crashes. Benefits are presented in the form of percent effectiveness, where 0% means no crashes were avoided with I-ADAS and 100% means all crashes were avoided with I-ADAS. This is comparable to the methods used in other works which evaluate active safety systems (Haus et al., 2019; Haus and Gabler, 2019; Holmes et al., 2018; L. Riexinger et al., 2019; L. E. Riexinger et al., 2019; J. M. Scanlon et al., 2016). Crash avoidance benefits are presented in Figure 7 for the single vehicle equipped case. When only one vehicle was equipped with I-ADAS, 0%-26% of crashes were avoidable for a warning based system. I-ADAS designs with a higher TTC threshold avoided a greater percentage of crashes. System latency was not as strongly related to crash effectiveness as it was in SCP I-ADAS (J. M. Scanlon et al., 2016). The sightline assumption had a strong impact on effectiveness. Peak warning effectiveness was 26% in the best-case sightline assumption and only 10% in the worst-case sightline assumption. In the AEB system design, 18%-73% of crashes were avoidable. System latency was not correlated to crash avoidance effectiveness in the best-case sightline assumption. However, using the worst-case sightline assumption, AEB system effectiveness dropped by 1-5 percentage points for each 125ms of additional computational latency time. Peak effectiveness was 73% for the best-case sightline assumption and 59% for the worst-case sightline assumption.

Figure 8 describes I-ADAS effectiveness when both vehicles in the crash were equipped with I-ADAS. I-ADAS effectiveness was higher when both vehicles were equipped with I-ADAS. For a warning based system, 0%-32% of crashes were avoidable. Peak warning system effectiveness was 32% in the best-case sightline assumption and 15% in the worst-case sightline assumption. In the AEB system design, 36%-84% of crashes were avoidable. In the worst-case sightline assumption, AEB system effectiveness dropped by 2-11 percentage points for each 125ms of additional computational latency time.

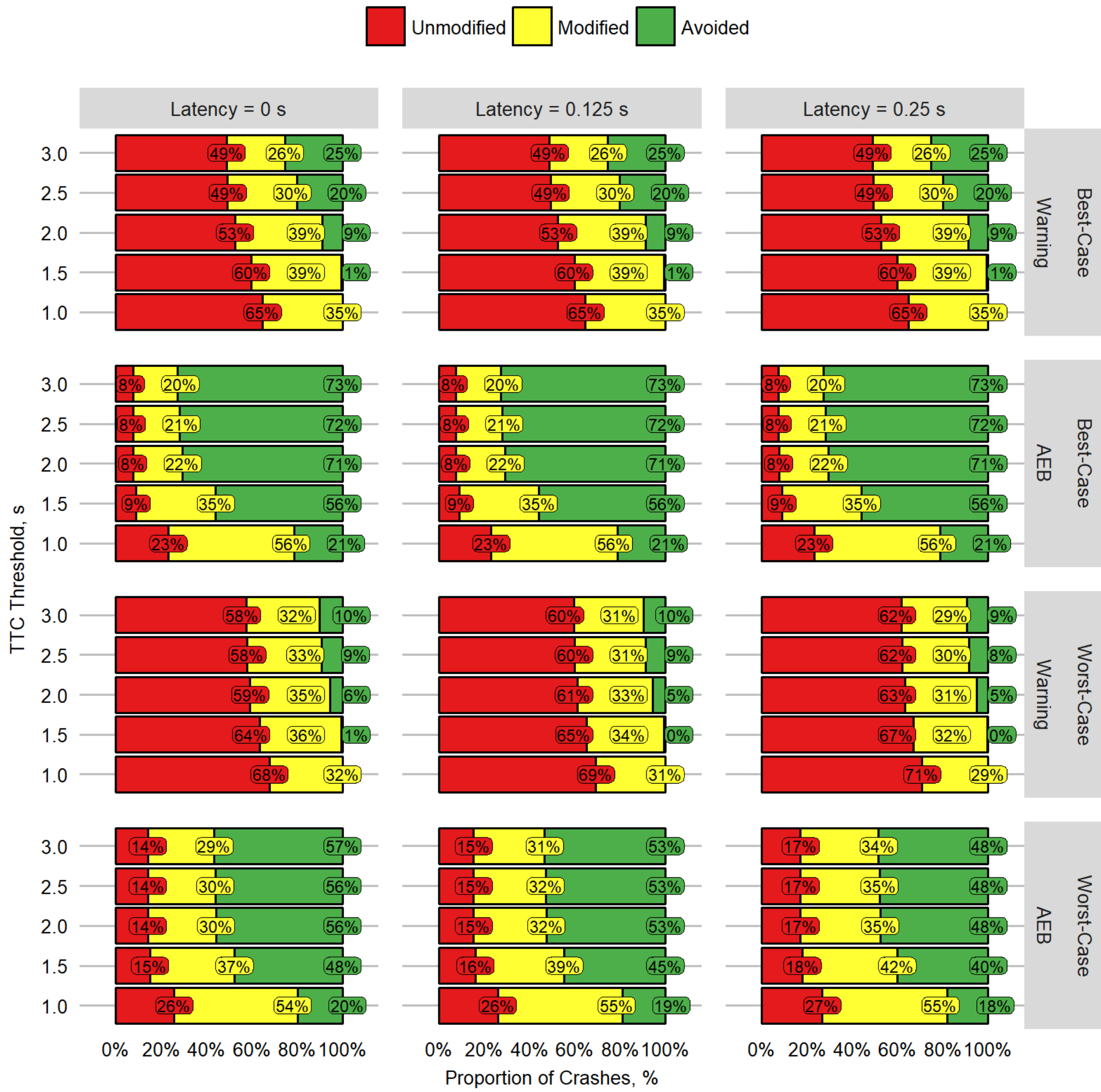

Figure 7. All crash results for the potential benefits of I-ADAS in LTAP/OD crash scenarios. These results are for a scenario where only one of the vehicles was equipped with I-ADAS. Each bar represents a unique latency-threshold-system-sightline assumption.

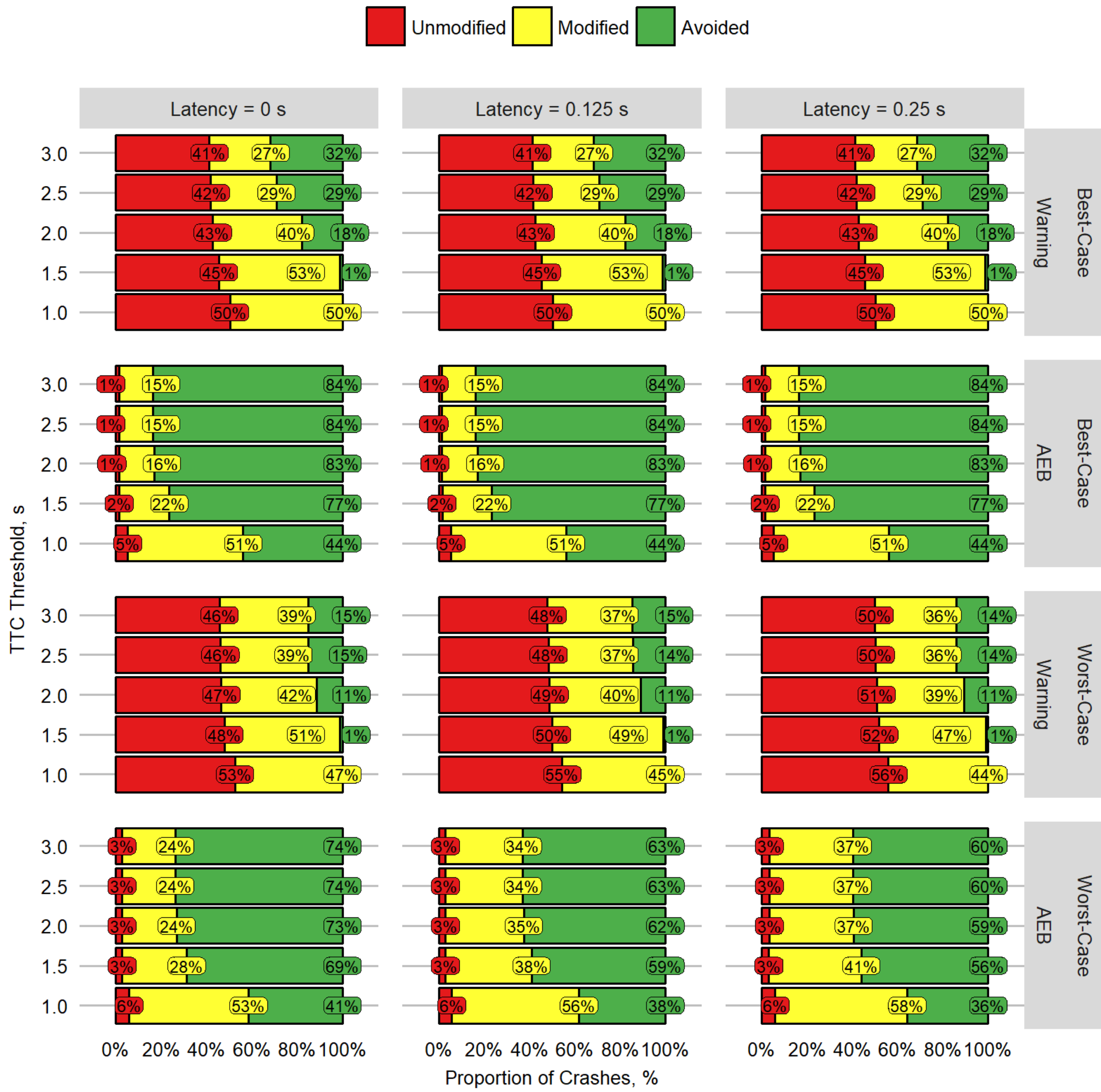

Figure 8. All crash results for the potential benefits of I-ADAS in LTAP/OD crash scenarios. These results are for a scenario where both of the vehicles were equipped with I-ADAS. Each bar represents a unique latency-threshold-system-sightline assumption.

Injury Reduction Benefits

The second goal of this chapter was to predict injury reduction benefits of I-ADAS in LTAP/OD crashes. Injury reduction benefits were defined as the percentage reduction in number of MAIS2+F injured occupants 12 year old or older in the front row of the vehicle. An MAIS2+F occupant is a person who received an injury to any body region with an Abbreviated Injury Scale score of 2 or higher, including those occupants who received unknown injuries (AIS=7) but were fatally injured. AIS coding was based on the 2008 update (Gennarelli, 2008). In this study, an MAIS2+F injured front row occupant age 12 or older was referred to as an injured occupant. We assumed occupants in avoided crashes had no injuries. Injured occupant reduction effectiveness is presented in Figure 9 for the single vehicle equipped case. Warning-based I-ADAS systems were able to avoid 1%-30% of injured occupants. The maximum injury effectiveness was 30% for the best-case sightline assumption and was 10% for the worst-case sightline assumption. In the worst-case sightline assumption, warning system effectiveness dropped by 0-1 percentage points for each 125ms of additional computational latency time. AEB-based I-ADAS systems were able to avoid 44%-85% of injured occupants. The maximum AEB effectiveness was 85% in the best-case sightline assumption and 65% in the worst-case sightline assumption. In the worst-case sightline assumption, AEB system effectiveness dropped by 3-6 percentage points for each 125ms of computational latency time.

Figure 10 describes the I-ADAS injured occupant reduction effectiveness when both vehicles in the crash were equipped with I-ADAS. I-ADAS injury reduction effectiveness was higher when both vehicles were equipped. Warning based I-ADAS systems were able avoid 1%-36% of injured occupants. The maximum injured occupant reduction effectiveness was 36% for the best-case sightline assumption and was 16% for the worst-case sightline assumption. In the worst-case sightline assumption, warning effectiveness was reduced by 0-2 percentage points for each 125ms of computational latency time. AEB-based I-ADAS systems were extremely effective at avoiding injured occupants, with effectiveness values ranging from 62%-94%. The maximum AEB effectiveness was 94% for the best-case sightline assumption and 84% for the worst-case sightline assumption. In the worst-case sightline assumption, benefits reduced by 5-9 percentage points for each 125ms of additional computational latency time.

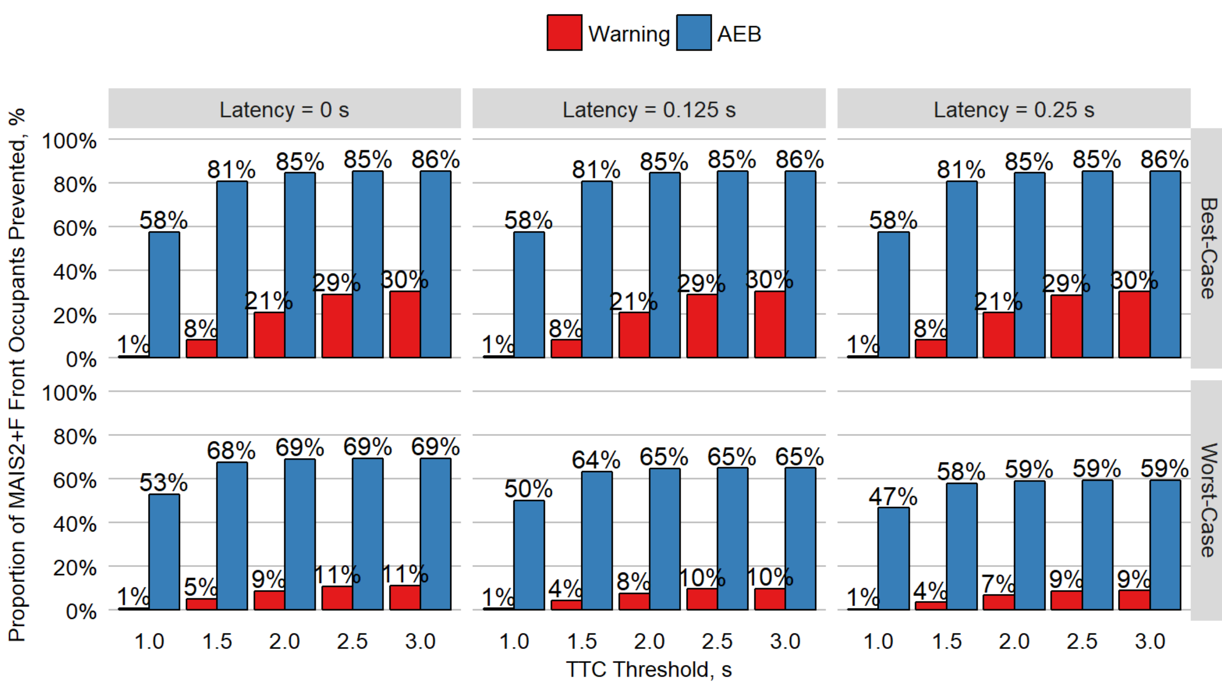

Figure 9. Proportion of injured occupants avoided with I-ADAS. These results are for the case where one vehicle was equipped with I-ADAS. Each bar represents a unique system-latency-threshold-sightline assumption.

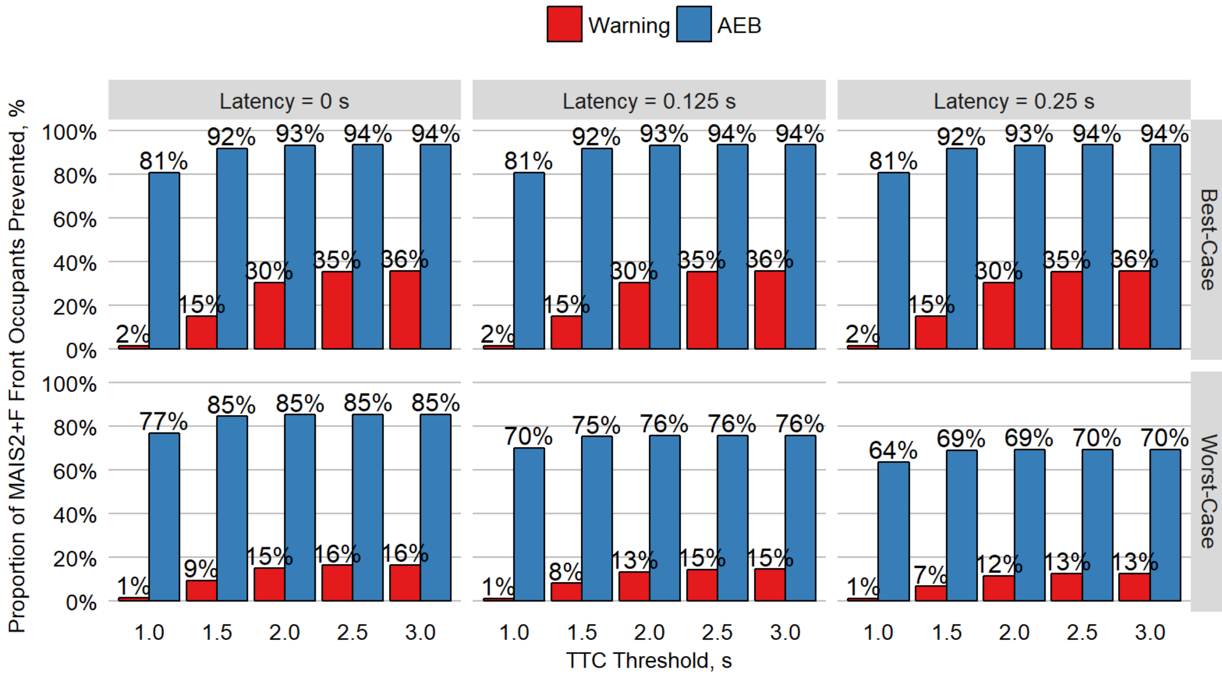

Figure 10. Proportion of injured occupants avoided with I-ADAS. These results are for the case where both vehicles were equipped with I-ADAS. Each bar represents a unique system-latency-threshold-sightline assumption.

Discussion

I-ADAS system effectiveness in LTAP/OD crashes was strongly related to TTC threshold and system design (warning vs. AEB). TTC threshold and system design governed the total delay in response. I-ADAS system designs with higher TTC thresholds responded sooner to a potential crash. Warning systems included a driver perception-reaction time delay and responded later to a potential crash. Higher computational latency times reduced the effectiveness of the I-ADAS system under the worst-case sightline assumption. In these cases, a large computational delay decreased the amount of time available for braking, reducing effectiveness. In the best-case sightline assumption, fewer cases were affected by the increased computational latency time. I-ADAS benefits in both crash avoidance and injury reduction were high; in many I-ADAS system designs, more than half of all crashes or injured persons could be avoided. Results were similar to previously published work on I-ADAS in Straight Crossing Path intersection crashes (Sander and Lubbe, 2018; J. M. Scanlon et al., 2016; Scanlon et al., 2017). Injury benefits followed the same trends as crash benefits. However, injury benefits were higher than crash benefits. This is because in many cases in which the crash was not avoided (no crash avoidance benefit), the I-ADAS system was able to reduce the severity of the crash and reduce the risk of injury. In some cases, injury outcomes were worse in these modified cases, which we refer to as disbenefit cases. The properties and causation of these disbenefit cases are not fully understood and will be the subject of future research.

Increasing the TTC threshold above two seconds did not significantly increase system effectiveness. We believe that this is due to the relationship between the earliest detection opportunity and the TTC threshold in some cases. In these cases at high TTC thresholds when the opposing vehicle is detected or becomes a threat (started turning) the TTC value is already under the threshold. AEB braking or warning begins immediately upon detection or when the turning vehicle starts turning, regardless of the TTC threshold. In this situation, increasing the TTC threshold does not change the crash outcome. For a sufficiently high TTC threshold all crash situations would trigger the AEB braking or warning at the earliest detection opportunity and increasing the TTC threshold would have no effect on I-ADAS effectiveness. In a realistic deployment, however, this would produce a large number of false activations. The I-ADAS system in this study was only simulated for crash situations and false activations were not considered.

Limitations

This study has a number of limitations. First, normal variations in driver behavior, such as deceleration and acceleration profiles, rolling stop speed, and alertness were not considered. This study used median values for these characteristics of driver behavior. Modeling I-ADAS using "normal" driving could limit the application of this methodology for drivers who exhibit non-normal behavior, such as situations with aggressive drivers.

Second, we assumed two sightline assumptions: no obstructions and complete obstruction. Real-world situations are a mix of these two cases. Additionally, NMVCCS cases contained no information about fixed and moving obstructions, such as vehicles, pedestrians, cyclists, infrastructure, or flora. Objects such as trees and traffic signs in the median have the potential to limit sensor visibility and affect I-ADAS benefits.

Third, we assumed a hypothetical I-ADAS system design. Production vehicle active safety systems are subject to engineering, practical, and regulatory constraints not considered in this study and are highly proprietary. To reduce the sensitivity of our conclusions to the choice of I-ADAS design, we modeled a variety of I-ADAS design parameters. In addition, this study used Time to Collision as the trigger criterion for activation, while other systems have used minimum required braking for braking-based intersection assist systems (Sander, 2017). Fourth, we assumed that no secondary collisions occurred after the first collision. This assumption caused the model to overestimate I-ADAS effectiveness in some crashes.

5. THE LONG-TERM EVOLUTION OF LEFT TURN ACROSS PATH / OPPOSITE DIRECTION CRASHES IN THE UNITED STATES: THE POTENTIAL OF INTERSECTION ACTIVE SAFETY SYSTEMS

Introduction

The previous chapter established that a warning-based system had lower effectiveness than a system which applied automated braking. The effectiveness of automated braking systems was 20-30 percentage points higher than warning-based systems. In the best warning-based system, only 59% of drivers were able to react to the warning. Crash avoidance and injury prevention estimates were presented assuming all vehicles had I-ADAS. The objective of this chapter was to present realistic estimates of the number of LTAP/OD crashes and injuries in the United States from 2019 to 2060 accounting for fleet penetration.

Approach

Relative Effectiveness

When two vehicles approach at an intersection, there are three possible scenarios: (1) both vehicles are equipped with I-ADAS, (2) only one of the vehicles is equipped with I-ADAS, and (3) neither vehicle is equipped with I-ADAS. These scenarios are shown in Figure 11. We refer to this approach as a conflict, since a given conflict may not be a crash if it is avoided with I-ADAS. As shown in the previous chapter and also in SCP crashes (J. M. Scanlon et al., 2016), I-ADAS effectiveness in avoiding crashes was greater in conflicts where both vehicles were equipped with I-ADAS than in conflicts where only one vehicle was equipped. The probability of each of these scenarios as a function of the percent of vehicles equipped with I-ADAS is given in Equations 8-10, where Eqp is the proportion of vehicles in the fleet equipped with I-ADAS.

$$P(None|Eqp) = (1 - Eqp)^2 \tag{8}$$

$$P(Single|Eqp) = 2 * Eqp * (1 - Eqp) \tag{9}$$

$$P(Both|Eqp) = Eqp^2 \tag{10}$$

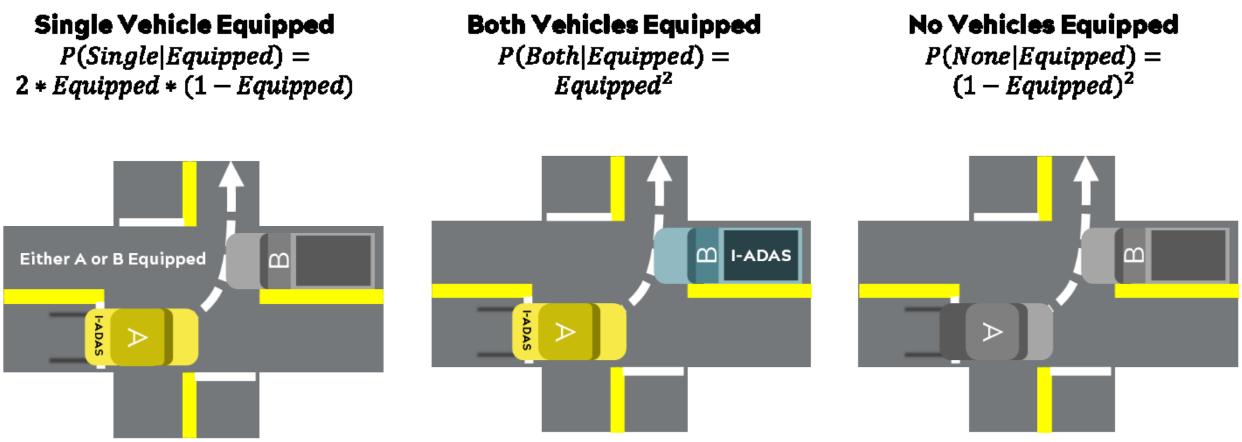

Figure 11. Conflict types of LTAP/OD crashes with an I-ADAS system.

I-ADAS effectiveness for these fleet penetrations is given in Equations 11 and 12 as the sum of the single-vehicle-equipped and both-vehicle-equipped effectiveness values weighted by the probabilities in Equations 8-10, where Eff_{Crash} is the crash effectiveness and Eff_{Injury} is the injury effectiveness.

$$Eff_{Crash}(Eqp) = P(Single|Eqp) * Eff_{Crash,Single} + P(Both|Eqp) * Eff_{Crash,Both} \tag{11}$$

$$Eff_{Injury}(Eqp) = P(Single|Eqp) * Eff_{Injury,Single} + P(Both|Eqp) * Eff_{Injury,Both} \tag{12}$$

I-ADAS effectiveness when neither vehicle was equipped was zero. I-ADAS effectiveness assumed a system with no system latency, 3.0s TTC threshold, and automated braking from the previous chapter. This system will be referred to as the model I-ADAS. Injury benefits were defined as the reduction in MAIS2+F (maximum Abbreviated Injury Scale score of 2 or higher across all body regions) injured front row occupants age 12 or older. In this chapter, we will refer to this group as injured occupants.

To determine I-ADAS effectiveness in the United States, effectiveness as a function of fleet penetration was coupled with fleet penetration predictions. We assumed that fleet penetration follows the Automated Emergency Braking (AEB) model published by the Highway Loss Data Institute (HLDI) (Highway Loss Data Institute, 2017). HLDI did not have a fleet penetration model specifically for systems like I-ADAS. The HLDI model describes fleet penetration as a function of year. I-ADAS crash and injured person reduction each year was modeled as a function of fleet penetration predictions and I-ADAS effectiveness. Crash and injured person reduction effectiveness was previous derived for a given fleet penetration in Equations 11 and 12. The predicted fleet penetration each year is given by the HLDI data, which we denote as $HLDI(Year)$ in Equation 13. Crash and injured person reduction effectiveness for a given year is a function of the crash and injury reduction effectiveness for a given fleet penetration, combined with the predicted fleet penetration for that year, as shown in Equations 14 and 15.

$$Eqp(Year) = HLDI(Year) \tag{13}$$

$$Eff_{Crash}(Year) = Eff_{Crash}\big(Eqp(Year)\big) \tag{14}$$

$$Eff_{Injury}(Year) = Eff_{Injury}\big(Eqp(Year)\big) \tag{15}$$

Absolute Effectiveness

We then computed absolute effectiveness by combining the relative effectiveness with the expected number of LTAP/OD crashes per year without I-ADAS. First, we assumed that LTAP/OD crashes from 2019 to 2060 will be similar to crashes in NMVCCS (2005-2007), so that our estimates for I-ADAS effectiveness were appropriate over that time span. This assumption is further discussed in the limitations section. The number of LTAP/OD crashes was determined each year using a target population. The target population was the group of crashes which the I-ADAS benefits computed in Chapter 4 would be applicable to (K. D. Kusano and Gabler, 2014; Kusano and Gabler, 2015). The target population was defined to be all NASS/CDS eligible LTAP/OD crashes in the United States where both vehicles were cars or LTVs and neither vehicle rolled over during the crash. Cases with a sampling weight greater than 5,000 were excluded based on the methodology of Kononen et al. (2011). In cases where the injury outcome was unknown, the number of people injured per crash was assumed to be the same as it was in the population where the injury outcomes were known. The simulation population used in Chapter 4 excluded cases which were missing information needed to compute I-ADAS effectiveness. I-ADAS would still be effective in these cases, so they were included in the target population. The target population was derived from NASS/CDS, not NMVCCS, in order to be comparable to the results of a separate project. We also assumed that the number of LTAP/OD crashes each year was proportional to the number of Vehicle Miles Traveled (VMT) in the United States. We modelled a VMT increase year-over-year of 1.01% based on projections by the Federal Highway Administration (Office of Highway Policy Information and FHWA, 2017). The most recent full VMT data was available for 2015. Given the number of LTAP/OD crashes each year without I-ADAS and the effectiveness each year, the estimated number of crashes each year with I-ADAS was found. We used the same method for computing crashes per year to compute injured occupants per year.

Results

Relative Effectiveness

The proportion of I-ADAS crashes with no vehicles equipped, one vehicle equipped, or two vehicles equipped by fleet penetration is given in Table 8. This table was generated from Equations 8-10.

Table 8. Proportion of crashes where one or both vehicles were equipped with I-ADAS based on fleet penetration.

Fleet Penetration (Eqp)	$P(None)$	$P(Single)$	$P(Both)$	Total
0%	100%	0%	0%	0%
20%	64%	32%	4%	36%
40%	36%	48%	16%	64%
60%	16%	48%	36%	84%
80%	4%	32%	64%	96%
100%	0%	0%	100%	100%

When I-ADAS systems first enter the fleet, the number of conflicts where both vehicles have I-ADAS will be small. As fleet penetration continues to expand, almost all conflicts will have I-ADAS in both vehicles. The sum of $P(Single)$ and $P(Both)$ is the total number of conflicts impacted by I-ADAS. I-ADAS impact quickly rises with increasing fleet penetration (30% fleet penetration impacts half of all conflicts), but the marginal benefit of increased fleet penetration decreases near full roll-out; the last 20% of fleet penetration only impacts an additional 4 percent of conflicts.

I-ADAS system effectiveness values are given in Table 9. I-ADAS effectiveness at different fleet penetration values is given in Figure 12. Effectiveness increased quickly at low fleet penetrations and more slowly at high fleet penetrations. The intersection AEB system in Sander and Lubbe (2018) showed the marginal effectiveness in reducing MAIS2+F injured occupants was highest at low fleet penetrations, which was the same trend shown in this study.

Table 9. System effectiveness of I-ADAS in preventing crashes and injuries in LTAP/OD crashes for the model I-ADAS design using a TTC threshold of 3.0s, no system latency, and the best-case sightline assumption.

	Proportion of Crashes Avoided	Proportion of MAIS2+F Injured Front Row Occupants Avoided
Single Vehicle Equipped	71%	85%
Both Vehicles Equipped	83%	94%

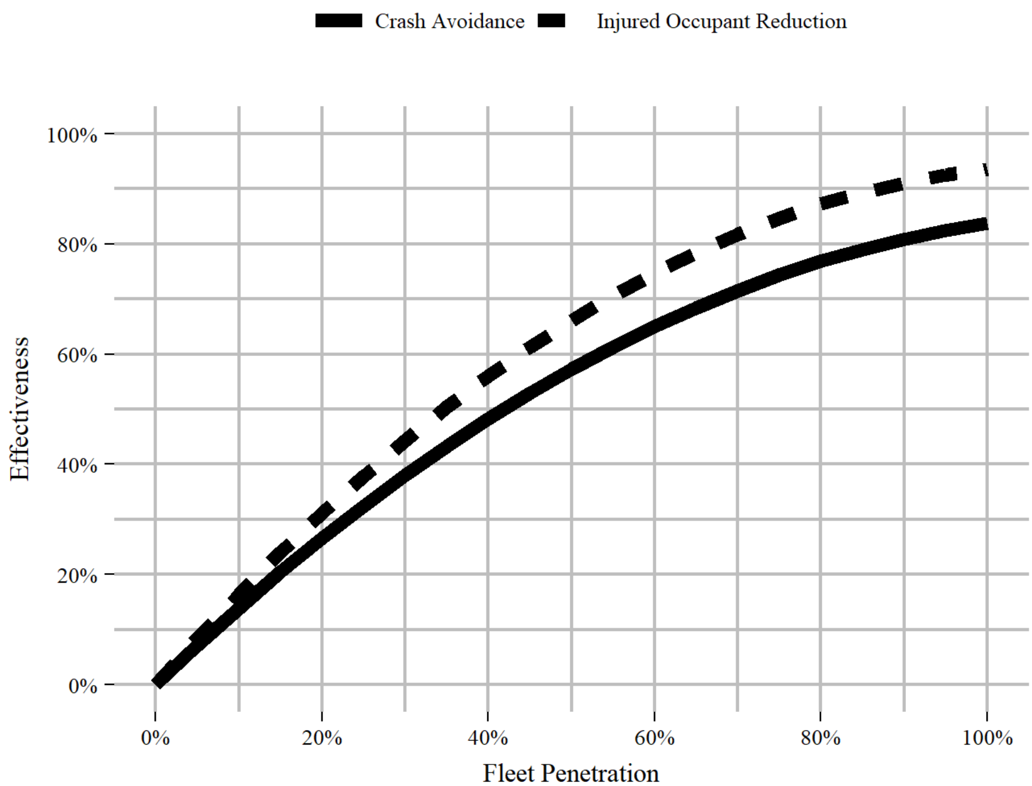

Figure 12. Crash and injury reduction effectiveness for I-ADAS systems with varying fleet penetration. The solid line is the result of Equation 11 and the dashed line is the result of Equation 12.

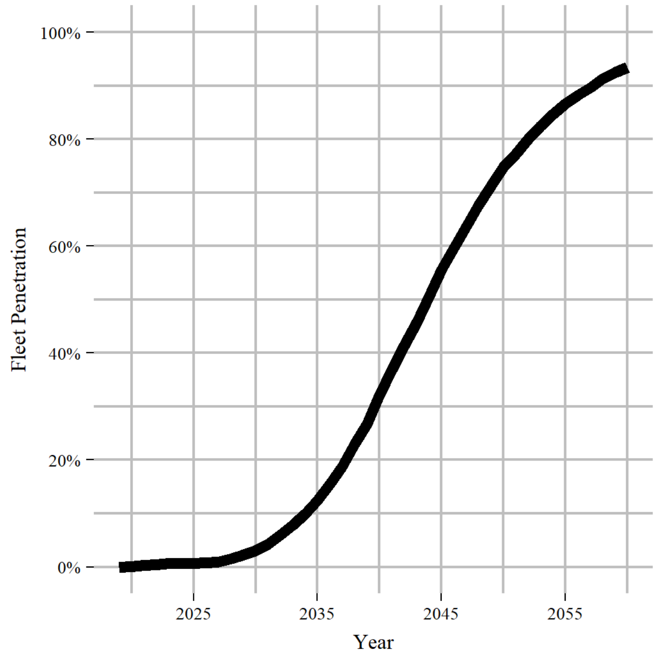

Figure 13. Estimated fleet penetration of LTAP/OD I-ADAS from 2015 to 2060 from the Highway Loss Data Institute.

The HLDI fleet penetration model as a function of time is shown in Figure 13. Crash avoidance effectiveness as a function of time is shown in Figure 14. Injured occupant reduction effectiveness as a function of time is shown in Figure 15. Crash and injury reduction was largely predicted to occur from 2035 to 2056. We predicted LTAP/OD crashes and injured persons will stay at pre-I-ADAS levels roughly until 2035. After roughly 2056, the marginal benefit largely plateaus.

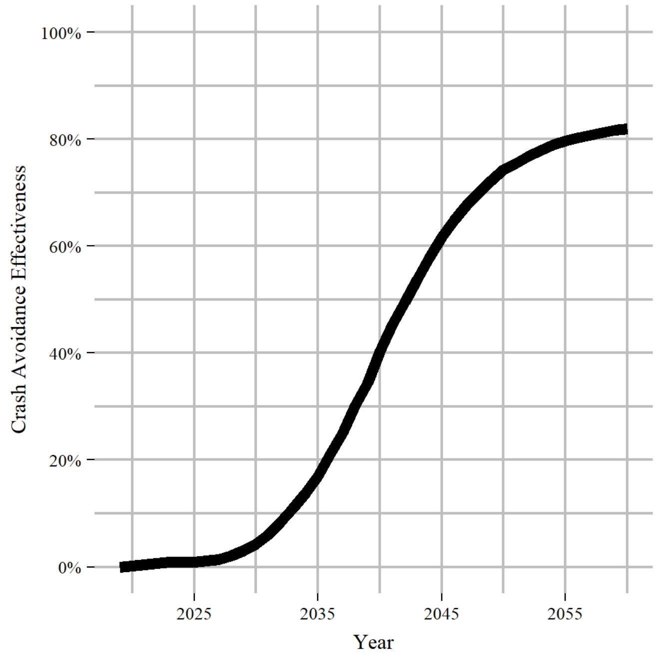

Figure 14. LTAP/OD crash avoidance effectiveness due to I-ADAS as a function of time. This is the result of Equation 14.

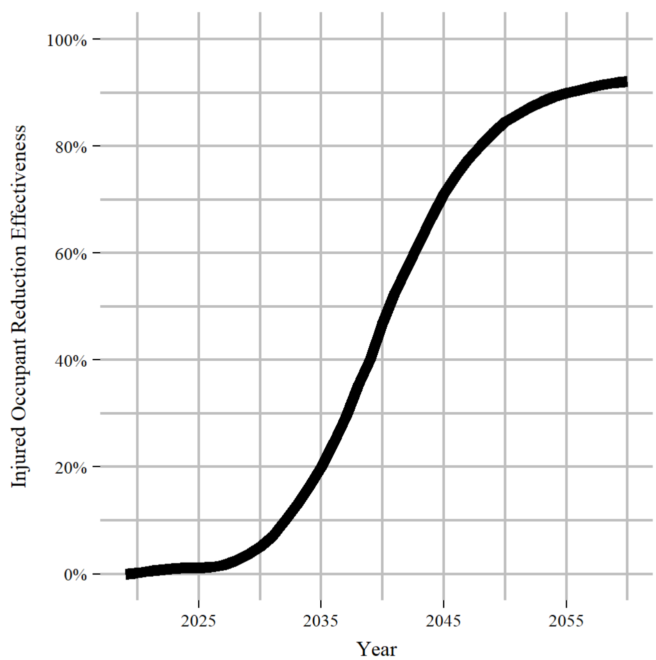

Figure 15. LTAP/OD MAIS2+F injured person reduction effectiveness due to I-ADAS as a function of time. This is the result of Equation 15.

Absolute Effectiveness

The target population was computed from NASS/CDS case years 2010-2015 and contained 156,528 crashes per year. A total of 24 cases were excluded because the sampling weight was greater than 5,000. These cases had a combined case weight of 30,735 crashes per year. During the year 2015, U.S. vehicles traveled 3.095 trillion miles (FHWA, 2016). The crash rate was therefore:

$$CR_{Target} = \frac{Crash_{Target}}{VMT_{2015}} = 0.0506\, per\ Million\ VMT \tag{16}$$

Given the crash rate and number of VMT per year, the number of crashes per year without I-ADAS is given in Figure 16.

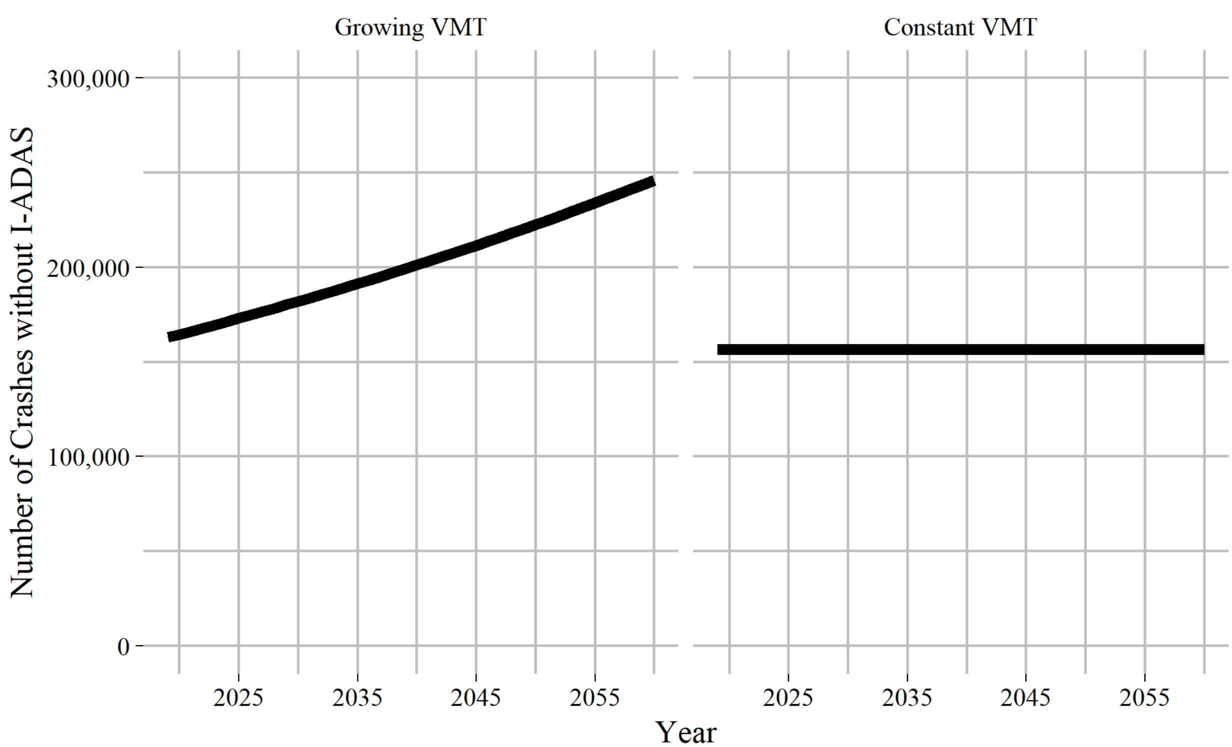

Figure 16. Estimated number of target population LTAP/OD crashes each year.

The predicted number of target population LTAP/OD crashes from 2019 to 2060 is given in Figure 17. I-ADAS crashes were predicted to remain at pre-I-ADAS levels until approximately 2035. After this point, the crash rate was expected to drop dramatically to a minimum of 70,439 LTAP/OD crashes per year in 2060 under the growing VMT assumption.

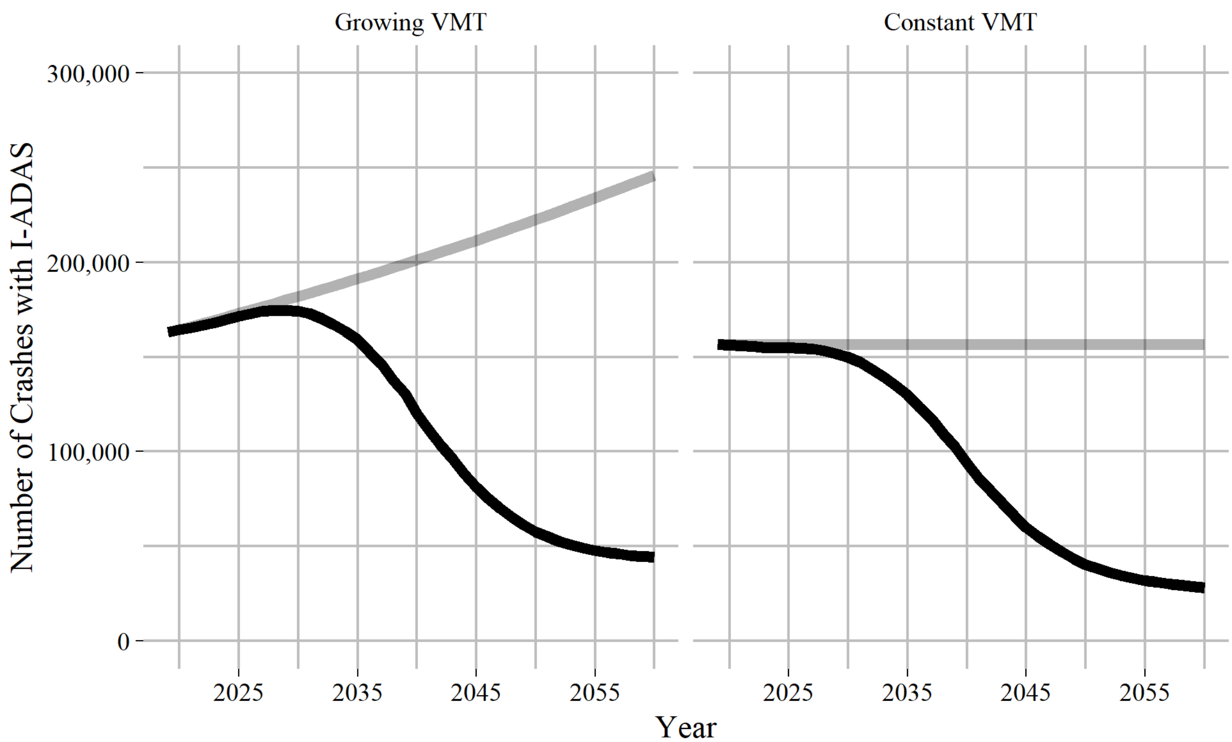

Figure 17. Predicted number of target population LTAP/OD crashes each year where I-ADAS was present in the fleet. The estimated number of crashes each year without I-ADAS is shown for reference.

There were an estimated 14,425 MAIS2+F injured front row occupants age 12 and older exposed to LTAP/OD crashes in the target population per year. The injury rate per VMT is as follows:

$$IR_{Target} = \frac{Injury_{Target}}{VMT_{2015}} = 0.00466 \ per\ Million\ VMT \tag{17}$$

The predicted number of injured occupants without I-ADAS is given in Figure 18. After applying the predicted I-ADAS fleet penetration, the predicted number of injured occupants with I-ADAS is given in Figure 19. I-ADAS effectiveness in injury reduction was greater than in crash avoidance, so the reduction in injured persons takes approximately the same shape as the reduction in crashes but the reduction was larger. The number of MAIS2+F injured persons per year in 2060 was estimated to be 3,836 under the growing VMT assumption.

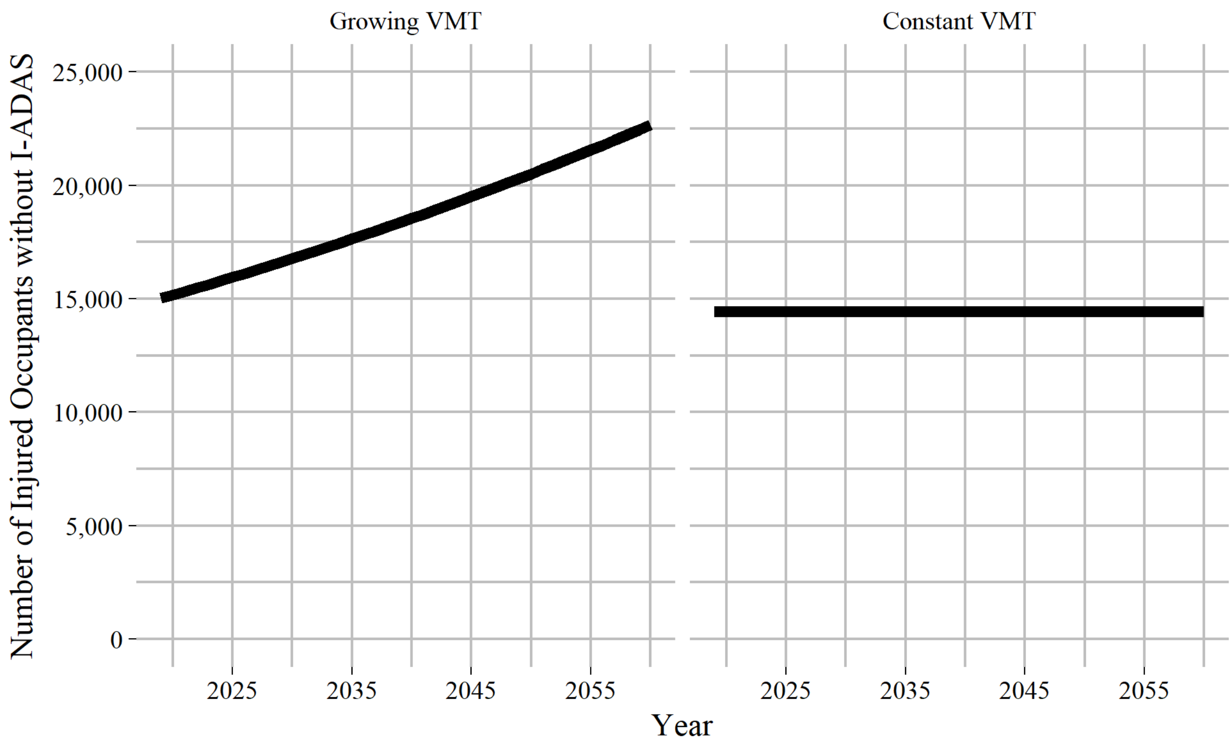

Figure 18. Predicted number of injured occupants in LTAP/OD crashes each year without the impact of I-ADAS.

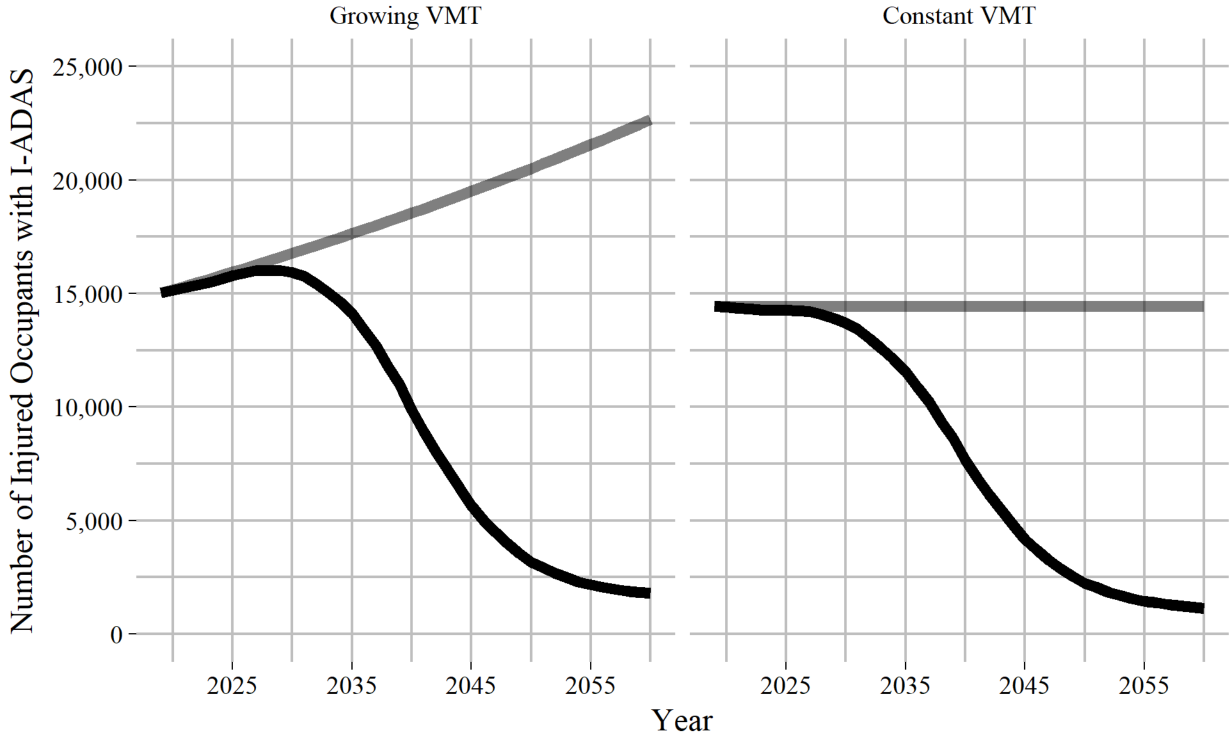

Figure 19. Predicted number of injured occupants in LTAP/OD crashes each year including the effect of I-ADAS. The estimated number of injured occupants without I-ADAS is shown for reference.

In order to validate the model, the predicted remaining crashes per year in the constant VMT model in the year 2067 was compared to the limiting case where 100% of vehicles have I-ADAS. The shifted HLDI fleet penetration curve ends in 2067. These two predictions should be similar, as fleet penetration at the end of the HLDI fleet penetration curve should be near 100%. The fleet penetration model predicted a fleet penetration of I-ADAS of 98.0% in 2067. The predicted number of remaining crashes per year at 100% deployment with the constant VMT model was 25,498. The predicted number of remaining crashes per year in 2067 with the constant VMT model was 26,282, overpredicting by 1.5%. This is because the end of the HLDI curve assumed some vehicles will never have I-ADAS. These vehicles could be historical and specialty vehicles which may never be removed from the fleet.

Limitations

A number of assumptions were made to develop this model. First, we assumed a fleet penetration model. Predicting fleet penetration for systems which presently have almost no fleet penetration and are not mandated is inexact.

Additionally, we assumed a specific I-ADAS system design. Vehicle manufacturer active safety system designs are highly proprietary and vary in function. We considered the best possible I-ADAS system design without taking into consideration implementation difficulty, reliability requirements, or cost limitations.

Next, we assumed that LTAP/OD crashes from the NMVCCS timeframe would be similar to LTAP/OD crashes in 2019-2060. If some fundamental character of these crashes changed, the I-ADAS effectiveness based on NMVCCS crashes would not be valid in 2019-2060. One defining metric of LTAP/OD crashes is delta-v. We examined LTAP/OD crash delta-v distributions from 1997 to 2012 in the National Automotive Sampling System / Crashworthiness Data System (NASS/CDS). NASS/CDS represents a similar crash population to NMVCCS (police reported towaway crashes). We hypothesize that if delta-v did not change during this time period in NASS/CDS, than LTAP/OD crashes are reasonably similar over time. The distribution of delta-v values in LTAP/OD crashes in NASS/CDS is shown in Figure 20. Delta-V values were qualitatively similar over the 15-year timespan.

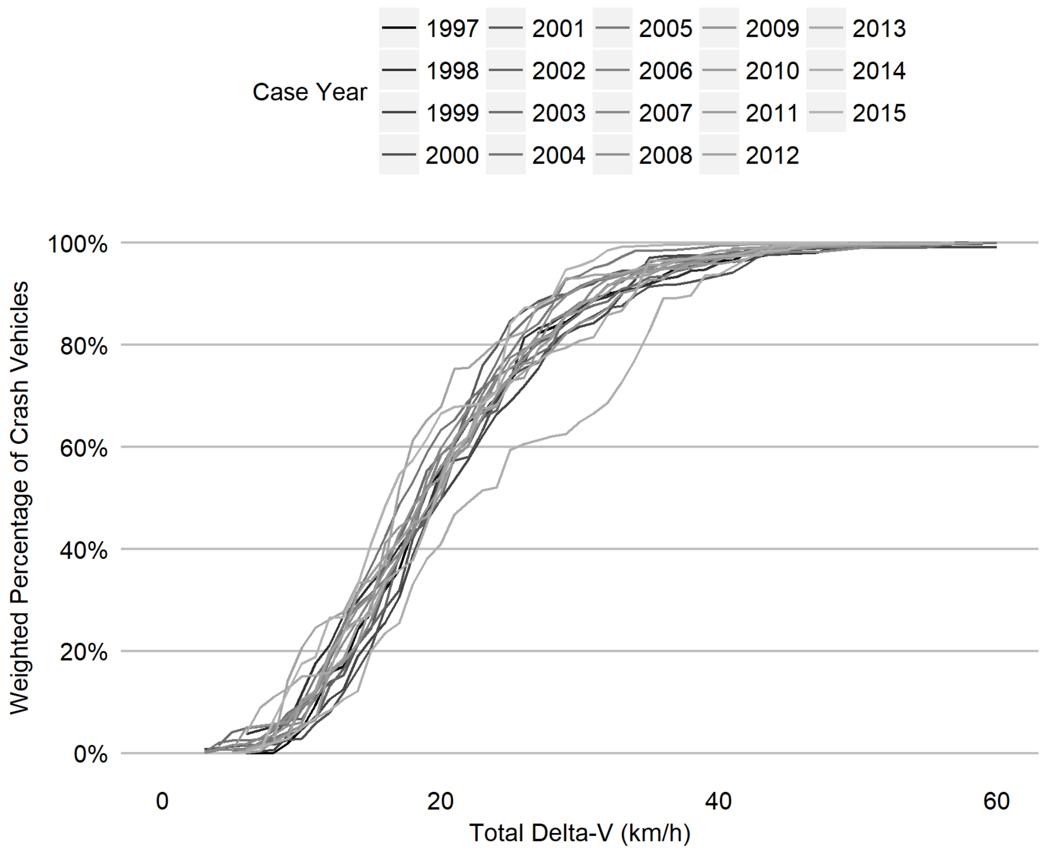

Figure 20. Distribution of delta-v values in NASS/CDS LTAP/OD crashes.

Figure 21. Average LTAP/OD crash delta-v value each year in NASS/CDS from 1997 to 2015.

The average value per year is shown in Figure 21. A linear model fit to the data shows a small decrease per year. Delta-V in NASS/CDS is discretized in 1 km/h steps. For the average Delta-V value to change one step from 2015 to 2025, a delta-v trend greater than 0.1 km/h per year would be required. Assuming the error in the delta-v trend is normally distributed, the probability of the delta-v trend being greater than 0.1 km/h per year or less than -0.1 km/h per year is $2.3 * 10^{-5}$. Finally, we assumed that the LTAP/OD crash rate is proportional to the number of Vehicle Miles Traveled in the United States. Additional factors, such as the aging of the U.S. population, may cause the crash rate to change independently of the number of Vehicle Miles

Traveled. In addition, increased VMT might increase congestion, and roads with increased VMT may be upgraded to different intersection types, changing the distribution of intersection types assumed by the effectiveness model. The crash rate per vehicle mile traveled in NASS/CDS is shown in Figure 22.

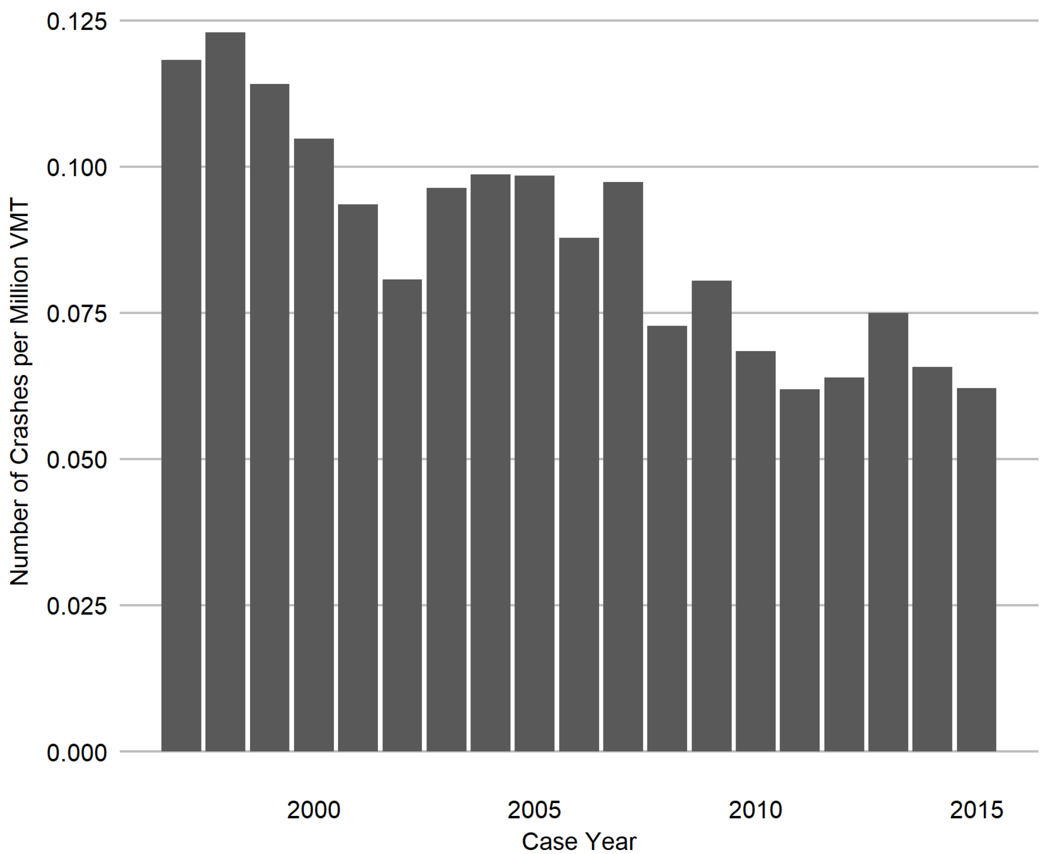

Figure 22. LTAP/OD Crashes per VMT in NASS/CDS. This value cannot be directly compared with the value in Equation 16 because NMVCCS and NASS/CDS have difference selection criteria and represent a different crash popuation.

The absolute number of crashes per VMT is different in this figure than the CR_{NMVCCS} value computed earlier because NASS/CDS represents a different crash population than

NMVCCS. This shows that the number of LTAP/OD crashes per VMT is decreasing year-over-year in NASS/CDS, and that our assumption that it is constant may be invalid.

Additionally, the injury models developed previously were developed from the current, non-automated fleet. Previous work has shown that occupants may be thrown out of position before a crash due to the effect of hard, potentially unexpected automated braking (Eungseo et al., 2017). This effect cannot be quantified using the epidemiological methods included in this thesis until several years of AEB crash data are present in national databases such as CRSS.

This work also assumes a human fleet: we assumed that each vehicle was driven by a human driver and had front row occupants typical of human driving. While a future fleet may have automated vehicles, no prediction was made of the proportion of automated vehicles in the fleet or their propensity to cause LTAP/OD crashes and associated injuries.

Finally, the method which estimated the relative effectiveness of I-ADAS (Chapter 4) assumed both vehicles in each crash had side airbags and excellent passive safety, measured by a five star U.S. NCAP rating. Not all vehicles in 2015 had side airbags and excellent passive safety. While I-ADAS penetrates the fleet, the proportion of vehicles with side airbags and excellent passive safety will increase until nearly all vehicles have these features. During the fleet penetration of these passive safety systems, the method in this chapter will underestimate the number of residual injuries because we did not include the additional injuries sustained by occupants due to the absence of these systems. Residual injuries will not be underestimated in the very near future because passive safety system fleet penetration will be similar to the present. Residual injuries will also not be underestimated in the far future, when all vehicles have side airbags and excellent passive safety.

Conclusion

The objective of this chapter was to estimate the number of LTAP/OD crashes each year from 2019 to 2060 as intersection active safety systems (I-ADAS) are introduced into the United States fleet. We assumed that the number of LTAP/OD crashes each year without I-ADAS was proportional to the number of vehicle miles traveled in the United States, which is predicted to increase each year. Based on prior work estimating I-ADAS effectiveness in crashes with 100% fleet penetration, we computed the I-ADAS effectiveness in fleets with less than 100% fleet penetration. Then, using HLDI models for fleet penetration over time, we computed the number of crashes each year based on I-ADAS effectiveness and fleet penetration. We followed a similar procedure for MAIS2+F injured front row occupants. By 2035, we predicted the number of target population LTAP/OD crashes to reach pre-I-ADAS levels. After this point, we predicted the crash rate would continue to decrease. In 2060, the predicted number of LTAP/OD crashes per year with I-ADAS was 70,439. Injury reduction effectiveness was higher than the crash avoidance effectiveness, so the number of MAIS2+F injured occupants per year reached pre-I-ADAS levels in approximately the year 2033. In 2060, the predicted number of MAIS2+F injured persons per year was 3,836. This analysis shows that even in the long-term fleet penetration of Intersection Active Safety Systems, many injuries will continue to occur. This underscores the importance of maintaining passive safety performance in future vehicles.

6. CONCLUSIONS

The objective of this thesis was to evaluate crash and injury reduction in a future United States fleet equipped with intersection advanced driver assistance systems (I-ADAS). This chapter summarizes the findings of the thesis.

Injury Risk Modeling

The objective of this chapter was to estimate the risk of injury to occupants of vehicles in frontal, near-, and far-side impacts. The dataset used to evaluate injury risk was the National Automotive Sampling System / Crashworthiness Data System (NASS/CDS). Case years 2007 to 2015 were used. An injured occupant was defined as vehicle occupant who experienced an injury of maximum Abbreviated Injury Scale (AIS) of 2 or greater, or who were fatally injured. Injury severity was scored using AIS-2005 (2008 update). Cases were selected in which front-row occupants of late-model vehicles were exposed to a frontal, near-, or far-side crash. Logistic regression was used to develop an injury model with occupant, vehicle, and crash parameters as predictor variables. For the frontal and near-side impact models, New Car Assessment Program (NCAP) test results were used as a predictor variable. This work quantitatively described the injury risk for a wide variety of crash modes, informing the effectiveness estimates of the following chapters. The injury models take the form of equations 18-21 and the model coefficients are given in

Table 10.

$$P[MAIS2{+}F] = \frac{1}{1 + e^{-logit}} \tag{18}$$

$$logit_{frontal} = \beta_0 \cdot \Delta v + \beta_2 \cdot isbelt + \beta_3 \cdot ismale + \beta_4 \cdot senior + \beta_5 \cdot P_{Frontal}(AIS3+) + \beta_5 \cdot compat_{CT} + \beta_6 \cdot bmi + \beta_7 \cdot target_{rear} \quad (19)$$

$$logit_{near} = \beta_0 + \beta_1 \cdot \Delta v + \beta_2 \cdot ismale + \beta_3 \cdot senior + \beta_4 \cdot P_{MDB}(AIS3+) + \beta_5 \cdot bmi + \beta_6 \cdot driver \quad (20)$$

$$logit_{far} = \beta_0 + \beta_1 \cdot \Delta v + \beta_2 \cdot isbelt \quad (21)$$

Table 10. Predictor variables for equations 18-21.

Predictor Variable	**Parameter**	**Coefficient**	**Lower Bound**	**Upper Bound**	**P-Value**
		Frontal Model			
—	β_0, Intercept	-6.516	-8.206	-4.825	<0.001**
Delta-V	β_1, Delta-V (kph)	0.090	0.053	0.128	<0.001**
Belt Use	β_2, Belted	-0.769	-1.545	0.008	0.054
Gender	β_3, Gender = male	-0.891	-1.544	-0.238	0.008**
Age	β_4, Age ≥ 65	1.070	0.106	2.034	0.031**
Crash Compatibility	β_5, Car struck LTV	1.222	0.500	1.943	0.001**
Body Mass Index	β_6, BMI (kg/m^2)	0.084	0.042	0.125	<0.001**
Struck Vehicle Impact Location	β_7, Struck rear	-1.455	-2.437	-0.472	0.004**
		Near-Side Model			
—	β_0, Intercept	-20.726	-33.017	-8.436	0.002**
Delta-V	β_1, Delta-V (kph)	0.194	0.072	0.315	0.003**
Gender	β_2, Gender = male	-3.550	-5.742	-1.358	0.002**
Age	β_3, Age ≥ 65	2.693	0.961	4.424	0.004**
NCAP Risk	β_4, $P_{MDB}(AIS3+)$	12.578	4.801	20.355	0.002**
Body Mass Index	β_5, BMI (kg/m^2)	0.083	0.010	0.156	0.030**

Seating Position	β_6, Driver Seat	0.765	0.011	1.519	0.052
Far-Side Model					
—	β_0, Intercept	-4.332	-5.868	-2.796	<0.001**
Delta-V	β_1, Delta-V (kph)	0.124	0.052	0.196	0.001**
Belt Use	β_2, Belted	-2.573	-4.665	-0.480	0.018**

Crash and Injury Prevention Estimates for Intersection Driver Assistance Systems in Left Turn Across Path / Opposite Direction Crashes in the United States

The objective of this chapter was to estimate the number of LTAP/OD crashes and injuries that could be prevented in the United States if vehicles were equipped with an I-ADAS. This study reconstructed 501 vehicle-to-vehicle LTAP/OD crashes in the United States which were investigated in NMVCCS. The performance of thirty different I-ADAS system variations was evaluated for each crash. These variations were the combinations of five TTC activation thresholds, three latency times, and two different response types (automated braking and driver warning). In addition, two sightline assumptions were modeled for each crash: one where the turning vehicle was visible long before the intersection, and one where the turning vehicle was only visible within the intersection. For resimulated crashes which were not avoided by I-ADAS, a new crash delta-v was computed for each vehicle. The probability of MAIS2+F injury to each front row occupant was computed.

Depending on the system design, sightline assumption, I-ADAS variation, and fleet penetration, an I-ADAS system that automatically applies emergency braking could avoid 18%-84% of all LTAP/OD crashes. Only 0%-32% of all LTAP/OD crashes could have been avoided using an I-ADAS system which only warns the driver. An I-ADAS system which applies emergency braking could prevent 44%-94% of front row occupants from receiving MAIS2+F injuries. A system that warns the driver in LTAP/OD crashes was able to prevent 0%-36% of front row occupants from receiving MAIS2+F injuries. I-ADAS crash and injured person reduction effectiveness was higher when both vehicles were equipped with I-ADAS. This study presented the simulated effectiveness of a hypothetical intersection active safety system on real crashes which occurred in the United States, showing strong potential for these systems to reduce crashes and injuries.

The Long-Term Evolution of Left Turn Across Path / Opposite Direction Crashes in the United States: The Potential of Intersection Active Safety Systems

The potential safety benefit of I-ADAS was examined in the previous chapter based on real-world cases drawn from NMVCCS. However, that chapter made the idealized assumption of full installation in all vehicles of a future fleet. The objective of this work was to predict the reduction in LTAP/OD crashes due to I-ADAS systems in the United States over time. The proportion of new vehicles with I-ADAS was modeled using Highway Loss Data Institute (HLDI) fleet penetration predictions. The number of potential LTAP/OD conflicts was modeled as increasing year over year due to a predicted increase in Vehicle Miles Traveled (VMT) each year. Finally, the combined effect of these changes was used to predict the number of LTAP/OD crashes each year from 2019 to 2060. In 2060, we predicted 70,439 NMVCCS-type LTAP/OD crashes would occur. The predicted number of MAIS2+F injured front row occupants in 2060 was 3,836. This analysis shows that even in the long-term fleet penetration of Intersection Active Safety Systems, many injuries will continue to occur. This underscores the importance of maintaining passive safety performance in future vehicles.

PUBLICATION SUMMARY

The following studies were published, presented, or in review as a part of my MS program:

Bareiss, M., David, M., Gabler, H.C., 2018. Preliminary Estimates of Near Side Crash Injury Risk in Best Performing Passenger Vehicles. Presented at the SAE World Congress, SAE International. doi:https://doi.org/10.4271/2018-01-0548

Bareiss, M., Gabler, H., Sherony, R., 2019a. Long-Term Evolution of Straight Crossing Path Crash Occurrence in the U.S. Fleet: The Potential of Intersection Active Safety Systems. Presented at the WCX SAE World Congress Experience. doi:10.4271/2019-01-1023

Bareiss, M., Gabler, H.C., 2019a. Injury Risk Prediction in Far-Side Impacts. Presented at the VT/WFU SBES Symposium, Blacksburg, VA.

Bareiss, M., Gabler, H.C., 2019b. Optimizing Pre-Crash Steering Systems with Reinforcement Learning, in: Proceedings of the 5th International Symposium on Future Active Safety Technology toward Zero Accidents (FAST-Zero '19). Presented at the FAST-zero 2019, Blacksburg, VA.

Bareiss, M., Gabler, H.C., 2018a. Preliminary Characteristics of a Potential Test Procedure for Intersection Active Safety Systems in the United States. Presented at the VT/WFU SBES Symposium, Winston-Salem, NC.

Bareiss, M., Gabler, H.C., 2018b. Preliminary Estimates of Frontal Crash Injury Risk in Best Performing Passenger Vehicles. Presented at the The Ohio State University's Injury Biomechanics Symposium, Columbus, OH.

Bareiss, M., Gabler, H.C., 2018c. Automatic Extraction of Driver Behavior in Car Following from SHRP 2 Video: A Preliminary Analysis of SHRP 2 NDS Training Data, in: Naturalistic Driving

Research Symposium. Presented at the Naturalistic Driving Research Symposium, Blacksburg, VA.

Bareiss, M., Gabler, H.C., 2018d. Potential Test Characteristics for Intersection Active Safety Systems in the United States. Presented at the AAAM 2018, Nashville, TN.

Bareiss, M., Gabler, H.C., 2018e. Estimates of Frontal Crash Injury Risk in Best Performing Passenger Vehicles, in: 2018 World Congress of Biomechanics. Presented at the World Congress of Biomechanics, Dublin, Ireland.

Bareiss, M., Scanlon, J., Sherony, R., Gabler, H.C., 2019b. Crash and injury prevention estimates for intersection driver assistance systems in left turn across path/opposite direction crashes in the United States. Traffic Injury Prevention 20 sup1 , S133–S138. doi:10.1080/15389588.2019.1610945

Bareiss, M., Gabler, H.C., 2019. Estimating Near Side Crash Injury Risk in Best Performing Passenger Vehicles in the United States. Accident Analysis and Prevention (in review).

APPENDIX – RESULTS FOR AN ALTERNATE SENSOR CONFIGURATION

I-ADAS benefits were also computed for a sensor with a 46 degree field of view. Crash avoidance and injury reduction effectiveness are given below.

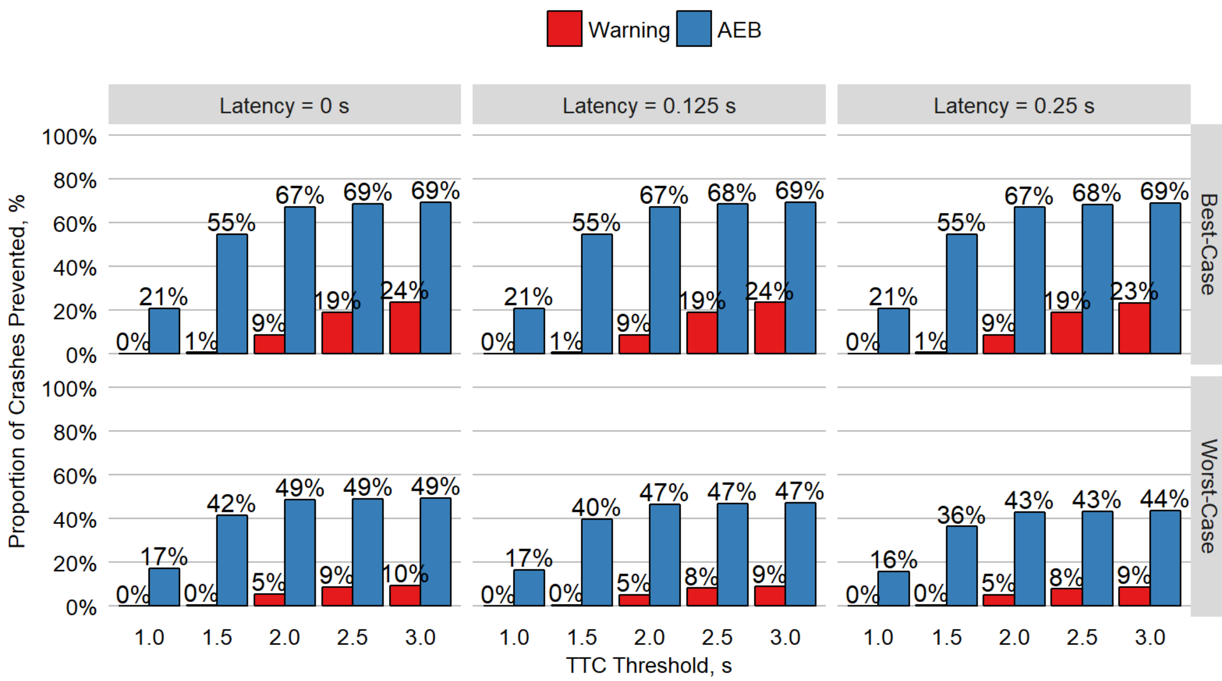

Figure 23. All crash prevention results for the potential benefits of I-ADAS in LTAP/OD crash scenarios with an alternate sensor configuration. These results are for a scenario where only one of the vehicles was equipped. Each bar represents a unique system - sightline assumption.

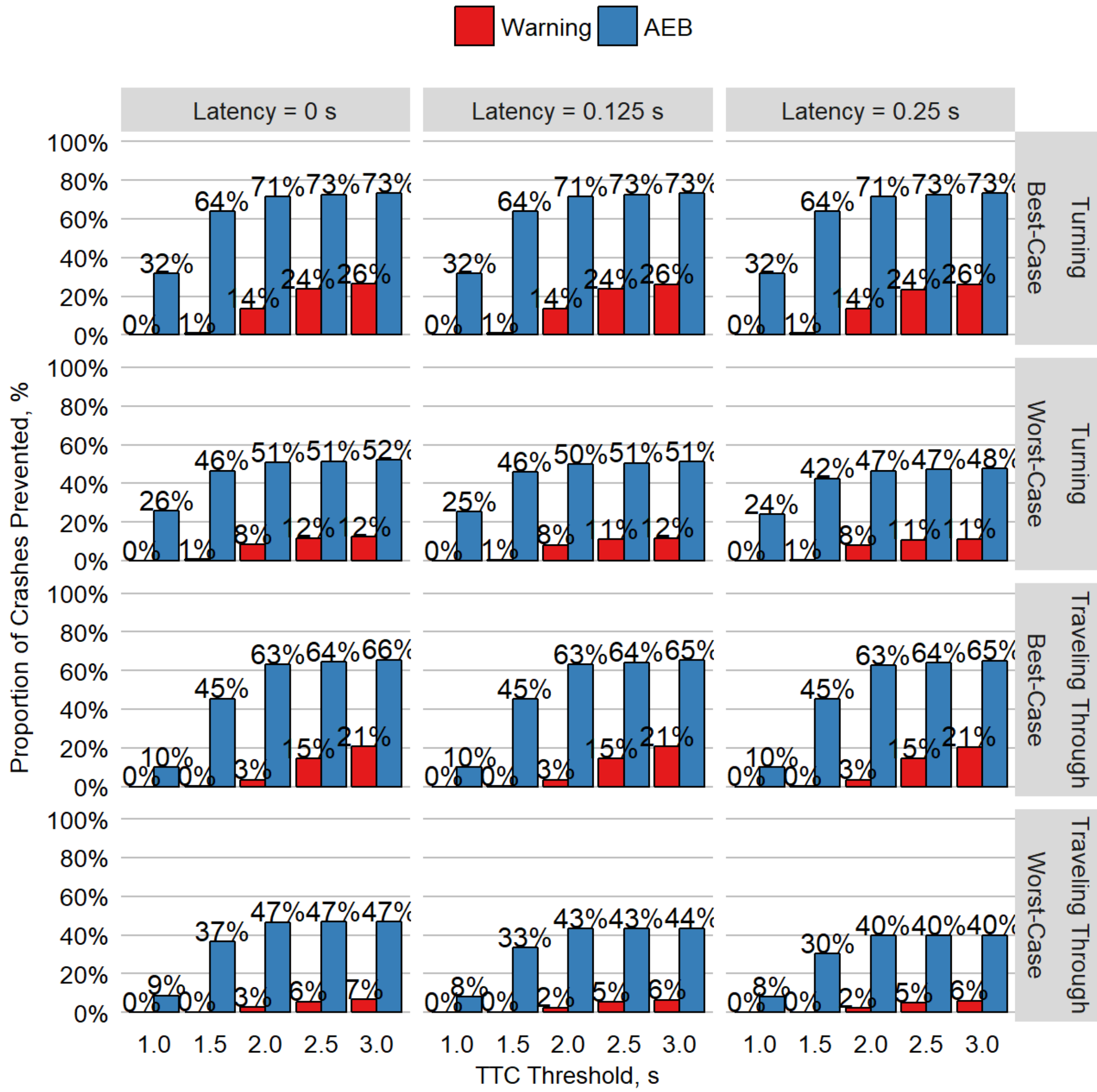

Figure 24. All crash prevention results for the potential benefits of I-ADAS in LTAP/OD crash configurations with an alternate sensor configuration. These results are only for the scenario where one vehicle was equipped. The vehicle equipped with I-ADAS is shown on the right as either the turning vehicle or the traveling through vehicle. Each bar represents a unique system-sightline-equip status assumption.

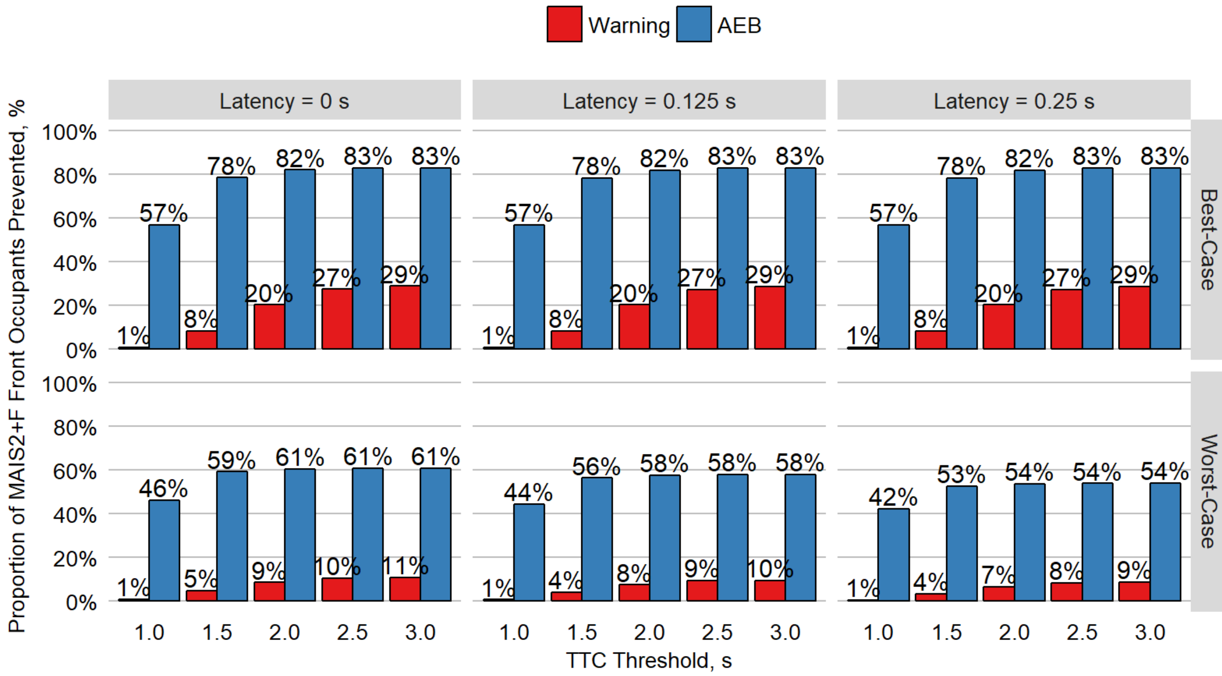

Figure 25. All MAIS2+F occupant results for the potential benefits of I-ADAS in LTAP/OD crash scenarios in an alternate sensor configuration. These results are for a scenario where only one of the vehicles was equipped. Each bar represents a unique system - sightline assumption.

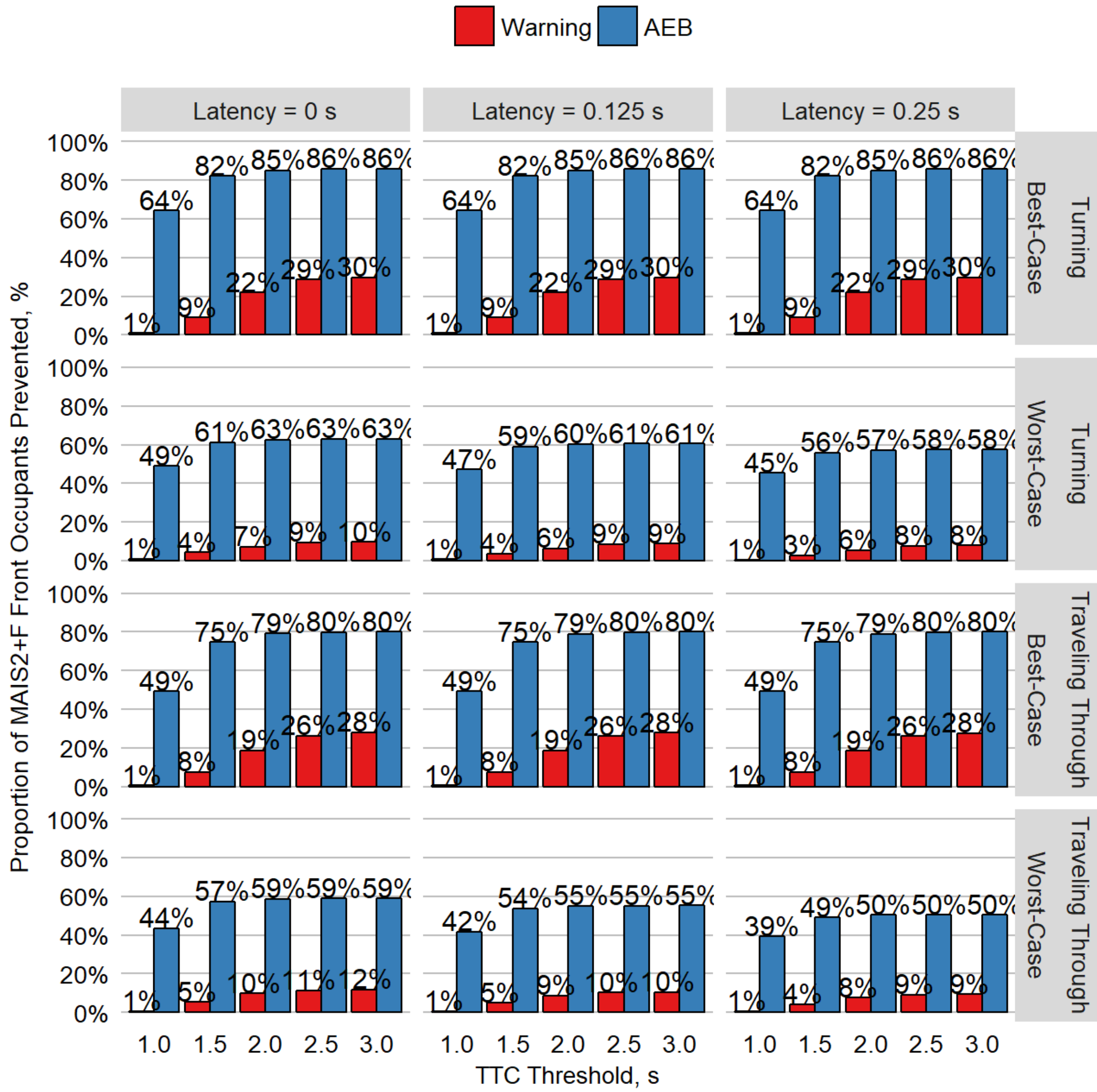

Figure 26. All MAIS2+F prevention results for the potential benefits of I-ADAS in LTAP/OD crash configurations with an alternate sensor configuration. These results are only for the scenario where one vehicle was equipped. The vehicle equipped with I-ADAS is shown on the right as either the turning vehicle or the traveling through vehicle. Each bar represents a unique system-sightline-equip status assumption.

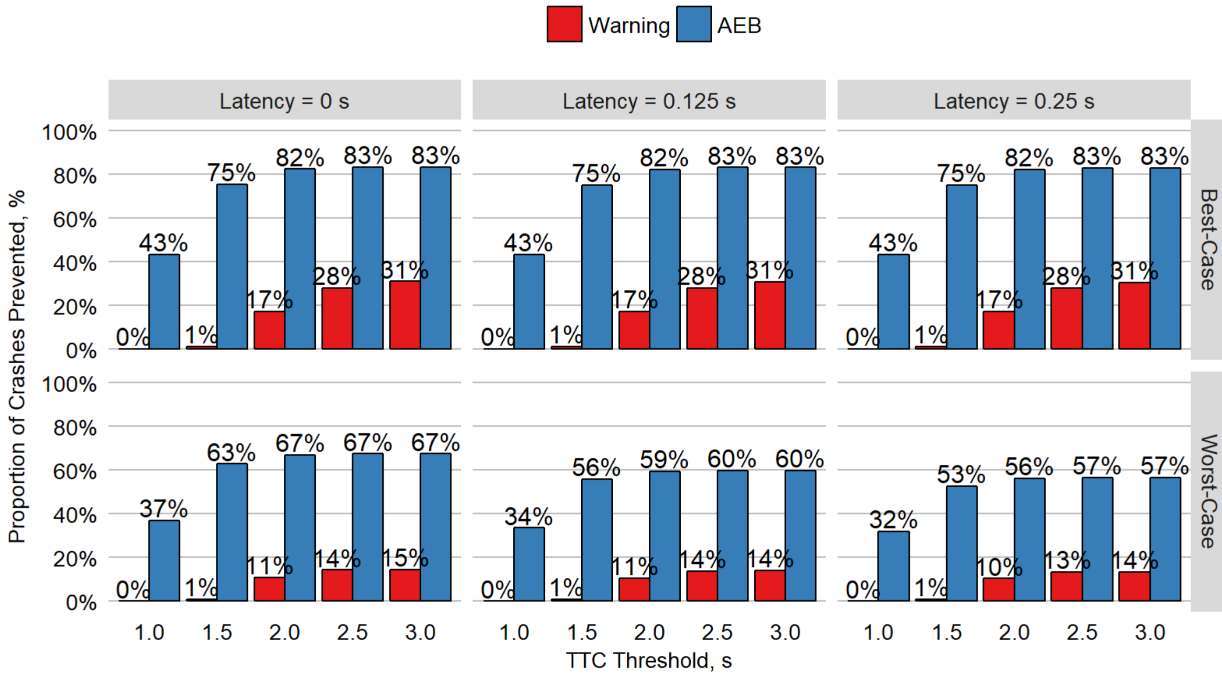

Figure 27. All results for the potential crash prevention benefits of I-ADAS in LTAP/OD crash scenarios with an alternate sensor configuration if both vehicles were equipped. Each bar represents a unique system - sightline assumption.

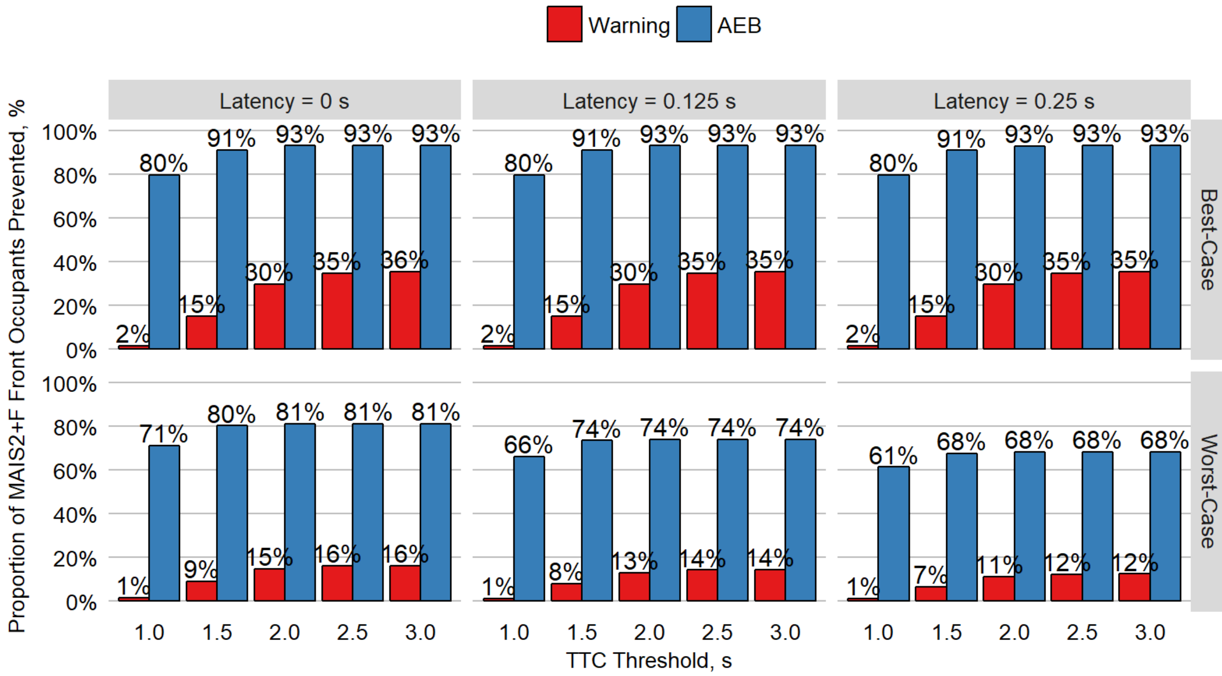

Figure 28. All MAIS2+F occupant results for the potential benefits of I-ADAS in LTAP/OD crash scenarios with an alternate sensor configuration if both vehicles were equipped. Each bar represents a unique system - sightline assumption.

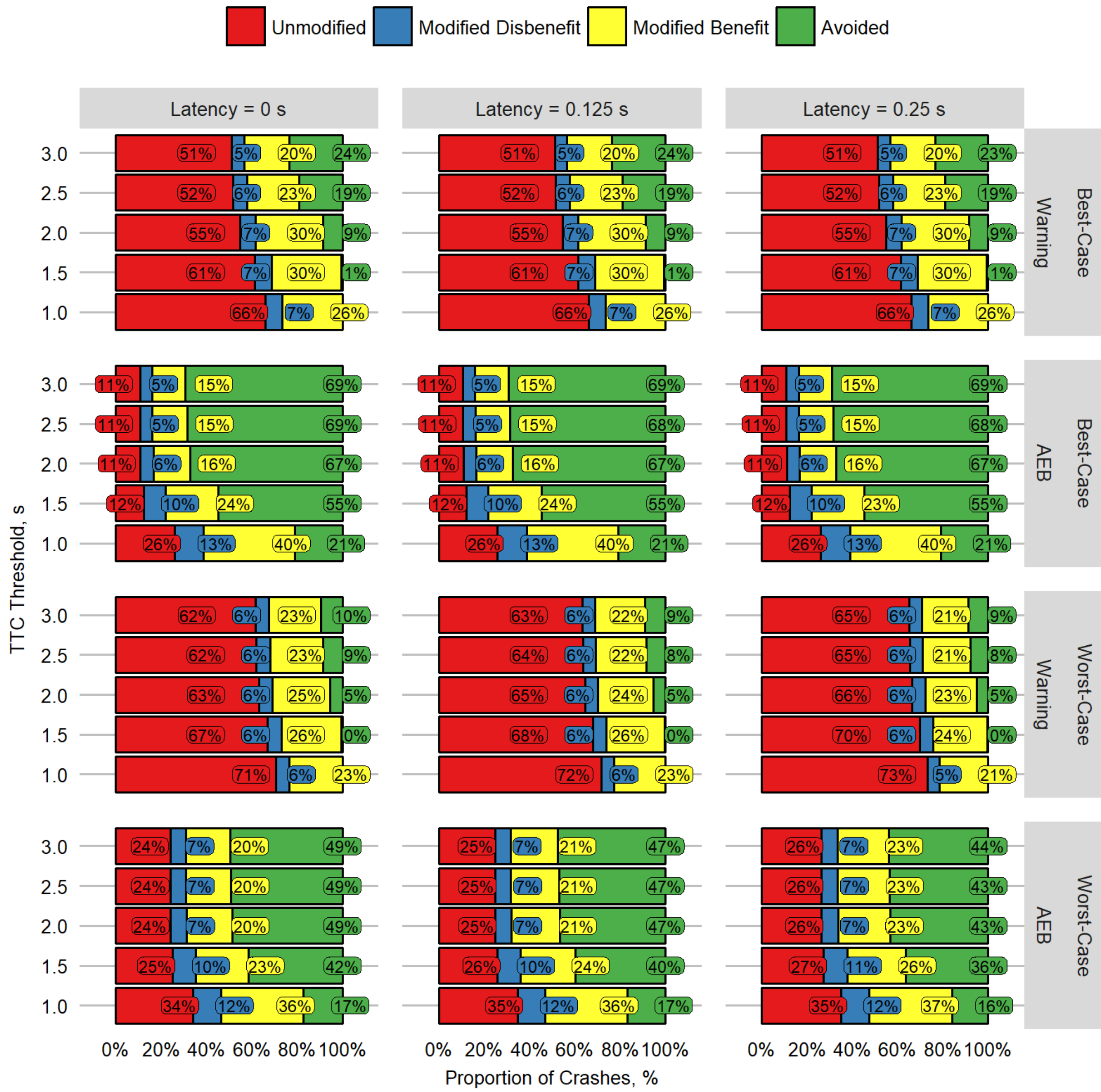

Figure 29. I-ADAS crash outcomes in LTAP/OD crash scenarios with an alternate sensor configuration where one vehicle was equipped with I-ADAS. Each bar represents a unique latency-system-sightline-threshold combination.

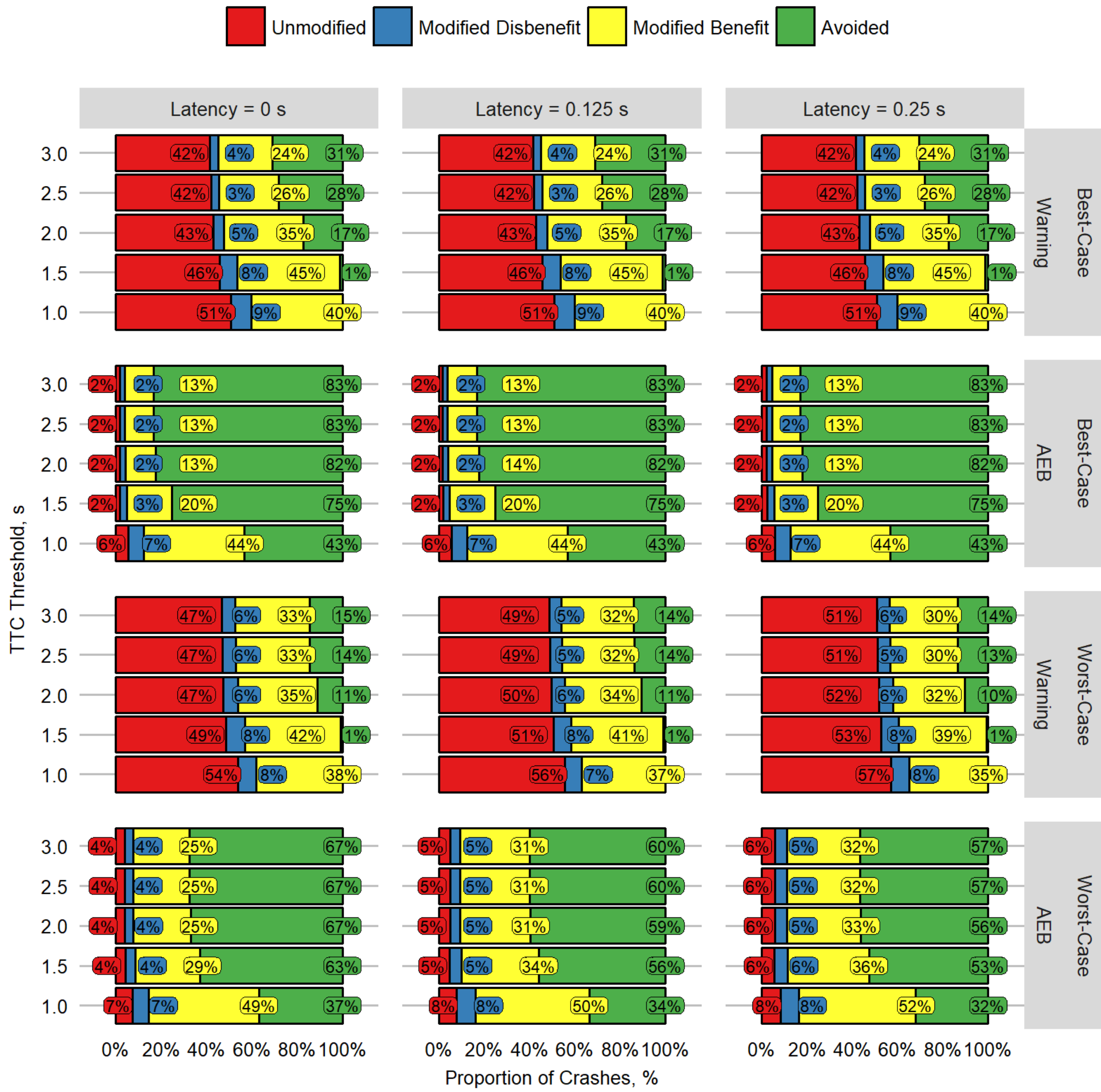

Figure 30. I-ADAS crash outcomes in LTAP/OD crash scenarios with an alternate sensor configuration where both vehicles were equipped with I-ADAS. Each bar represents a unique latency-system-sightline-threshold combination.

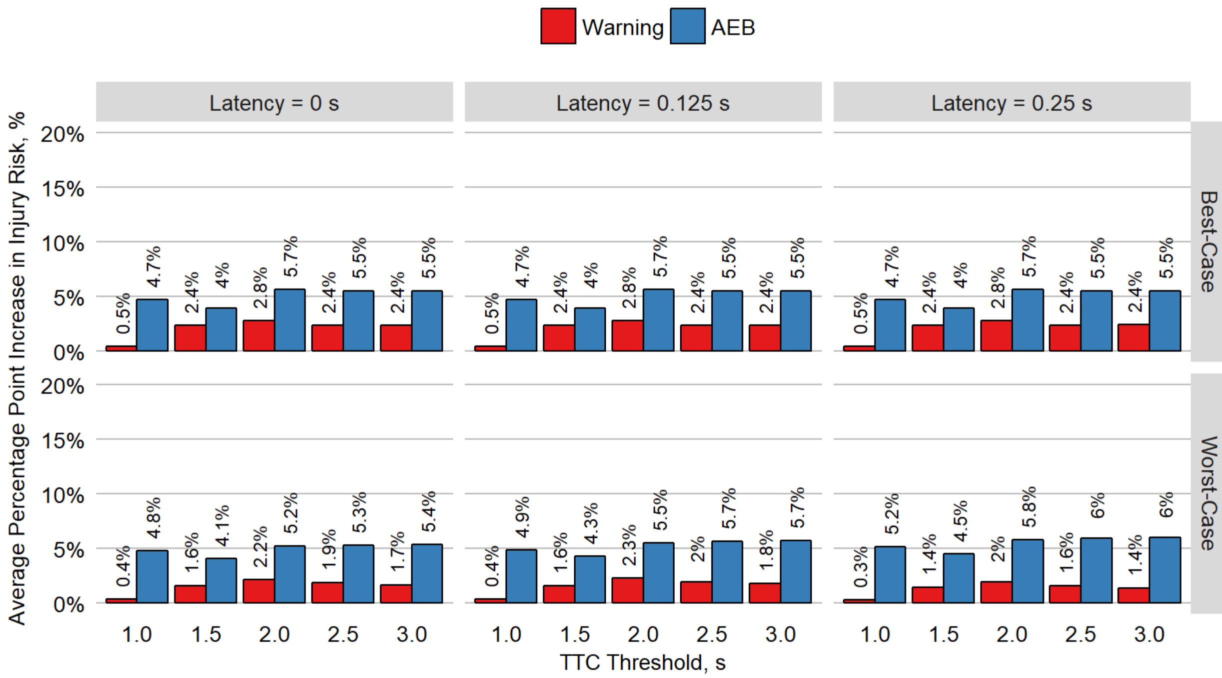

Figure 31. Average absolute percentage point increase in injury risk for disbenefits cases in LTAP/OD crash scenarios with an alternate sensor configuration where one vehicle was equipped with I-ADAS. Each bar represents a unique latency-system-threshold combination.

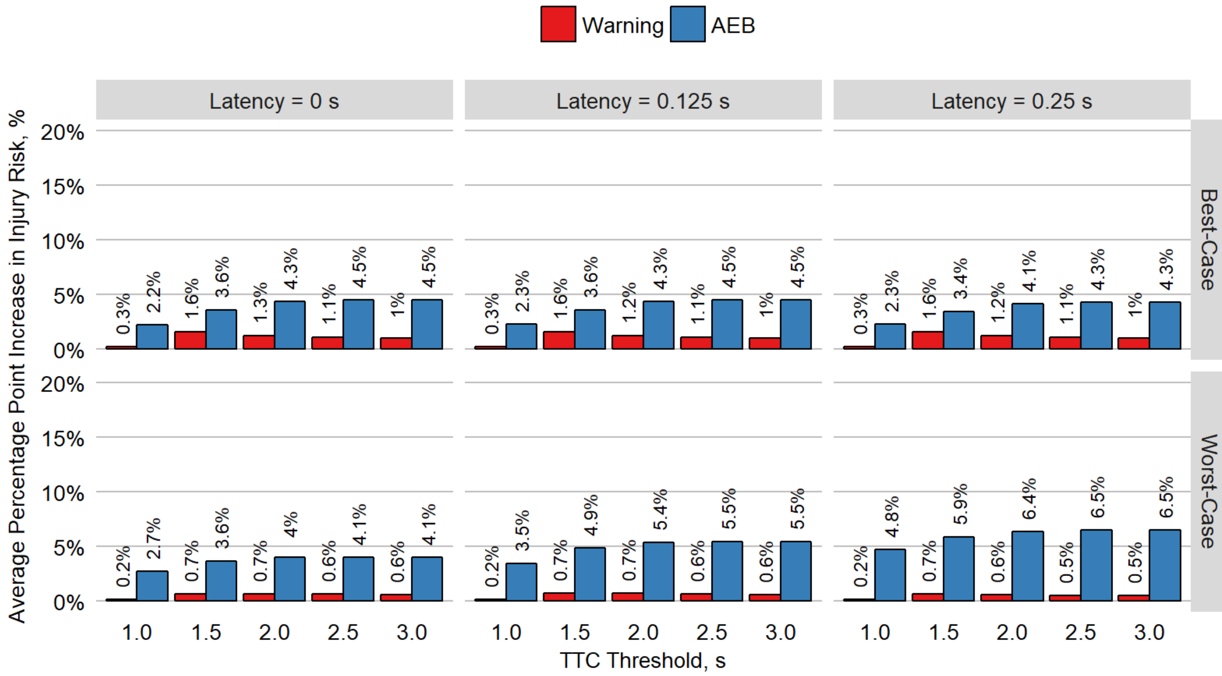

Figure 32. Average absolute percentage point increase in injury risk for disbenefits cases in LTAP/OD crash scenarios with an alternate sensor configuration where both vehicles were equipped with I-ADAS. Each bar represents a unique latency-system-threshold combination.

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