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Crash Avoidance Systems-Safety Evaluation of an Important Class of Electronic Control Systems

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16. Abstract

Crash avoidance systems are intended to help drivers avoid or mitigate the severity of crashes by providing warnings or active control interventions. This research program was conducted to provide new knowledge, models, and tools to enable improved designs of automotive crash avoidance systems and more effective deployment strategies. To undertake a comprehensive approach to analyzing these systems, this project considered other effects that influence crash types and mechanisms, including the use of other technologies, driver behavior differences, new public policies, driver demographics, or other influences.

As the first of several analyses, the team estimates the effectiveness and safety benefits of forward crash avoidance and mitigation technologies (FCAM), as well as lateral assist technologies. Crash data analyses were used to understanding causal mechanisms, particularly lateral crashes. Monte Carlo simulations seeded by crash data details and naturalistic driving crashes were then used to estimate effectiveness for different crash subtypes. A second activity was performing human factors experiments in vehicles with assistive technology or partial automation to explore the effect of experience on a driver's mental model of those systems, particularly the understanding of the limits of the technology. Finally, two efforts focusing on teen safety were completed, including an investigation of the effect of teen passengers on teen driver behaviors and performance, and the effect of different state graduated licensing policies on teen driver safety outcomes relative to the effect of crash avoidance systems.

The UTMOST (Unified Theory for Mapping Opportunities for Safety Technology) tool is designed to allow visualization of the benefits of multiple safety countermeasures and to understand how combinations of those countermeasures might influence the crash population. As part of this project, the UTMOST module was upgraded to add allow estimation of the safety benefits of several crash avoidance features, as well as the effects of safety legislation.

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Acronyms

ACC	Adaptive cruise control
ADAS	Advanced driver assistance system
AEB	Automatic emergency braking
AIS	Abbreviated Injury Scale
CDS	Crashworthiness Data System
CIB	Crash imminent braking (now called AEB)
DBS	Dynamic brake support
EDR	Electronic data recorder
FC	Forward crash
FCAM	Forward crash warning
FCW	Forward crash warning
GDL	Graduated driver licensing
GES	General Estimates System
IVBSS FOT	Integrated Vehicle-Based Safety System Field Operational Test
L/RD	Lane- and/or road-departure
LCC	Lane centering control
LDP	Lane departure prevention system (now called LKA)
LDW	Lane departure warning
LKA	Lane-keeping assist
LTV	Light trucks and vans
LV	Lead vehicle
MAIS	Maximum Abbreviated Injury Scale
NASS	National Automotive Sampling System
NDS	Naturalistic Driving Study
NHTSA	National Highway Traffic Safety Administration
NMVCCS	National Motor Vehicle Crash Causation Study
SHRP2	Strategic Highway Research Program - 2
UTMOST	Unified Tool for Mapping Opportunities for Safety Technology

1 Introduction

This is the final technical report for a grant entitled, “Crash Avoidance Systems: An Important Class of Electronic Control Systems,” awarded to the University of Michigan Transportation Research Institute (UMTRI) as part of the Toyota Class Action Settlement Safety Research and Education Program. This grant has supported a three-year research project involving an interdisciplinary team seeking to make a significant impact on the safety of automotive transportation by developing methods and specific findings to help the community determine the best suite of crash avoidance systems for real-world operations, while considering other approaches to reduce the target crash set.

This final technical report describes the research goals, methods, results, and findings from this project. The project also provides an online tool for public use that integrates effectiveness results so users can study how crash avoidance systems and other safety technologies, policies, or behaviors may impact highway safety. Section 2 presents the high-level motivations and goals of the project, the structure of the research tasks (as originally proposed and as conducted), concepts behind the approaches taken, and the nature of the project outcomes.

Section 3 provides an overview of the model and associated online tool that provides the framework for the project. The UTMOST (Unified Theory for Mapping Opportunities for Safety Technology) tool is designed to allow visualization of the benefits of multiple safety countermeasures and to understand how combinations of those countermeasures might influence the crash population. The project supported a major upgrade of the UTMOST model including the inclusion of several new modules with estimates of the safety benefits of several crash avoidance features, as well as effects of state laws on child restraint systems and teen graduated licensing.

Section 4 of this report documents the project efforts to improve the estimated effectiveness and safety benefits of forward crash avoidance and mitigation technologies (FCAM). Section 5 describes a significant human factors experiment to explore the effect of experience with active safety technologies on a driver’s mental model of those systems. Section 6 addresses effectiveness and safety benefits for lateral assist technologies, employing significant progress in aligning new insights into lane- and road-departure crashes with a simulation approach to estimating benefits of crash avoidance technologies.

Two efforts focusing on teen safety were completed, including an investigation of the effect of teen passengers on teen driver behaviors and performance, presented in Section 7, and the effect of different state graduated licensing policies on teen driver safety outcomes, presented in Section 8. Section 8 also addresses estimates of comprehensive benefits using the UTMOST framework, and the example used is how different sets of countermeasures affect the benefits for teens, including graduated licensing and crash avoidance systems.

The dissemination of this research is briefly described in Section 9, and Section 10 describes conclusions. Appendices provide additional material and analytical developments. A companion final report on administrative matters and research dissemination efforts is also submitted as part of this effort.

2 Project Overview

2.1 Research Overview

Crash avoidance systems are intended to help drivers avoid or mitigate the severity of crashes by providing warnings or active control interventions. However, they are deployed in the context of a host of other safety countermeasures including legislation, roadway design, demographic characteristics of occupants, and occupant protection technology. A major goal of this research program is to provide new knowledge, models, and tools to enable improved designs of automotive crash avoidance systems and more effective deployment strategies. To take a more comprehensive look at these systems, we consider in this approach other effects that influence crash types and mechanisms, whether those effects are via the use of other technologies, driver behavior differences, new public policies, driver demographics, or other influences.

More specifically, this research provides:

- Improved methods and a public tool for computing comprehensive benefits estimates for combinations of crash avoidance systems. UTMOST provides automakers and others with a decision-making tool to optimize the tradeoff between potential safety benefits and system costs.
- Methods and new results for estimating the potential safety benefits of both forward crash avoidance and mitigation systems as well as lane departure warning and prevention systems
- Human factors experiments addressing whether additional information about crash avoidance systems will improve drivers' understanding and willingness to use the systems.
- Work on understanding the unique considerations of teen drivers, including analysis of crash data to estimate how safety may be impacted by specific elements of state laws addressing graduated driver licensing and child restraint systems.
- Research on driving performance effects, including effects of crash avoidance on driver performance.
- Research on evaluating active semi-automated lane keeping systems.

Together these activities are designed to inform crash avoidance system design, and to provide a way to simultaneously consider deployment of these devices and other approaches to improve highway safety.

The Unified Theory Mapping Opportunities for Safety Technology (UTMOST) model was initially developed in 2007 (Flannagan & Flannagan, 2007). The goal of UTMOST is to allow visualization of the benefits of multiple safety countermeasures, including those from all portions of the Haddon Matrix (Williams, 1999), to understand how combinations of those countermeasures might influence the crash population. The underlying model for UTMOST separates the causal components of crashes to allow estimation of the influences of different types of countermeasures on the appropriate causal components. Separable causal components include:

- Crash type
- Crash characteristics
- Direction of impact
- Crash severity
- Driver age
- Occupant age
- Restraint use

By separating these components in the model, we can implement countermeasures that influence any portion of the causal pathway. The crash avoidance countermeasures at the heart of this program generally prevent crashes, but in some cases, may mitigate crash severity (especially forward systems such as AEB or FCW). Other countermeasures, such as Graduated Driver Licensing (GDL) laws, influence specific driver demographic groups, while occupant protection measures such as airbags and seat belts influence injury risk but do not affect crash involvement.

Given the complexity of crash causation and the variety of measures being taken, it is important to be able to place the effects of vehicle technologies in the context of how prevalent the addressable crash type is, who is involved in such crashes, and what other measures might also influence those crashes. When a countermeasure or set of countermeasures is implemented in UTMOST, the problems that remain are highlighted, allowing the user to consider a suite of countermeasures that might most efficiently reduce a larger number of crashes and injuries.

While UTMOST is an effective integration and visualization tool, it does not itself estimate effectiveness of any countermeasure. Instead, effectiveness is an input to UTMOST. Much of this research project was thus aimed at estimating benefits of countermeasures to provide that input.

A literature review was the starting point to gather information to form the basis for the work that followed. In particular, the literature review focused on several key areas: 1) existing estimates of safety benefits for a variety of countermeasures with special emphasis on lateral and forward crash avoidance systems; 2) methods used to estimate system effectiveness; 3) details of lateral and forward crash avoidance technologies themselves; 4) human factors issues that might influence effectiveness; and 5) the effects of different countermeasures on teen driver risk.

From a basis in the literature including our own previous work, we did extensive data-driven, simulation-based evaluations of the potential effectiveness of two classes of crash-avoidance technologies: forward crash avoidance and mitigation (FCAM) and lateral assist technologies. For FCAM, we extended simulation methods work from heavy trucks to light vehicles. We were also able to test different driver braking models and difference FCAM algorithms to understand the potential effectiveness range for these systems (and given human responses).

The FCAM data-driven simulation approach was then extended to the class of lateral avoidance systems. In contrast to rear-end crashes addressed by FCAM, lateral crashes are far more complex and varied in their etiology. Different lateral systems are designed to address different lateral crash types, and we addressed these differences in the effectiveness estimations and the implementation in UTMOST. The lateral assist systems assessment approach combined analysis crash data, event-data-recorder (EDR) data, naturalistic driving data, and kinematic simulation to accomplish its goals.

A major barrier to realizing the full potential of crash-avoidance technologies is, perhaps ironically, the driver. Whether the technology is a warning that relies on the driver to take proper action, an active vehicle control system that relies on the driver to not interfere inappropriately with its operation, or a driver assistance system that relies on the driver to initiate action under appropriate conditions, the driver is an essential partner with these technologies. At the most basic level, the driver may turn off systems he/she does not understand or trust.

Figure 2-1 illustrates ways in which the human and the system may interact. The red boxes show factors that can influence the effectiveness of the system. Two of these, training/experience/education and use, are key human factors.

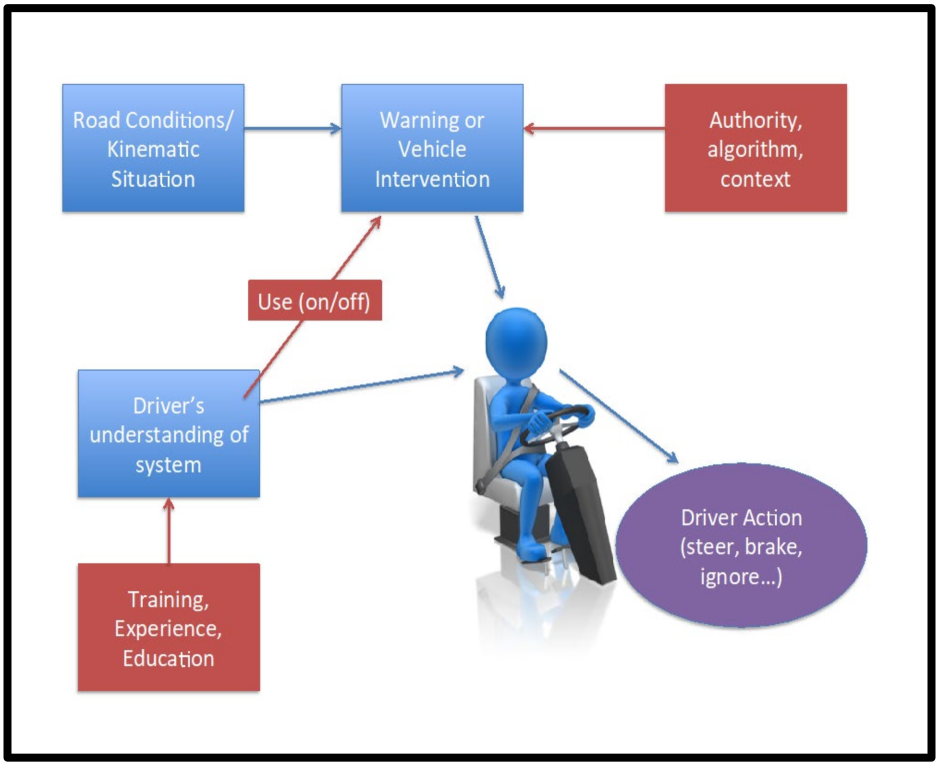

Figure 2-1 Diagram of human factors associated with crash countermeasures

To address the effect of the driver's understanding of lateral systems on his/her use of those systems, we conducted a set of human factors experiments. These experiments with production vehicles involved experimental manipulations designed to change the driver's understanding of each system. In addition, vehicles with a range of system function and authority were tested to evaluate how the variety of available systems affects drivers' understanding and use.

Teens represent a special target group for this research project. Crash risk per mile is highest for teen drivers and the primary countermeasures in use are legislative (GDL). Crash avoidance technologies have the potential to address crash types that teens are particularly prone to: rear-end collisions (as the striking vehicle) and road departure crashes. The specific driving challenges experienced by teens and the potential benefit of crash-avoidance countermeasures were studied and compared to the effectiveness of existing legal countermeasures.

Finally, the results of each of the activities that composed this project were implemented in UTMOST. Effectiveness estimates from the simulations were implemented as the default effectiveness values for those systems. The information from the human factors experiments does not generate specific numeric changes to the effectiveness estimates from the simulation studies. However, it does provide guidance on how training and experience choices might influence effectiveness. This information is implemented in the guidance to users in UTMOST. Finally, UTMOST has separate tabs for different age groups, so that the user can focus on the relative effectiveness of different countermeasures for a particular group such as teens.

2.2 Task Structure

The research tasks are shown below in Table 2.1. Task 1 consisted of a literature survey (reported in the first annual report) and also included program management. Task 2 addressed the initial year's work on the UTMOST too that incorporated early effectiveness results from the project. Some of those results came from Task 3, which included some unique methods and improved models for a modified Monte Carlo approach to generating effectiveness data for FCAM technologies. (FCAM is identified to include forward crash warning (FCW) and automatic emergency braking (AEB), as shown in Table 2-2). Injury models were constructed to estimate potential safety benefits and integrated into UTMOST, as also depicted in Figure 2-2.

Task 4 consisted of an experiment in which drivers were exposed several times to advanced active safety technologies, in order to observe the effect of training and experience on a driver's mental model for the system. Appropriate mental models reduce the risk of drivers misunderstanding the functionality and increasing the level of risk in driving.

Task 5 addresses the effectiveness of two lateral assist systems – lane departure warning (LDW) and lane-keeping assist (LKA). For this report, LKA refers to the function that applies modest and short-lived lateral control action when a driver is believed to be departing the lane or road unintentionally. (In Task 4, however, LKA sometimes refers also to an ongoing lane-centering function, because the automaker of a test vehicle uses the term in this manner.)

Table 2-1 List of Technical Tasks

Task 1: Project Foundations
Task 2: UTMOST Phase I: Public Tool for Comprehensive Safety Benefits of Crash Avoidance Technologies
Task 3: Forward Crash Avoidance and Mitigation Systems: Benefits Estimation for Light Vehicles
Task 4: Lateral Assist Systems: Human Factors Experiments in Vehicles
Task 5: Lateral Assist Systems: Benefits Estimation for Light Vehicles
Task 6: Teen Driver Performance: Differences Impacting Potential Safety Benefits with Crash Avoidance Technology
Task 7: UTMOST Phase II: Assimilating New Findings and Added User Functions
Task 8: Disseminating Research Findings

Table 2-2 Updated terminology for targeted technologies

Technology class	**Specific technology elements**	**Crash types to address:**
FCAM – forward collision avoidance and mitigation	Forward collision warning (FCW) and automatic emergency braking (AEB).	Crashing into the rear-end of other vehicles
Lateral assistance systems	Lane departure warning (LDW), short-lived lane-keeping assist system (LKA).	Unintentionally drifting from the lane or the road

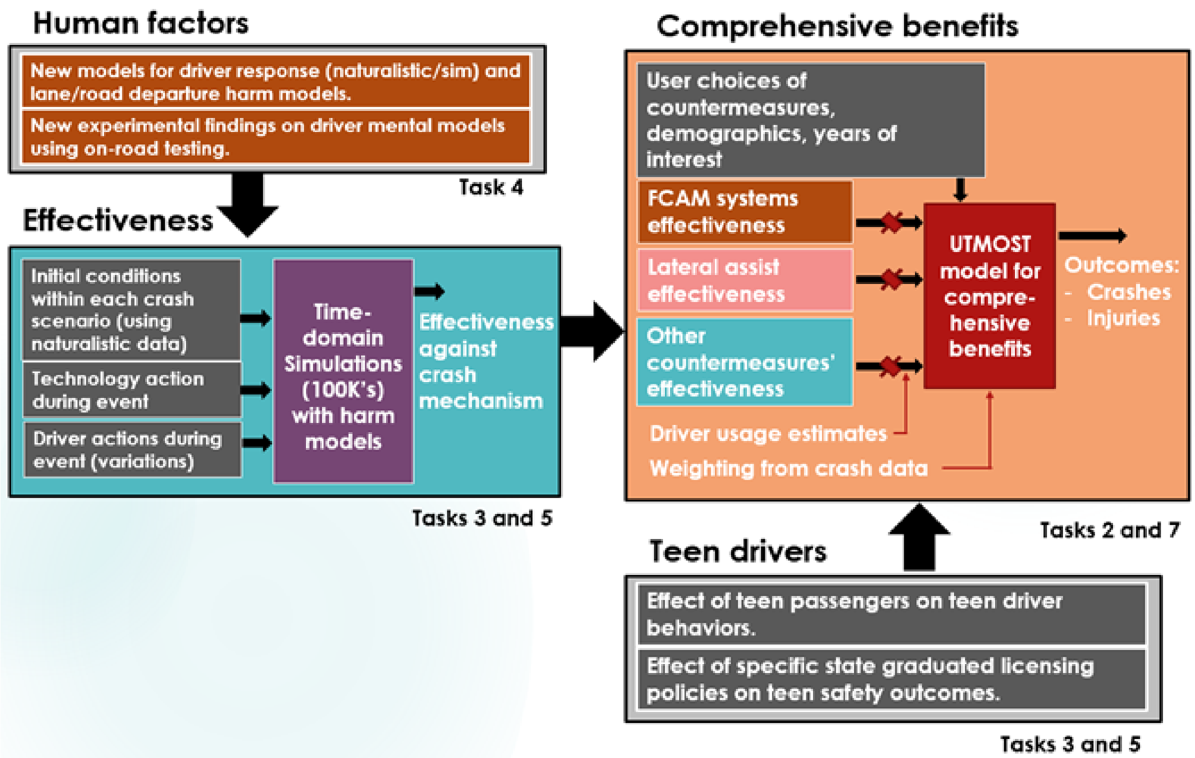

Figure 2-2 Overall project activities

Task 6 consisted of two separate studies on teen drivers. The first investigated the role of state laws in reducing teen driver-related crash harm. This was done by relating specific elements of such laws to changes in state crash outcomes. The second study used naturalistic data with teenagers to understand basic influences of teen passengers on surrogate measures of safety. Prior crash data analyses demonstrate that teen passengers can introduce added risk; this study sought to understand the mechanism.

In Task 7, the UTMOST system was upgraded with new mathematical models representing improved ways of combining different influences. This has resulted in a major new release, and represents a substantial step forward in the allowing the safety community to make efficient choices to accelerate safety in the US. Task 8 disseminates sharing information from this large project with the public as well as safety professionals and decision-makers.

Tasks 3, 4, and 5 address specific technologies. The common terminology for some of the crash avoidance systems has evolved since the project launched. The updated terminology of the targeted technologies for these tasks is shown in Table 2.2. Lane departure prevention (LDP) has been replaced by lane-keeping assistance system (LKA). Crash-imminent braking (CIB) is now called automatic emergency braking (AEB).

3 Task 2: UTMOST Development

3.1 UTMOST Background

The Unified Theory Mapping Opportunities for Safety Technology (UTMOST) model was initially developed in 2007 (Flannagan & Flannagan, 2007). The goal of UTMOST is to allow visualization of the benefits of multiple safety countermeasures, including those from all portions of the Haddon Matrix (Williams, 1999), to understand how combinations of those countermeasures might influence the crash population.

The underlying model for UTMOST separates the causal components of crashes to allow estimation of the influences of different types of countermeasures on the appropriate causal components. Separable causal components include:

- Crash type (e.g., influenced by crash-avoidance systems such as lane-departure warning)
- Crash characteristics (e.g., alcohol involvement, time of day)
- Direction of impact (influences crash severity and injury risk)
- Crash severity (influences injury outcomes)
- Driver age (e.g., influenced by legislation)
- Occupant age (influences injury risk)
- Restraint use (influences injury risk)

To populate these components with data, we use a combination of national datasets. First, the 2013-2015 National Automotive Sampling System—General Estimates System (NASS-GES) dataset was used to create a table of person counts. For each combination of crash type, crash direction, and alcohol, the crash severity distribution was calculated using a method described in Flannagan (2013) using NASS-GES as well. Injury risk curves were modeled using the 2010-2015 National Automotive Sampling System—Crashworthiness Data System (NASS-CDS) dataset. Details are in the next subsections.

3.1.1 Crash Distribution and Delta-V

Crash avoidance technologies typically apply to crashes defined according to the action that caused the crash, such as run-off road or backing. For this study, the 37 types of crashes proposed by Najm, Smith, and Yanigasawa (2007) were collapsed to a set of 25 types of crashes. The reduction collapses crash types that are very similar with respect to damage and crash types that have too few cases to analyze separately (collectively called “Other” crashes). Within each of these 25 types of crashes, we must account for the resulting damage location to each car involved in a crash. For example, most backing crashes result in rear damage to the striking vehicle and frontal or side damage to the struck vehicle, and most animal crashes involve frontal damage to the striking vehicle.

The NASS-GES dataset was analyzed to develop a baseline distribution of crashes according to the following variables:

- Overall crash direction (front, near-side, far-side, rear, rollover, pedestrian, pedalcyclist, motorcyclist, and other)
- Crash type or mechanism (run-off-road, backing, etc.)
- Occupant age group: (0-1,2-4,5-7,8-10,11-13,14-15,16-17,16-20,21-65,66+)
- Occupant gender (Male, Female)
- Driver age group (<16,16-17,18-20,21-25,25-65,66+)
- Driver gender (Male, Female)
- Driver alcohol involvement (Yes, No)
- Light condition (light [includes dusk and dawn], dark, dark but lighted, other/unknown)
- Pedestrian alcohol involvement (Yes, No for pedestrians only)
- Vehicle type (Passenger car, SUV, Van, Pickup, Pedalcyclist, Motorcyclist, Pedestrian, Other)

The cross-tabulation of these variables produces a table of 43,658 rows. Each row contains the annual number of occupants in crashes that occur involving each combination of variables. The mean and standard distribution of delta V (crash severity in mph) are provided for each row except for pedestrian, pedalcyclist, motorcyclist, and rollover crashes. Delta-V distribution varies with crash type, crash direction, and alcohol involvement.

3.1.2 Injury Risk: Vehicle Occupants in Frontal, Near-Side, Far-side, and Rear Impacts

Injury risk models for use in the software tool were developed using the NASS-CDS database. A dataset was constructed for analysis using case years from 2002-2010 and limiting vehicle model years to those less than 10 years old relative to each case year. Pregnant occupants were not included, nor were children under 14. Occupants wearing 3-point belts or not using belts were included; those with lap belt only or shoulder belt only were not. Seating position was classified as driver, front passenger (including the few front center positions), and rear passenger.

Logistic regression models were used to predict the risk of AIS3+ injury. Models were developed separately for each crash category (frontal, near-side, far-side, rear). The following predictors were included in the model:

- delta V (expressed as ln [delta V])
- Occupant age and gender
- Belt restraint (yes/no)
- Vehicle type (passenger car vs. other)
- Alcohol involvement

3.1.3 Injury risk: Rollover Crashes

Injury risk for rollover crashes was calculated using NASS-CDS, but only considered occupant age and belt use as predictors, because delta-V is not estimated in rollovers. Risk of injury in rollovers was estimated using 2000-2010 NASS-CDS data as a function of occupant belt use and age.

3.1.4 Injury Risk: Pedicyclists and Motorcyclists

The NASS-GES database from 2000-2010 was used to estimate the risk of pedestrian and pedalcyclist injury, given that a pedestrian or pedalcyclist crash occurred, as a function of pedestrian/pedalcyclist age, striking vehicle type, pedestrian/pedalcyclist alcohol use, and light level as predictors. Motorcyclist injury risk was also calculated from this dataset, using motorcyclist age, alcohol use, and light level as predictors.

Because NASS-GES categorizes injury severity using the KABCO scale rather than an AIS value, injury models were developed for pedicyclists and motorcyclists to predict the likelihood of a K or A injury. Then, using relationships between AIS and KABCO in NASS-CDS, a scale factor was derived to translate risk of KA injury into risk of AIS3+ injury.

3.1.5 Injury Risk: Restraints

Restraint effectiveness was evaluated separately for children (by age group and child restraint type), motorcyclists (helmet use), and vehicle occupants age 14+. For vehicle occupants age 14+, the effect of using a lap/shoulder belt was estimated using NASS-CDS. For motorcyclists and children, it was necessary to use NASS-GES to obtain enough sample size to conduct analyses. For the NASS-GES analyses, K or A injury (Killed or Suspected Serious Injury) was used as the outcome of interest rather than MAIS3+. This will, in general, overestimate injury risk, but total injuries were adjusted to account for this. For each of these groups, the current use rates of restraints were established as the baseline corresponding to current injury outcomes in the crash data, and the risk models were implemented as adjustments to the current rates.

3.2 Countermeasures

A variety of countermeasure types were implemented in UTMOST within this project. The focus of a large portion of the project was certain classes of crash avoidance technologies. However, to understand the role of these technologies in improving safety, it is important to be able to place the effects of crash avoidance systems in the context of many other types of countermeasures. In particular, for teens, most countermeasures involve legislation of licensing. Thus, we developed models of legislative countermeasures, crash-avoidance countermeasures, and restraint countermeasures.

3.2.1 Crash Avoidance Technologies

In UTMOST, each crash-avoidance technology is implemented as a reduction in the number of people involved in certain relevant crash types. Based on the effectiveness literature, we identify the crash type(s) influenced by each technology and the default effectiveness. If a technology is 25% effective, then it results in a reduction of 25% of relevant crashes. However, if more than one technology influences the same crash type, the effectivenesses do not add. If, for example, Technology 1 reduces a crash type by 25% and Technology 2 reduces the same crash type by 50%, then the combined effectiveness is 1-(1-0.25)*(1-0.5)=62.5% rather than 75%. Benefits estimates from the results of work in this study (discussed in later chapters) were implemented in UTMOST as default levels of effectiveness.

Table 3-1 shows the technologies and crash types influenced. These were based on an overview of crash avoidance technologies (Bayley 2007). The user can change the effectiveness to see how a better (or worse) system might influence crashes, and the user can also change the fleet penetration of each technology.

Table 3-1 Updated technologies available for selection, default value of effectiveness, applicable crash types, and sources.

Crash Avoidance technology	Relevant Crash Types
Lane departure warning	Head-on (from lane drift); Run-off-road
Adaptive cruise control	Rear-end crashes
Alcohol interlock	Alcohol involved
Electronic Stability Control	Single-vehicle run-off-road crashes rollovers
Frontal collision warning	Rear-end crashes, object crashes
Intelligent lighting systems	Pedestrian/cyclist low-visibility crashes
Lane change warning	Drifting and lane change crashes
Lane keeping assistance	Head-on collisions from lane drift, sideswipe crashes, run-off-road crashes
Pedestrian detection system	Pedestrian crashes
Reverse collision warning system	Backing crashes
Road departure warning	Run-off-road crashes

3.2.2 Mitigation Effects

For some crash-avoidance technologies, such as forward collision warning and automatic emergency braking, the system may mitigate the severity of some crashes without fully avoiding the crash. To implement this effect, we subtract a constant from delta-V. Since delta-V is represented as a distribution of values for each row, this amounts to a left shift of the entire distribution by a fixed value. Subtracting a value will result in some crashes having negative delta-V, which represents a crash that has been avoided.

Figure 3-1 illustrates the mitigation process. The red curve represents the original delta-V distribution for one row in the table (e.g., rear-end crash with frontal damage, no alcohol involved). If a crash avoidance technology reduces delta-V by 10 mph on average, the resulting distribution of delta-V will be shifted to the left as illustrated by the green curve. All crashes that were originally below 10 mph delta-V would be avoided and the remaining crashes will be less severe. The selection of 10 mph is determined by the crash avoidance effectiveness estimate, which will be equal to the area to the left of 0 (i.e., avoided crashes) in the shifted distribution.

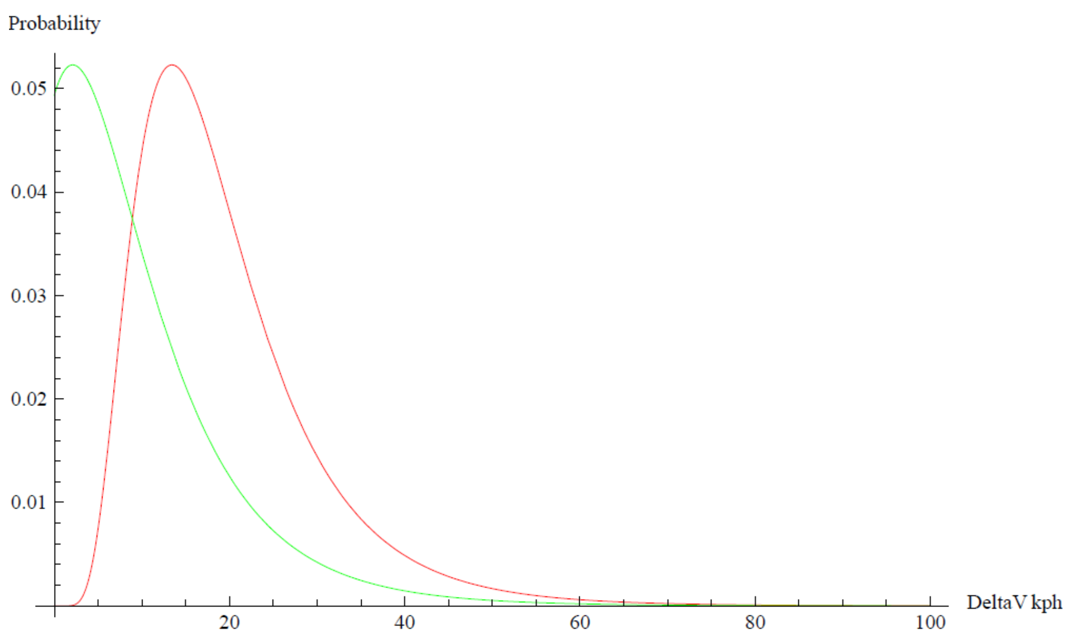

Figure 3-1 Illustration of delta-V shift for mitigated crashes

3.2.3 Effects of Legislation

Legislation is a common approach to improving traffic safety. Notably, the primary approach to mitigating teen-driver risk is through legislation. To provide context and a point of comparison for the potential of crash avoidance technologies to reduce crashes and injuries, we developed models of the effectiveness of various classes of laws designed to improve safety. The groups of laws include: graduated driver licensing, alcohol impairment, and restraint use (both seatbelts and child restraints). We also implemented effects of universal motorcycle helmet laws based on results showing the relative rates of helmet use for states with and without helmet laws (Pickrell & Ye, 2012), as well as estimates of relative risk for riders with and without helmets (Deutermann, 2004). The details of the models of legislation effectiveness are given in Appendix A.

4 Task 3: Forward Crash Avoidance & Mitigation – Effectiveness and Benefits Estimation

The objective of this task is to estimate the effectiveness and potential safety benefits of the FCAM systems. The section begins with a description of forward crashes, including some new material from using the General Estimate Systems (GES) database, as well as new work with electronic data recorders from the US Crashworthiness Data System and SHRP2 data. The method used to compute FCAM effectiveness and benefits is described below. Final analysis of data is underway, so there are no findings presented at this time.

4.1 Characteristics of Forward Crashes using the GES

The estimation of potential safety benefits for a countermeasure begins by investigating the crash problem that might be addressed with the countermeasure. For FCAM systems, the crash analysis focused on crashes into same-direction vehicles located in the travel lane of the striking vehicle. For this study, the interest is in light vehicles striking other vehicles. Light vehicles include all passenger cars as well as light trucks and vans (which includes SUVs, minivans, standard vans, and light duty pickups); this is the definition used by NHTSA. This report refers to this set of light vehicles, trucks, and vans as “LTVs.” In addition, since the analysis addressed driver interventions, particularly FCAM systems, crashes in which the driver was impaired by alcohol or drugs were excluded.

The crash analysis used the NASS-GES data. The GES file is compiled by the National Highway Traffic Safety Administration (NHTSA) from a nationally-representative sample of police-reported crashes. GES data are the standard source for crashes of all severities on U.S. roads. The GES data include a significant amount of detail on the vehicles and drivers involved, the crash environment, as well as details of the events of the crashes. Crash data from 2011 to 2013 were used to develop the estimates of crash types relevant to FCAM systems.

As earlier literature has shown, FC events are geometrically simple, with scenarios differentiated by the pre-crash motion of the lead vehicle (LV). The subsets of FC crashes are (a) LV stopped, (b) LV travelling at a steady pace but slower than the striking vehicle, (c) LV decelerating in front of the striking vehicle, and (d) LV cutting in front of the striking vehicle. Crash types were identified in GES using the ACC_TYPE variable for the striking vehicle and the pre-crash maneuver (P_CRASH1) variable for the LV. The LV motion is indicated on police reports and transferred into the GES file. There is no independent verification of LV motion, and in the case of vehicles coded as stopped at impact, there is some reason to question whether the vehicles were truly stopped. Analysis of similar crashes involving truck-striking crashes showed that about 20% of vehicles coded as stopped in fatal crashes, and up to 60% of the vehicles in nonfatal crashes, were likely in motion as the striking vehicle approached (Woodrooffe, Blower et al. 2012).

Table 4-1 shows the annual number of police-reported crashes associated with the four FC types, totaling almost 1.6 million annually in the U.S. Of those, crashes reported as LV stopped constituted

66.3% of these crashes, with 23.2% reported as LV decelerating. The LV slower and LV cut-in types represented 9.9% and 0.6%, respectively. LV cut-in was rare.

Table 4-1 Annual average forward crash types

FC crash involvements	N	%
LV stopped	1,031,770	66.3
LV slower	154,610	9.9
LV decelerating	360,030	23.2
LV cut-in	8,770	0.6
Total	1,555,180	100.0

The FC crash set was studied by analyzing these crash types. The details of the analysis are included in Appendix B, but the highlights of the remaining analyses follow:

- FC crashes tended to be less severe in terms of fatalities and serious injuries than other crash types. Nevertheless, about 828 persons were killed annually and 18,752 suffered incapacitating injuries in these crashes.
- In most (75-80%) FC crash involvements, the striking vehicles were simply going straight immediately prior to the crashes. In about 7.7%, the striking vehicles were just starting in lane, suggesting that these crashes occurred in stop-and-go traffic. A small percentage occurred immediately after the striking vehicles changed lanes, so the drivers may not have anticipated that the lanes were occupied. However, in the large majority of FC crashes, striking vehicles were simply lane-keeping prior to colliding with forward vehicles in their lanes.
- More often than other crash types, FC crashes occurred in daylight and not in darkness. About 15.8% occurred in dark conditions, compared with 23.5% of other crashes. LV-slower crashes were more likely in darkness than the other FC types, suggesting that the LV-slower type may have occurred more often in rural areas, and of course at night. In these conditions, reduced sight distances in darkness may have contributed to the crashes.
- With respect to the speed limit of the roads, FC crashes tended to occur on higher speed roads compared with other crash types. Most (64.7%) occurred on roads with speed limits 35 to 50 mph. Crashes in which the LV was coded as stopped were somewhat more likely on lower speed roads than the other FC types, probably because this type was more likely in stop-and-go traffic.
- Drivers aged 25 and younger were significantly overinvolved in FC crashes, particularly where the LV was coded as stopped. FC crashes accounted for almost 25% of the LTV involvements of drivers under 18, compared with 17.6% of all LTV drivers. Older drivers were substantially under-involved (12.5%).
- Driver fatigue was not particularly salient for FC crashes, with the exception of the LV-slower type, which could be related to the fact that that type occurred more frequently in dark conditions compared with the other types. However, driver distraction was identified in a substantial proportion of all FC crash types, with the exception of the insignificant LV cut-in type. Distraction was coded for 28.4% of LTV drivers in LV stopped crashes, 22.7% of LV

slower, and 20.7% of LV decelerating. These percentages compare with only 7.7% of LTV involvements in all other crash types.

In summary, the large majority of FC events represent a rather straightforward set of characteristics that would seem to be addressable with FCAM technologies. The next section describes the safety benefits methodology.

4.2 Forward Crash Characteristics using Electronic Data Recorders from CDS and SHRP2

Data from Event Data Recorders (EDRs) were used for detailed information on driver behavior prior to FC crashes, primarily whether and how drivers braked prior to impact. EDRs record a time-series of data on vehicle state prior to and up to some triggering event. In the current case, the triggering event was a crash. EDRs typically retain data for a short period (e.g., 5s.) prior to the triggering event. The data are recorded at a rate of every second or less (e.g., 0.5s, 0.1s) up to the triggering event, and include information such as vehicle speed, brake status (on/off), accelerator status, engine speed, steering wheel angle, and so on. Information such as whether the driver braked, how long before impact, and braking profile prior to impact can be extracted from the EDR time-series data.

The EDR data used here were retrieved from two sources. The first was the NASS CDS, often called just CDS. The CDS data are from a sample of relatively late-model light vehicle crashes in which at least one vehicle was towed. Researchers perform an in-depth data collection on each crash, and collect a standard set of crash variables that matched the data in GES (which is complementary to CDS). The fact that CDS uses the same set of variables as GES to capture pre-crash maneuvers and crash geometry means that it was possible to identify precisely the same types of crashes as were used in the FC crash description elsewhere in this report.

Some of the vehicles in the CDS data were equipped with EDRs, and the data from those vehicles were available in the form of Portable Document Format (pdf) documents. Data were retrieved from and built into analytical files. Data on braking and vehicle speed at different time points were used to compute levels of deceleration in *g*'s, and to construct braking profiles of the striking vehicle in FC crashes. These data were used in simulations of different FC crash types to estimate the effectiveness of different interventions.

Drivers in a surprising number of striking vehicles in FC events did not apply the brakes at all prior to impact (Figure 4-1). Over a quarter, 26.1%, of striking vehicles in FC crashes did not brake. The proportion varied by FC type. Where the lead vehicle (LV) was stopped or traveling slower than the striking vehicle, about 24.1% and 21.1%, respectively, did not brake prior to the collision. In crashes in which the LV was decelerating, fully 36.7% never applied the brakes to avoid the collision. The number of crashes for which EDRs were available was relatively small, so some of the differences between specific types of FC crashes may not be statistically significant. However, it was clear that a substantial percentage of striking-vehicle drivers did not brake.

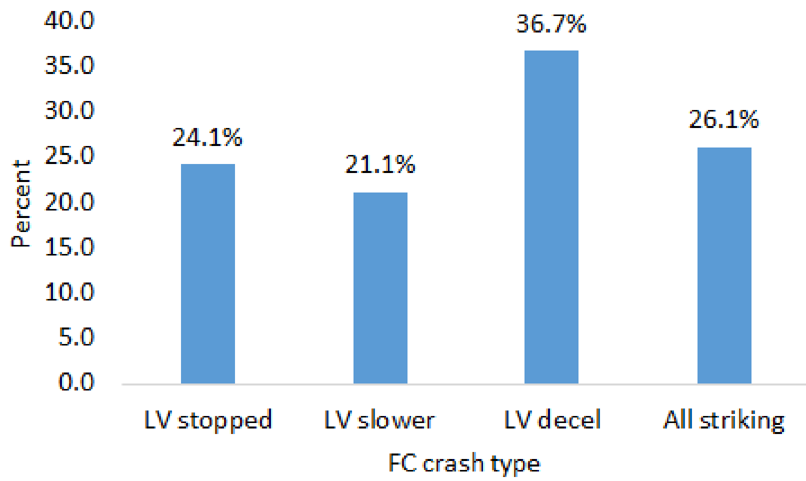

Figure 4-1 Percent striking vehicles that did not brake prior to impact, by FC crash type

Striking vehicle drivers also tended to brake late. Figure 4-2 shows the distribution of seconds prior to impact at which drivers first applied the brakes. For the LV-stopped crash type, the mode (most frequent value) was 1 second prior to impact. For the LV-decelerating type, it was 0.5 seconds.

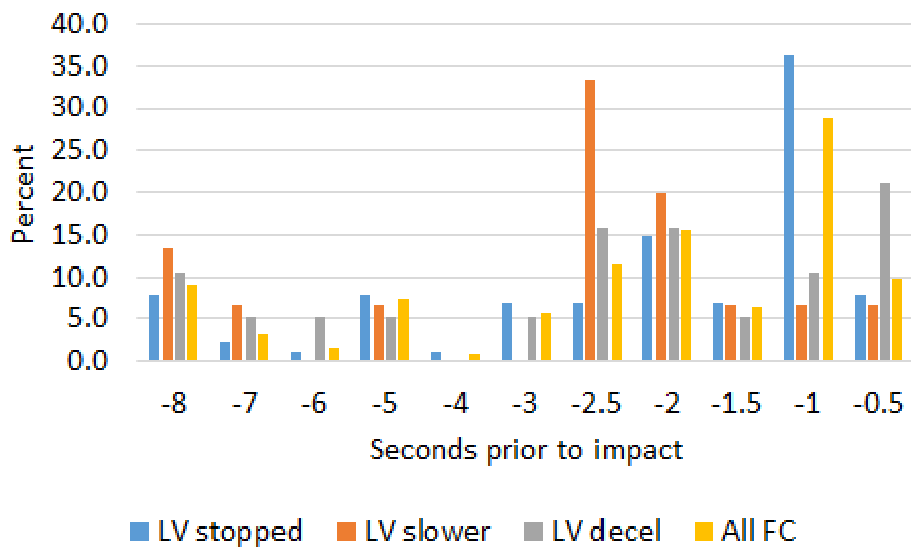

Figure 4-2 Time of first brake application prior to collision, for FC crash types and all FC crashes

In addition, drivers tended not to brake to the capacity of their vehicles. Mean deceleration levels ranged from about -0.25*g* to -036*g.* Table 4-2 provides descriptive statistics on the maximum level of braking in *g*'s for each individual FC crash type and for all FC crashes. The levels that rounded to zero were very low. Levels greater than 1.3 *g* were omitted as likely erroneous—some in the range of 4*g* were reported, but these were certainly errors. In any case, the EDR data showed that drivers tended to brake late, in some cases as little as 0.5s prior to impact, and most did not brake to the capacity of the vehicles.

Table 4-2 Deceleration in *g*'s for striking vehicles that braked

FC type	N	Mean	Std. dev	Max	Min
LV stopped	80	-0.34	0.28	-0.87	0.00
LV slower	9	-0.25	0.28	-0.77	0.00
LV decel	17	-0.36	0.32	-0.91	0.00
All FC	106	-0.34	0.29	-0.91	0.00

Figure 4-3 shows the speed profile for FC crash events extracted from EDRs in the CDS data. Profiles were categorized by the number of seconds prior to collision at which drivers initiated braking. The red line shows drivers who never braked at all. In addition, deceleration rates for the last second prior to impact are shown. The profiles for 1s, 2s, and 3s show that deceleration levels of 0.5*g* to 0.55*g* were achieved immediately prior to impact, but braking levels were much lower for the other profiles. When they braked, drivers tended to brake late, and many failed to brake as hard as they could have.

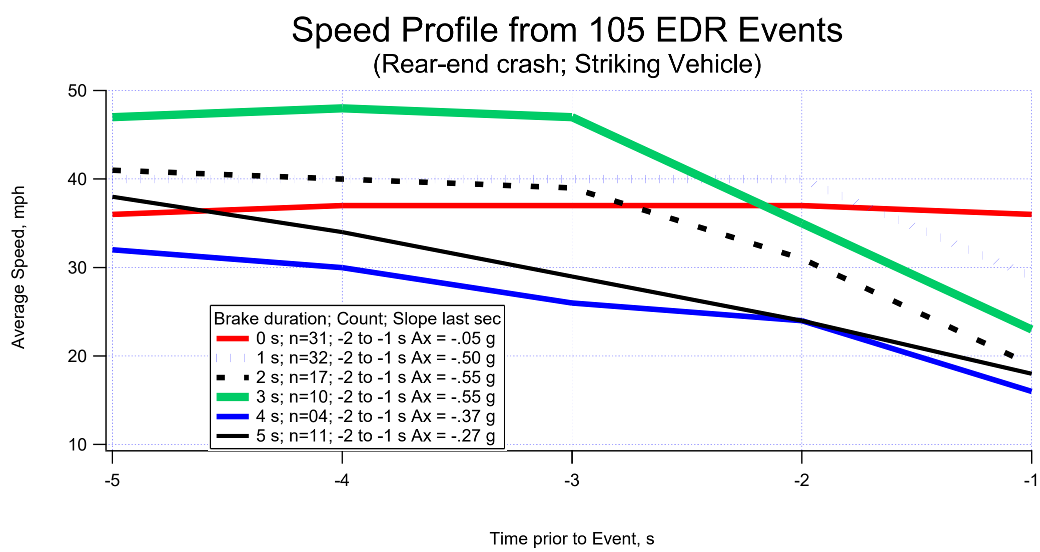

Figure 4-3 Speed profile for FC crashes by brake initiation

The second source of EDR data analyzed was from the Strategic Highway Research Program 2 (SHRP-2) Naturalistic Driving Study (NDS). In the SHRP-2 project, over 2,000 subjects participated. Their vehicles were instrumented to record a wide variety of data, including vehicle state and condition, driver actions, and video of the driver and the scene outside the vehicles. The vehicles were used by the participants as they normally would. Participants were enrolled in the program for a year or more, so many vehicle-years of data were collected, including some crashes. EDR data were extracted for 45 FC crashes to further characterize how drivers react in FC crash events.

Review of the 45 FC crashes suggested that they could be grouped into five profiles: Ramp, Plunge-and-release, Plunge-and-hold, Plunge, and no reaction. In the Ramp profile, drivers braked early and gradually increased braking pressure. Plunge-and-release drivers braked hard initially, but then eased off on the brake pedal. Plunge-and-hold drivers hit the brakes hard and held the pressure. The Plunge drivers braked hard but collided almost immediately. Finally, the no-reaction drivers did not brake at all.

Figure 4-4 shows a set of statistics for the five braking profiles extracted from FC crashes in the SHRP-2 data. The proportion of drivers in the SHRP-2 dataset who failed to brake at all (10 of 45) is similar to the proportion in the CDS dataset (Figure 4-1). Thirteen of the 45 hit the brakes hard (Plunge), but then collided almost immediately. Brake-on duration for these drivers was the shortest (section B in the Figure), the time gap to the LV was the shortest of those that braked (D), and the range at brake application was the shortest at 2.7m. In contrast, the Ramp profile had the longest brake-on duration at 2.4s, the longest time gap (0.8s), and brakes were applied at the longest average distance (15.0m).

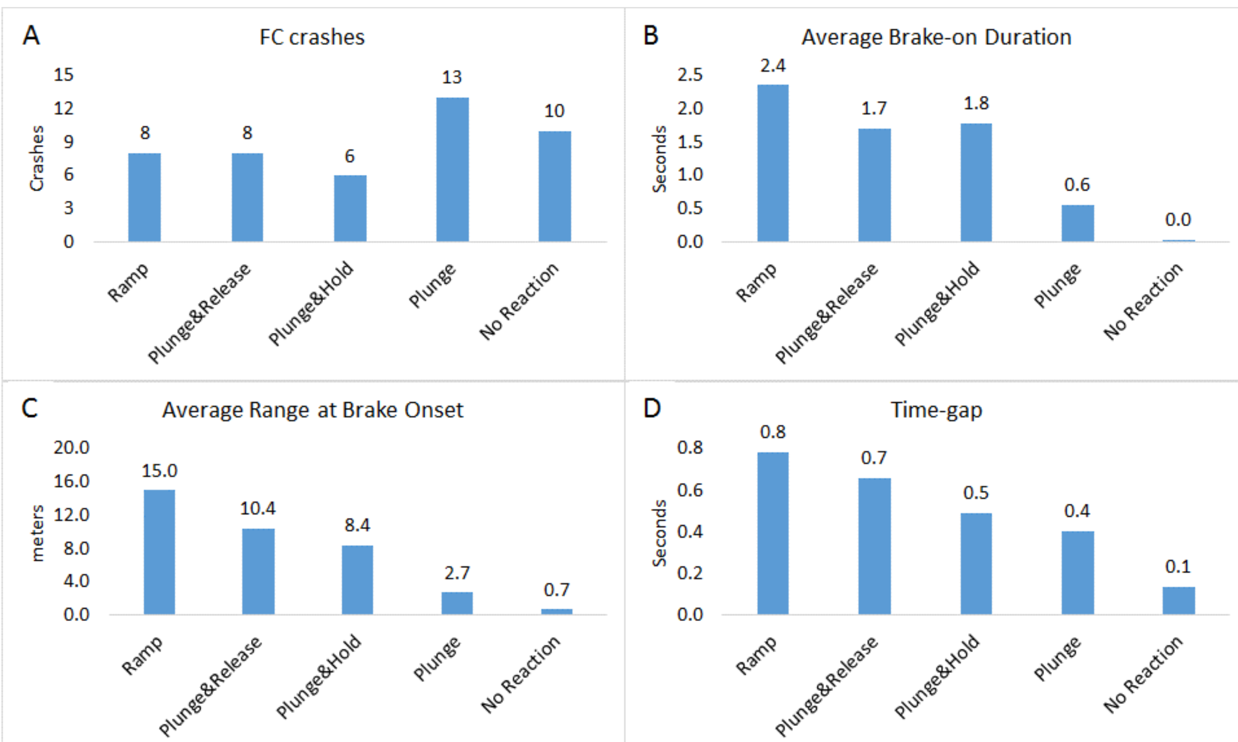

Figure 4-4 Selected statistics for braking profiles in FC crashes, SHRP-2 data

There were interesting differences in the composition of the different braking profiles by driver gender (Figure 4-5). The numbers are relatively small, but the patterns are suggestive. Male drivers tended to fall into the Plunge category, braking late, and too late. A higher proportion also did not brake at all. In contrast, female drivers were more likely to fall into the Ramp category, initiating braking early and ramping up, but obviously too slowly because they collided anyway. Females also were disproportionately represented in the Plunge-and-release category, in which drivers braked hard, but then eased off and then often braking hard again before colliding. All of the profiles, of course, resulted in collisions, but there were striking differences in the (failed) strategies.

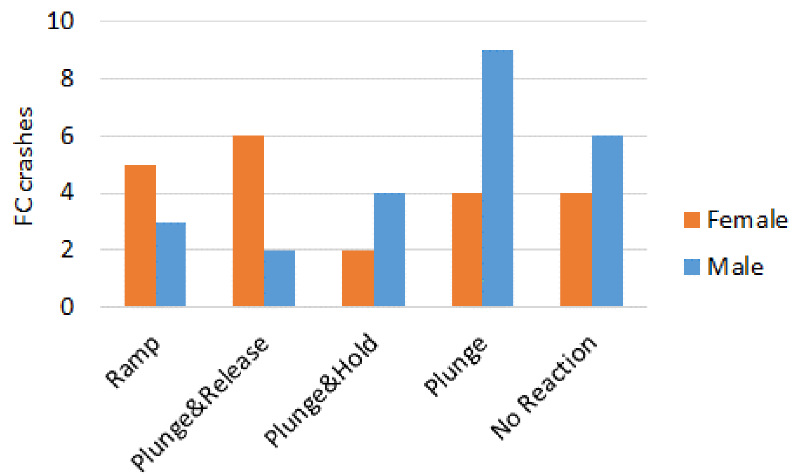

Figure 4-5. Driver gender by brake profile in FC crashes, SHRP-2 data

4.3 Simulation and Analysis Description

The light-vehicle frontal-collision prevention/mitigation simulation is based on previous work in the heavy-truck domain (Woodruff et al., 2011). The simulation approach is based on the assumption that rear-end crashes generally arise from normal initial vehicle-following conditions, but because the driver fails to react in a timely manner to developing conflict conditions (e.g. lead vehicle slowing or stopped, or range closure due to speed differentials), a crash occurs. This delay by the driver is most often due to distraction or inattention, although environmental, vehicle brake and roadway conditions can also contribute to the event. The approach for creating simulated crashes from naturalistic driving data contains the following steps:

1) A large number of vehicle-following events (or “conflicts”) are identified within a driving dataset. Starting conditions included lead vehicle braking, lead vehicle moving slower, lead vehicle stopped, and cut-in/cut-out situations. Braking profiles are developed for human drivers and automatic emergency braking (AEB). The driver braking profile is developed from Event Data Recorder (EDR) and the SHRP2 NDS data. This is used in Step 3 for both baseline crashes and any driver response to warnings. The AEB braking profiles are developed from deceleration profiles of AEB test conducted by UMTRI against both a moving and stationary target, as part of previous projects using several production AEB systems.

2) Initial kinematic conditions for each conflict are “played out” in a simulated environment by delaying driver reaction times incrementally (by 0.1 seconds for each step) until there is no braking at all (thus representing a worse case crash). This process creates a range of crash severities for each one of the starting conditions (i.e., conflicts). As a result, a large database

of simulated rear-end crashes was developed representing a wide range of crash types (LV slower, decelerating etc.), severity levels (small to large impact speeds), and initial starting conditions (high and low speed).

3) For each simulated crash, timing algorithms and braking profiles (from Step 2) for AEB and forward collision warning (FCW) are implemented. For FCW, a distribution of driver brake reaction times is used. For AEB, the countermeasure operates independent of simulated driver actions.

4) For each simulated crash outcome with and without countermeasures, we apply a distribution of vehicle mass ratios obtained from a national crash dataset. The mass ratio determines the distribution of impact speed to each vehicle as follows:

$$dv_1 = v * \frac{m_2}{(m_1+m_2)}$$

$$dv_2 = v * \frac{m_1}{(m_1+m_2)}$$

where dv_i is the delta-V for vehicle i, v is the impact velocity for the crash, and m_i is the vehicle mass for vehicle i

5) To ensure that the baseline simulated database accurately represents the frequency distribution of crashes in the real world in terms of severity levels (i.e. delta v's), weighting factors are developed from the delta-V distributions generated in the crash-data analysis task. The weighting factors are applied to each of the simulated crashes so that the delta-V distribution in the reference dataset matches the delta-V distribution from real world crashes.

A detailed description of the steps 1 through 4 is presented as Appendix C.

Driver warnings and automatic braking actions are initiated when specific kinematic threshold levels are met. These control algorithms include timing of warnings and automatic braking events as well as the braking deceleration levels (i.e., brake force). Algorithms typical of production systems as well as experimental algorithms with different characteristics can be implemented.

Within the computer simulation environment, the effects of driver warnings and/or automatic braking events can be evaluated as to whether that particular crash was prevented, or the degree to which impact severity (delta V) was reduced. To account for driver variability in responding to warnings, a distribution of reaction times was developed and applied to each of the simulated crashes. (See Appendix C for more details.)

4.4 Safety Benefits Analyses and Results

The results of the simulations are shown by scenario in the series of tables below. Table 4-3 shows the reductions in MAIS 2+ (moderate injury or worse) injuries, MAIS 3+ (serious injury or worse) injuries and crashes avoided for the lead-vehicle braking scenario. Shaded sections distinguish reductions for struck and striking vehicles. Crashes avoided are the same for these vehicles since avoidance affects both equally. However, the injury risk profiles differ rear and frontal damage, so injury reductions are affected differently by the level of mitigation. The two driving braking profiles show that Profile 2 (harder braking) consistently leads to greater reductions compared to Profile 1, even for AEB. Finally, each section of the table shows results for seven different countermeasures: FCW alone (relying on driver braking response), three different AEB system algorithms, and the combination of FCW and AEB for the three algorithms.

Table 4-4 shows the same information for the lead-vehicle stopped scenario, while Table 4-5 and Table 4-6 show the results for lead-vehicle slower and cut-in (other) scenarios, respectively. Across all results, the more aggressive AEB2 algorithm consistently reduces injury and crash risk more than the other two systems. Interestingly, with driver braking profile 2 (sustained harder braking), the FCW system contributes substantially to crash reductions over and above the effect of the AEB. This is not as dramatic for the weaker driver braking profile. Thus, the willingness and ability of the driver to brake hard in these circumstances is critical to the system’s overall effectiveness, even when automatic braking is available.

Table 4-3 Simulation results for lead-vehicle braking scenario

Braking	Vehicle	Intervention	P(AIS 2+) Reduction	P(AIS 3+) Reduction	% Avoided
Profile 1	Struck	FCW	57.5%	58.0%	36.8%
Profile 1	Struck	AEB1	34.0%	34.6%	2.5%
Profile 1	Struck	AEB2	87.0%	87.2%	78.4%
Profile 1	Struck	AEB3	53.6%	54.0%	20.8%
Profile 1	Struck	FCW+AEB1	72.5%	72.9%	45.1%
Profile 1	Struck	FCW+AEB2	95.8%	95.8%	92.5%
Profile 1	Struck	FCW+AEB3	81.7%	82.0%	59.7%
Profile 1	Striking	FCW	68.0%	68.5%	36.8%
Profile 1	Striking	AEB1	47.6%	48.2%	2.5%
Profile 1	Striking	AEB2	90.5%	90.6%	78.4%
Profile 1	Striking	AEB3	65.1%	65.6%	20.8%
Profile 1	Striking	FCW+AEB1	82.5%	82.8%	45.1%
Profile 1	Striking	FCW+AEB2	97.0%	97.0%	81.0%
Profile 1	Striking	FCW+AEB3	88.5%	88.7%	59.7%
Profile 2	Struck	FCW	83.9%	84.1%	74.6%
Profile 2	Struck	AEB1	44.1%	44.6%	15.9%
Profile 2	Struck	AEB2	88.3%	88.4%	80.2%
Profile 2	Struck	AEB3	58.2%	58.6%	29.5%
Profile 2	Struck	FCW+AEB1	94.3%	94.4%	87.0%
Profile 2	Struck	FCW+AEB2	98.4%	98.4%	97.3%
Profile 2	Struck	FCW+AEB3	95.4%	95.5%	89.2%
Profile 2	Striking	FCW	88.3%	88.5%	74.6%
Profile 2	Striking	AEB1	55.3%	55.8%	15.9%
Profile 2	Striking	AEB2	91.4%	91.6%	80.2%
Profile 2	Striking	AEB3	68.3%	68.7%	29.5%
Profile 2	Striking	FCW+AEB1	96.5%	96.5%	87.0%
Profile 2	Striking	FCW+AEB2	98.8%	98.8%	97.3%
Profile 2	Striking	FCW+AEB3	97.1%	97.2%	89.2%

Table 4-4 Simulation results for lead-vehicle fixed (stopped) scenario

Braking	Vehicle	Intervention	P(AIS 2+) Reduction	P(AIS 3+) Reduction	% Avoided
Profile 1	Struck	FCW	96.9%	97.0%	95.2%
Profile 1	Struck	AEB1	13.4%	13.9%	0.0%
Profile 1	Struck	AEB2	89.7%	89.7%	86.4%
Profile 1	Struck	AEB3	48.5%	49.1%	17.3%
Profile 1	Struck	FCW+AEB1	95.9%	95.9%	95.2%
Profile 1	Struck	FCW+AEB2	99.7%	99.7%	99.5%
Profile 1	Struck	FCW+AEB3	97.7%	97.7%	96.1%
Profile 1	Striking	FCW	97.8%	97.9%	95.2%
Profile 1	Striking	AEB1	24.9%	25.7%	0.0%
Profile 1	Striking	AEB2	90.0%	90.0%	86.4%
Profile 1	Striking	AEB3	60.7%	61.2%	17.3%
Profile 1	Striking	FCW+AEB1	96.6%	96.6%	95.2%
Profile 1	Striking	FCW+AEB2	99.7%	99.7%	99.5%
Profile 1	Striking	FCW+AEB3	98.4%	98.4%	96.1%
Profile 2	Struck	FCW	84.5%	84.7%	77.5%
Profile 2	Struck	AEB1	61.1%	61.4%	40.4%
Profile 2	Struck	AEB2	96.9%	97.0%	94.1%
Profile 2	Struck	AEB3	74.3%	74.6%	53.3%
Profile 2	Struck	FCW+AEB1	97.7%	97.8%	94.6%
Profile 2	Struck	FCW+AEB2	99.9%	99.9%	99.8%
Profile 2	Struck	FCW+AEB3	98.7%	98.7%	96.6%
Profile 2	Striking	FCW	88.2%	88.4%	77.5%
Profile 2	Striking	AEB1	69.4%	69.7%	40.4%
Profile 2	Striking	AEB2	98.0%	98.1%	94.1%
Profile 2	Striking	AEB3	82.0%	82.3%	53.3%
Profile 2	Striking	FCW+AEB1	98.8%	98.8%	94.6%
Profile 2	Striking	FCW+AEB2	100.0%	100.0%	99.8%
Profile 2	Striking	FCW+AEB3	99.3%	99.3%	96.6%

Table 4-5 Simulation results for lead-vehicle slower scenario

Braking	Vehicle	Intervention	P(AIS 2+) Reduction	P(AIS 3+) Reduction	% Avoided
Profile 1	Struck	FCW	46.6%	47.1%	23.9%
Profile 1	Struck	AEB1	38.3%	39.0%	0.2%
Profile 1	Struck	AEB2	94.5%	94.6%	85.3%
Profile 1	Struck	AEB3	63.7%	64.3%	21.6%
Profile 1	Struck	FCW+AEB1	68.3%	68.9%	31.7%
Profile 1	Struck	FCW+AEB2	99.3%	99.3%	97.0%
Profile 1	Struck	FCW+AEB3	84.7%	85.0%	54.0%
Profile 1	Striking	FCW	58.4%	59.0%	23.9%
Profile 1	Striking	AEB1	55.7%	56.3%	0.2%
Profile 1	Striking	AEB2	97.1%	97.2%	85.3%
Profile 1	Striking	AEB3	77.3%	77.6%	21.6%
Profile 1	Striking	FCW+AEB1	82.7%	83.1%	31.7%
Profile 1	Striking	FCW+AEB2	99.7%	99.7%	97.0%
Profile 1	Striking	FCW+AEB3	93.0%	93.2%	54.0%
Profile 2	Struck	FCW	81.7%	81.8%	73.1%
Profile 2	Struck	AEB1	44.9%	45.6%	4.5%
Profile 2	Struck	AEB2	95.2%	95.3%	85.7%
Profile 2	Struck	AEB3	65.7%	66.2%	27.8%
Profile 2	Struck	FCW+AEB1	94.9%	95.0%	86.0%
Profile 2	Struck	FCW+AEB2	99.9%	99.9%	99.1%
Profile 2	Struck	FCW+AEB3	97.2%	97.2%	90.5%
Profile 2	Striking	FCW	86.2%	86.4%	73.1%
Profile 2	Striking	AEB1	61.6%	62.1%	4.5%
Profile 2	Striking	AEB2	97.6%	97.7%	85.7%
Profile 2	Striking	AEB3	78.0%	78.4%	27.8%
Profile 2	Striking	FCW+AEB1	97.7%	97.7%	86.0%
Profile 2	Striking	FCW+AEB2	100.0%	100.0%	99.1%
Profile 2	Striking	FCW+AEB3	98.9%	98.9%	90.5%

Table 4-6 Simulation results for lead-vehicle cut-in (other) scenario

Braking	Vehicle	Intervention	P(AIS 2+) Reduction	P(AIS 3+) Reduction	% Avoided
Profile 1	Struck	FCW	38.3%	38.5%	22.9%
Profile 1	Struck	AEB1	41.8%	42.4%	0.3%
Profile 1	Struck	AEB2	97.8%	97.8%	89.9%
Profile 1	Struck	AEB3	64.6%	65.1%	21.2%
Profile 1	Struck	FCW+AEB1	64.9%	65.4%	30.5%
Profile 1	Struck	FCW+AEB2	99.3%	99.3%	96.4%
Profile 1	Struck	FCW+AEB3	80.3%	80.6%	51.3%
Profile 1	Striking	FCW	45.0%	45.1%	22.9%
Profile 1	Striking	AEB1	63.4%	63.8%	0.3%
Profile 1	Striking	AEB2	99.3%	99.3%	89.9%
Profile 1	Striking	AEB3	81.7%	81.9%	21.2%
Profile 1	Striking	FCW+AEB1	79.6%	79.8%	30.5%
Profile 1	Striking	FCW+AEB2	99.8%	99.8%	96.4%
Profile 1	Striking	FCW+AEB3	90.3%	90.5%	51.3%
Profile 2	Struck	FCW	75.0%	75.1%	67.5%
Profile 2	Struck	AEB1	49.7%	50.3%	4.9%
Profile 2	Struck	AEB2	97.7%	97.8%	89.9%
Profile 2	Struck	AEB3	68.4%	68.8%	25.6%
Profile 2	Struck	FCW+AEB1	92.9%	93.0%	82.6%
Profile 2	Struck	FCW+AEB2	99.7%	99.7%	98.7%
Profile 2	Struck	FCW+AEB3	95.3%	95.4%	86.5%
Profile 2	Striking	FCW	78.0%	78.1%	67.5%
Profile 2	Striking	AEB1	70.2%	70.6%	4.9%
Profile 2	Striking	AEB2	99.3%	99.3%	89.9%
Profile 2	Striking	AEB3	84.2%	84.4%	25.6%
Profile 2	Striking	FCW+AEB1	96.3%	96.3%	82.6%
Profile 2	Striking	FCW+AEB2	99.9%	99.9%	98.7%
Profile 2	Striking	FCW+AEB3	97.9%	97.9%	86.5%

4.5 Implementation in UTMOST

Of the various system algorithms, we consider AEB1 to be the closest to current production systems. Driver braking profile 2 is the most similar to how drivers likely brake in panic situations on average, and it produces slightly conservative benefits estimates.

In UTMOST, the percent effectiveness assigned to FCW affects the four rear-end crash types: Lead-Vehicle Stopped, Lead-Vehicle Decelerating, Lead-Vehicle Slower, and Lead-Vehicle Other. The reductions are only applied if alcohol is not involved. For AEB, the reductions are applied if the alcohol is involved, since the system operates independent of driver response.

For the default effectiveness (presented to the user initially), which is based on Profile 2 and AEB1, FCW reduces lead-vehicle braking crashes by 74.6%, lead-vehicle fixed crashes by 77.5%, lead-vehicle slower crashes by 73.1% and cut-in crashes by 67.5%. The default reductions for AEB alone are 15.9%, 40.4%, 4.5% and 4.9% for LVB, LVF, LVS, and cut-in crashes respectively. Finally, the percentages for AEB and FCW combined (which would be typical for any vehicle equipped with AEB) are 87%, 94.6%, 86% and 82.6%.

5 Task 4: Supplementing a Driver's Understanding of an Advanced Driver Assistance System (ADAS)

5.1 Introduction

Advanced driver assistance systems (ADAS) present a growing opportunity to improve driver safety by alerting drivers to dangerous conditions and relieving drivers of tedious control tasks through automation. However, the actual effectiveness of these systems for improving safety often depends on how drivers adapt their driving behavior to these systems, which in turn depends on how well drivers understand these systems. Current ADAS technologies include operating characteristics that often violate driver expectations or, at best, do not conform to a driver's mental model of the system's function. Several studies have documented instances in which drivers fail to recognize that an ADAS is functioning properly. For example, in simulator studies, drivers equipped with adaptive cruise control (ACC) were found to be generally slower than drivers equipped with manual control in reacting to critical traffic situations. These situations include abrupt lead vehicle braking, vehicle cut-ins, the sudden appearance of stationary vehicles on the roadway, and system failures (Bianchi Piccinini, Rodrigues, Leitão, & Simões, 2015; de Winter, Happee, Martens, & Stanton, 2014; Hoedemaeker & Brookhuis, 1998; Larsson, Kircher, & Andersson Hultgren, 2014; Nilsson, 1995; Stanton, Young, & McCaulder, 1997; Stanton, Young, Walker, Turner, & Randle, 2001; Vollrath, Schleicher, & Gelau, 2011; Young & Stanton, 2007). Nilsson (1995) observed later braking among ACC-equipped drivers approaching a stationary queue compared to manual driving. Stanton, Young, and McCaulder (1997) observed four of 12 drivers fail to regain control of their vehicle when the ACC system accelerated into a forward vehicle. Hoedemaeker and Brookhuis (1998) observed larger braking maximums and smaller minimum headway times for drivers equipped with ACC. Larsson, Kircher, & Andersson Hultgren (2014) observed longer brake reaction times in response to cut-ins with ACC compared to manual driving. A similar pattern was also observed in a test-track study of Rudin-Brown and Parker (2004) where drivers with ACC took about 2.6 to 2.8 s longer to react to a lead vehicle's brake lights than when driving manually.

Recent theories of driver behavioral adaptation have suggested that drivers apply some form of attentional control policy/process to allocate and reallocate visual/cognitive resources to things that are important to the driver. This often occurs when a driver's workload declines. A driver's sense of workload is influenced by how much he or she believes that the ADAS technology has covered some part of the driving task. This belief is a direct consequence of what the driver believes the level of ADAS capability actually is—that is, the driver's mental model of the ADAS functionality. Especially with short simulator-based or test-track exposures, drivers have relatively little experience with ADAS systems and appear to be poor at recognizing when an ADAS reaches a limit or malfunctions in an unanticipated way.

Drivers appear to overgeneralize ADAS capabilities and they do not appear to remember operational exceptions (even if told) unless they are given more direct experience of the exception (Beggiato, Pereira, Petzoldt, & Krems, 2015). It is likely that when a driver is first exposed to an ADAS, he or she will try to match it to prior experience with a similar form of intelligent support—maybe even another human acting as an operator. This suggests that drivers may require substantially more time to develop an accurate understanding of an ADAS function, especially when the conditions where ADAS limitations are apparent are also uncommon. Longer-term studies of driver interaction with ADAS technologies thus seem warranted. Initially, this might help insure that the driver develops a reasonably accurate mental model of the ADAS capability. After stabilization of this mental model, continued observations may be warranted to investigate how driving behavior changes on the tactical and strategic levels. Recent work has begun to focus on longer observation periods to examine the evolution of trust and mental models (Beggiato & Krems, 2013) as well as the involvement of experienced users of the technology (Bianchi Piccinini et al., 2015).

For most drivers, the principal means used to describe the functions and limitations of an ADAS is primarily the owner’s manual or supplemental video instruction provided by vehicle manufacturers. While the information provided in these materials is usually detailed and complete, it is unclear how well this information is studied by new vehicle owners. It may well be that owner’s manual accounts of ADAS exceptions in functionality are not sufficiently salient to drivers, or that drivers underestimate the complexity of ADAS technologies and assume no special effort is required to understand these new technologies. ADAS performance exceptions are thus unlikely to become fully integrated into the driver’s mental model of the ADAS. There is evidence that drivers often do not accurately remember this information even after receiving direct training (AAAFTS, 2008; Beggiato & Krems, 2013; Dickie & Boyle, 2009; Jenness, Lerner, Mazor, Osberg, & Tefft, 2008). If a driver’s mental model is flawed, it may be reflected in a driver’s use of an ADAS. Different flaws are likely to be manifest in different kinds of behavior adaptation. Thus, a behavior adaptation to ACC may result in a delay in braking because the driver’s mental model of ACC braking authority is based on the drivers knows he or she herself is able to do. Similarly, a behavior adaptation to active steering may result in lane departures on tightly curved roads, because the driver’s mental model of steering control is based on what the driver already knows about his or her own steering ability.

A driver’s development of a flawed mental model can happen several ways. In some cases, the driver has limited information about the performance envelope of the ADAS. For example, while a driver may be cautioned about the limited braking authority of an ACC or limited steering authority of an LKA, these actual limits may not be clearly understood. In other cases, there are discontinuities in the ADAS behavior that depart from what might be considered a “natural” model. For example, drivers may be surprised by a steering assist system’s blindness to objects in the middle of the road, especially when the system seems to be clearly able to see lane lines so well. Many ACC systems do not react to stationary or approaching vehicles, but easily detect moving forward vehicles; they may also be blind to smaller objects in the roadway like motorcycles, bicycles, and pedestrians.

This research project investigates driver understanding of two ADAS technologies: speed assistance or ACC, and steering assistance, or lane keeping assistance (LKA). Prior research on ACC suggests that drivers are unlikely to remember “exception” conditions, where the ADAS reaches some kind of performance limit, unless there is more direct experience with this condition (Beggiato & Krems, 2013; Beggiato et al., 2015; Bianchi Piccinini, Rodrigues, Leitão, & Simões, 2014; Bianchi Piccinini et al., 2015). When a driver's principal source of information about the operation of an ADAS is the owner's manual, and boundary conditions are unlikely to be encountered during normal driving experience, it seems clear that gaps in a driver's understanding of the system will commonly occur (Dickie & Boyle, 2009; Jenness et al., 2008). More troubling is that new gaps may also arise, as memories fade and are not reinforced by experience. Such knowledge gaps may result in the driver developing unrealistic expectations about the technology's capability leaving drivers unprepared to take control when the technology falters (Merat, Jamson, Lai, Daly, & Carsten, 2014) or failing to recognize when a malfunction occurs (Strand, Nilsson, Karlsson, & Nilsson, 2014).

This study examines a driver's mental model of two ADAS's as drivers gain progressive experience with these systems implemented in two vehicle models over a 5-week period. The study specifically examines whether a supplemental narrative portraying the functionality of each system might plant a sufficiently memorable or compelling image of each system's function to influence a driver's mental model of the system's operation. Prior work suggests that supplemental materials can be effective in enhancing an individual's ability to retain detailed information, and to enable more accurate predictions about the behavior of complex systems (e.g., Kieras & Bovair, 1984; Mayer & Gallini, 1990).

5.2 Method

5.2.1 Subjects

Participants in this study were recruited from the local licensed driver population. Two age groups were selected: an older-driver group between 60 to 70 years of age (mean, 64.2 years), and a young/middle-aged group between 20-50 years or age (mean, 32.0 years). Each age group was divided evenly by gender. Overall, thirty-two drivers were recruited for the study. However, one driver dropped out of the study after three of the driving sessions. Drivers were also screened based on their driving records to ensure they had no more than two moving-violations citations over the last five years.

5.2.2 Materials

Supplemental Narrative. Supplemental narratives were developed to enhance half of the driver's training about the respective ACC and steering assist ADAS functions. The narratives had a few specific objectives in mind. First, we wished to portray each system's limited intelligence and control authority by using a cartoon image of a diminutive character that would not suggest either great intelligence or significant physical strength. For example, we characterized the speed assist capability (ACC) as the support offered by a small elf with limited visual capabilities—i.e., blindness to small or stationary objects—and limited braking authority, implied by the character's small stature. We also noted the subservient nature of the character, such that drivers would understand that any assistance offered by the character would stop should the driver appear to intervene in controlling the vehicle. The objective was to calibrate the driver's expectations about the system and to sensitize the driver to areas of the system's performance that might require the driver to devote some attention. A second, similar narrative was developed to characterize the steering assist capability. In this case, the character was a small lane-keeping monkey that single-mindedly looks to maintain the vehicle within lane lines. The monkey's intelligence was portrayed as limited and easily confused by lane markings in construction areas, or when lane markings are obscured by weather or even a dirty window. Drivers were also alerted to the fact that the monkey was not very strong and might not successfully maintain the vehicle in the lane on banked roads, sharp curvy roads, or in strong crosswinds. The length of the ACC narrative was 355 words; the steering assist narrative was 366 words. Appendix D contains narrative materials.

Surveys. Participants were given three surveys to complete. An initial survey was used to obtain general demographic information about each driver, their driving habits, and their general level of familiarity with in-vehicle support technologies (e.g., blind spot warnings, smart-phone integration, and adaptive cruise control). This survey, called the Start of Study survey, was administered at the beginning of the study. Three participant-level experiential predictors were derived from their answers: 1) self-reported miles/week; 2) percent miles of driving on limited access roadways; and 3) general familiarity with in-vehicle technologies. Two other surveys were administered after each drive session that probed each driver's knowledge of the vehicle's ACC and LKA system, called the ACC Survey and the LKA Survey.

To assess each driver's knowledge about the ADAS functions, a survey was developed in which specific questions were asked about circumstances where the ADAS might not be fully functional, but in which drivers often fail to recognize such ADAS limitations. For ACC, drivers often show limited awareness that motorcycles, pedestrians, or bicycles may not be detected; or that ACC may not react to slow-moving or stationary vehicles on the roadway; or that alignment problems on curvy roads may result in false readings; or that the ACC radar may be limited in active weather. The diagnostic questions developed for this study were based on questions used by Beggiato (2015) in his dissertation that probed a driver's understanding about the operating envelope of an ACC system. Besides probing each driver's understanding of the ACC, other questions were included that were related to subjective ease of use, use-strategies, and use-preferences. The particular questions that targeted a driver's mental model of ACC operation were as follows:

Rate your level of agreement with the following statements (5 levels):

- *The ACC detects all sizes of vehicle ahead of me*
- *The ACC can help boost my braking in an emergency*

Rate how well ACC is suited to the following traffic conditions (5 levels):

- *When you encounter a stopped vehicle in the roadway*
- *On curvy roadways*
- *Along roadways with bicycles and pedestrians present*
- *In snowy or rainy conditions*

Additional questions were developed for probing each driver's mental model of the steering assist system. As with the ACC questions, drivers were asked to rate how well the lane keeping assist can deal with the following key traffic situations (5 levels):

- *Construction zones*
- *Very curvy roadways*
- *Roadways with bicycles and pedestrians present*
- *Snow-covered roadways*
- *Rainy conditions*
- *Responding to objects in the roadway*
- *Responding to potholes*
- *Deer or other animals in the roadway*

The surveys also contained questions related to any degree of confusion a driver might have had during a drive session about the operation of each of the respective systems. For example, drivers were asked to judge how often the respective systems acted unexpectedly (e.g., "How often did the system unexpectedly intervene"); drivers were also asked to report their degree of confusion about whether the system is active, when it warns, and when it does not intervene.

5.2.3 Vehicles

Two late-model vehicles equipped with steering assist and ACC were selected for use in this study. The models differed in size and implementation of their ADAS functions as shown in Table 5-1. Model A was a compact sedan priced at the lower-end of the vehicle market. Model B was a mid-sized sedan priced about $10,000 more than Model A. The two models were chosen for their full speed range of support for cruise control as well as the differences between their steering assist systems. Model A's steering assist provided continuous lane centering control (LCC) and asserted control continuously during the drive as long as lane markings were detectable on the roadway. Model B's steering assist intervened only after the vehicle was detected at (or near) the lane boundary. While no physical measures of steering assertiveness were made, the overall impression was that Model B's steering intervention was comparatively subtle.

Table 5-1. Comparative attributes of vehicle models.

Attribute	Model A	Model B
Adaptive Cruise Control	4 following distances Low speed down to stop—full speed range ACC.	3 following distances Low speed down to stop—full speed range ACC.
Steering Assist	Keeps vehicle centered in lane—Lane Centering Control (LCC)	Returns vehicle to lane on detection of lane boundary—Lane Keeping Assist (LKA)
Size Class	Compact	Mid-size
Max Weight	2,923 lb	3,388 lb
Price (approximately)	$21,000	$30,000

5.2.3.1 Vehicle Instrumentation

For this study, vehicles were instrumented to permit reviewing each driver's session and to help identify any anomalous events that might occur during the drive. Consequently, an UMTRI data acquisition system (DAS) was installed each vehicle, along with a complement of sensors and cameras. The UMTRI DAS uses proven software and architecture that has collected over 3 million miles of data during multiple naturalistic driving studies with very high reliability (98%). Figure 5-1 shows the enclosure. For this study, the DAS was installed in the trunk or cargo area of the vehicle under test.

The main features of the UMTRI DAS (see Figure 5-1) are:

- Two CAN bus inputs
- Support for up to four NTSC cameras at 30 Hz frame rate, full frame.
- Audio input
- Two Gigabit Ethernet ports
- 4 USB ports for interfacing to external sensors or other devices
- 640 GB of automotive-grade removable hard disk storage
- 20 Hz timing-grade GPS receiver; allows improved accuracy using post process correction methods; Untethered dead-reckoning for accurate positioning during short outages such as under bridges.
- Dedicated microcontroller and backup battery for power management

Data collection (including four channels of continuous compressed B/W video) consumes approximately 200 MB/hour. This rate, an assumed 12 hour/day duty cycle per vehicle, and a disk utilization of 75% results in an anticipated download cycle of 50 days or more for naturalistic studies. For this study, since data collection periods were short, the video compression was reduced, allowing for higher image quality.

Figure 5-1. UMTRI's generation-5 data acquisition system (GEN5 DAC).

5.2.4 Procedure

Participants were recruited to drive one of the advanced technology vehicle models for approximately 1.5 hours along a prescribed route, once a week, for five drive sessions. The thirty-two participants were divided into an experimental group (16 participants) and a control group (16 participants). In the initial session, all drivers were given a consent form that detailed several aspects of the study and the nature of the drives. Each driver was assigned to drive either the Model A or Model B vehicle and provided with excerpts from owner's manuals of each respective vehicle that described the operation of each vehicle's ACC and LKA system. The drivers in the experimental group were also provided with supplemental narratives (described above) that associated the ACC system with a whimsical "fairy tale" about an elf and the LKA to a tale about a monkey (described earlier). Drivers were given as much time as they required to review these materials. The overall experimental design is shown in Figure 5-2 which depicts the study factors—age group (middle, old), gender (male/female), vehicle model (A/B), and the use of a supplemental story (yes/no)—and the subject counts for each condition.

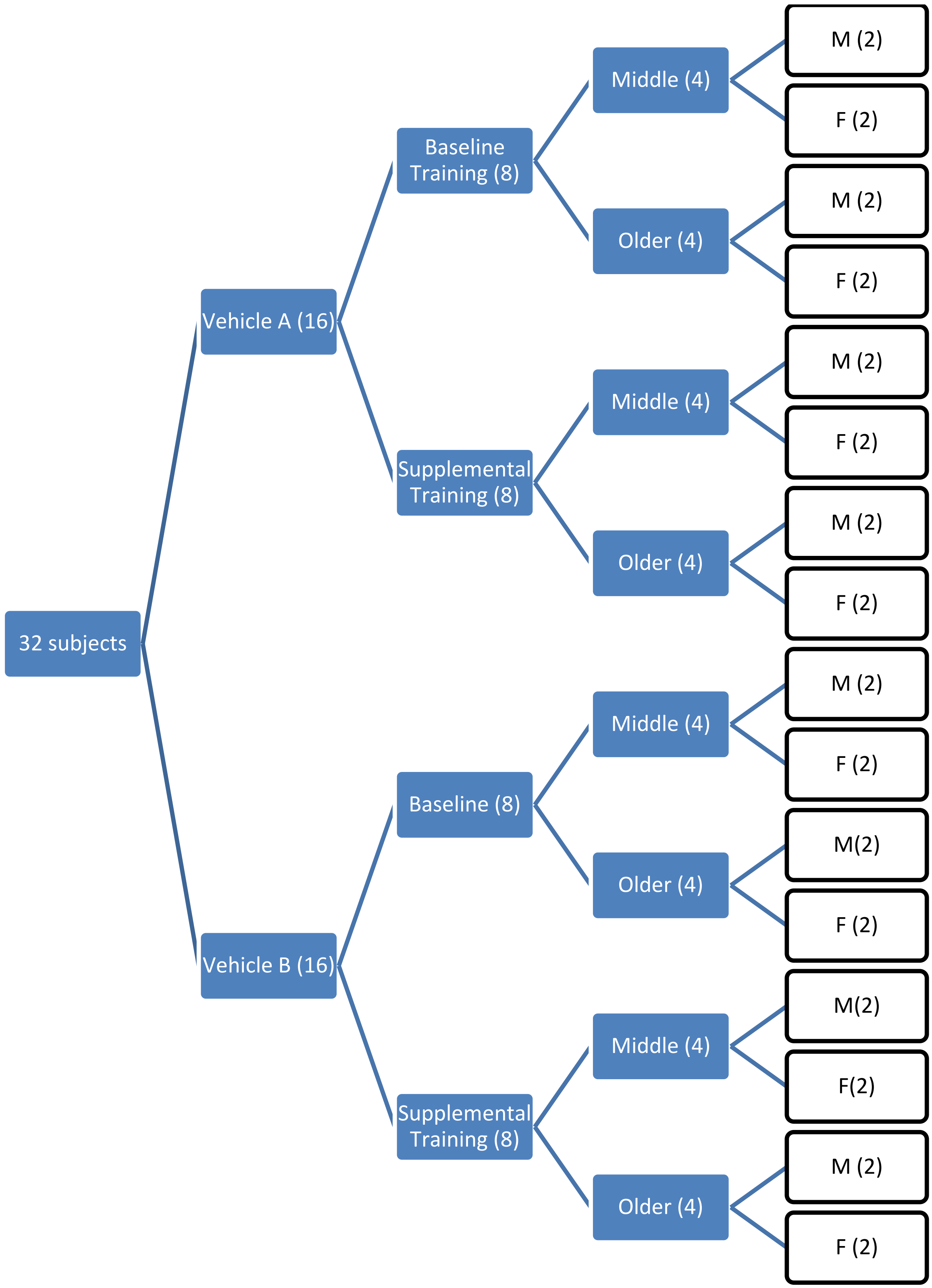

Figure 5-2. Distribution of subjects among factors: vehicles (A, B), training (Baseline, Enhanced), Driver Age (Middle, Older), and Gender (Male, Female).

Vehicle assignments to drivers were counterbalanced, with vehicle model serving as a between-subjects factor. Following review of the orientation materials, drivers were asked to drive a prescribed route along a limited access highway (i.e., 20 miles along southbound US-23, followed by 20 miles along northbound US-23) in the Ann Arbor area and asked to use the ACC and LKA systems as often as they felt appropriate. Drivers were also accompanied by experimenters seated in the rear of the vehicle. Experimenters were permitted to provide route guidance to participants, but did not provide any further information about the function of the ACC or LKA systems. If asked for information about the systems, experimenters advised participants that the study was interested in examining the early experiences of drivers becoming acquainted with this new vehicle technology, and that it was not likely that such a resource would be available to a new owner after taking possession of the vehicle. Participants were permitted to consult the owner’s manual after pulling off the road and stopping the vehicle. The overall drive was about a 40-mile round trip along a 2-lane divided highway with posted speed limits of 70 mph.

When the participants with the vehicle to UMTRI, both the ACC and the LKA surveys were administered directly after the drive session. Drivers returned to UMTRI about a week later to again drive the same route (also accompanied by an experimenter) and to complete another ACC and LKA survey. Five drive/survey sessions were conducted for each participant with the aim of monitoring the progression of a driver’s degree of understanding about each ADAS systems over the series of drive sessions.

5.3 Results

Survey answers were analyzed using a linear mixed effects model in which participant was modeled as a random effect and gender, age group, vehicle model, supplemental story were modeled as fixed effects. The principal analyses focused on answers to those questions that participants were most often likely to answer incorrectly if drivers overestimate or overgeneralize the capabilities of the ADAS. We will first review participant responses to the ACC mental model questions. This is followed by analysis of responses to the LKA questions. The analyses used the *lme4* package of the R statistical programing package (Bates, Machler, Bolker, & Walker, 2015) to perform a linear mixed effects analysis of the relationship between gender, age group, vehicle model, session number, and supplemental story on each dependent mental model measure. The preceding factors were modeled as independent fixed effects with the exception of an interaction between session number and supplemental training. This was done to determine if participants become more aware of system limitations with additional exposure, perhaps because of familiarity with the supplemental story. As random effects, we modeled separate intercepts for each participant. P-values were obtained by using the *anova* function from the *lmerTest* package in R, using the Kenward-Roger approximations for degrees of freedom (Kuznetsova, Brockhoff, & Christensen, 2014).

5.3.1 ACC Detects All Sizes of Vehicles

In both owner’s manuals, readers are explicitly cautioned that ACC may not detect small objects on the roadway. Despite this, drivers have been shown to eventually come to believe that the ACC system can detect “all forward vehicles” as well as motorcycles, as they gain progressively more experience with the ACC-equipped vehicle (Beggiato et al., 2015). Average rated level of disagreement with the statement that ACC systems are able to detect all forward vehicles appears to decline over the drive sessions. The fitted model estimated a small decline in rating by about 0.125 over successive sessions ($CI_{.05}$: -.24 to -0.01). A marginal difference was also observed between the models such that participants appeared more inclined to disagree that Model B detects vehicles of all sizes; the disagreement scores for Model B were about 0.33 greater than Model A ($CI_{.05}$: -0.02 to 0.68). Finally, an interaction was also observed between session and supplemental story; participants who were given the supplemental material appeared to have a less rapid decline over sessions in their level of disagreement that the ACC system is capable of detecting all forward vehicles. In particular, the slope of this rating decline was about 0.18 units shallower among the participants who received the supplemental story. This is illustrated in Figure 5-3.

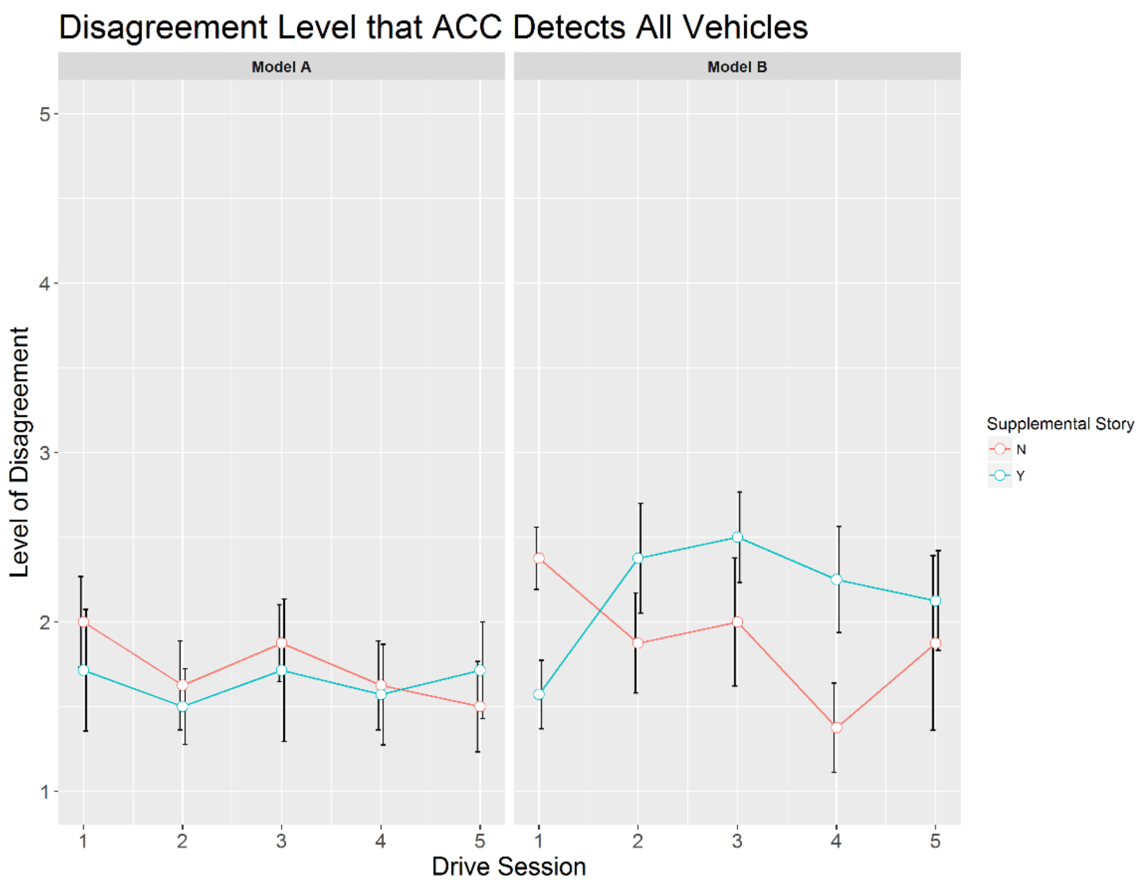

Figure 5-3. Average participant rating of disagreement with the statement that ACC detects all forward vehicles. Red indicates controls; blue indicates supplemental story condition. The difference in the two models is also apparent in this analysis.

5.3.2 ACC Can Boost My Braking in an Emergency Situation

This question attempted to understand the degree to which participants understood that any braking intervention that they might undertake would result in the ACC surrendering authority to the driver. This fact is noted in the owner's manual of each model. It also conforms to the general operating characteristics of conventional cruise control—any engagement of the brake results in cancellation of the cruise control function. This fact was also reinforced in the supplemental materials in which the two characters managing ACC and LKA were portrayed as timid and careful to surrender authority to the driver. Despite this, drivers appeared mildly to agree that it is true—that they would be assisted by ACC in emergency braking. No systematic influence of vehicle model, session number, and supplemental story, was observed on this effect (see Figure 5-4). A gender effect, however, was observed such that female participants appeared to disagree with their male counterparts by about 0.73 points about whether the ACC could assist in boosting emergency braking ($CI_{.05}$: 0.11 to 1.33); that is, female drivers disagreed that ACC would assist them with emergency braking. This is shown in Figure 5-4.

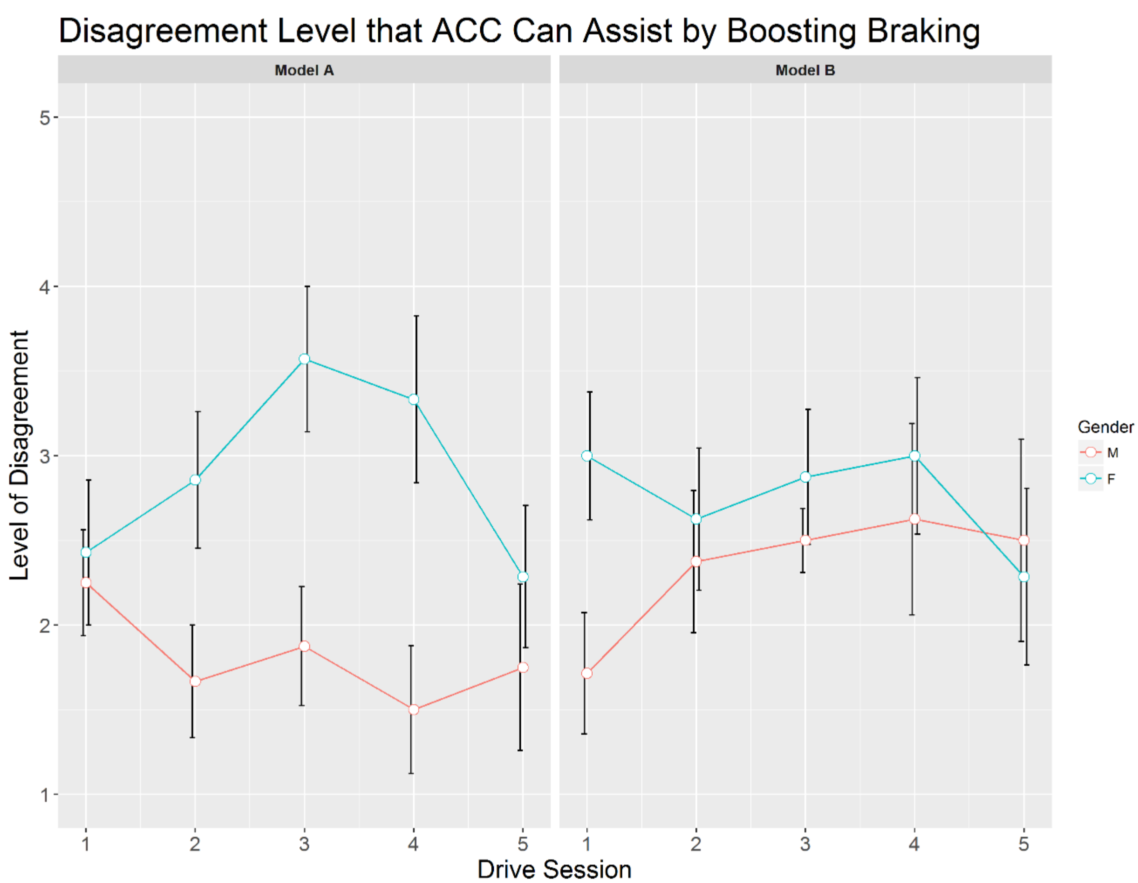

Figure 5-4 Average participant rating of disagreement with the statement that ACC can assist by boosting emergency braking.

5.3.3 Rated Inappropriateness of ACC around Stopped Vehicles on the Roadway

As before, both owner's manuals note that the ACC systems may not detect stopped or slow moving vehicles along the roadway. Despite this clearly described limitation, drivers appear to lose sight of this fact over time (Beggiato et al., 2015). Figure 5-5 shows the average ratings of judged inappropriateness over sessions for each model vehicle by each level of supplemental story introduced at the beginning of the study. In general, participants appeared to regard this roadway condition as less acceptable for ACC use, although participants who drove Model B generally appear to find it less acceptable than for Model A. Model B was rated on average to be about 0.8 points higher on the inappropriateness scale than Model A ($CI_{.05}$: 0.08 to 1.52).

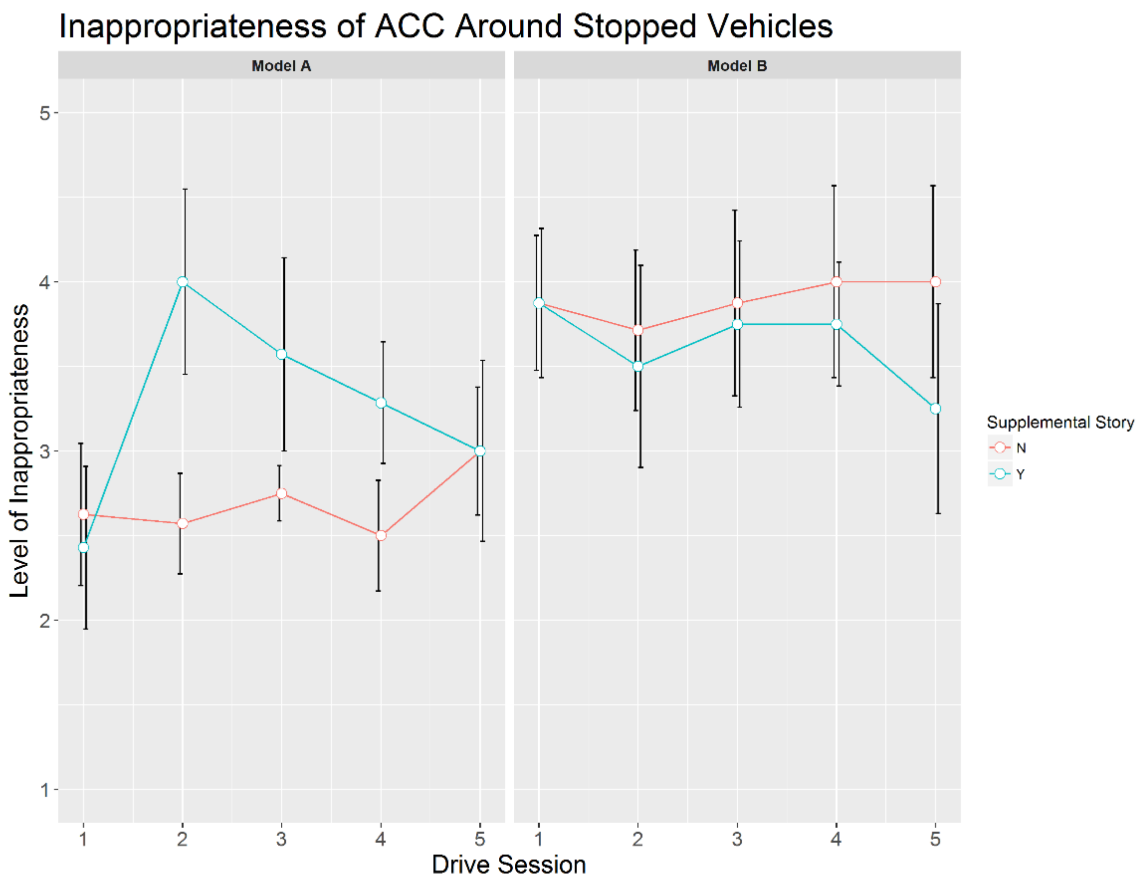

Figure 5-5. Average participant rating of the inappropriateness of using the ACC system around stopped vehicles on the roadway.

5.3.4 Rated Inappropriateness of ACC on Curvy Roadways

This question asked participants to evaluate the degree to which the ACC is suitable for use on curvy segments of roadway. For both models, participants were advised that the ACC radar might be misaligned with the forward direction on curvy roads. This could potentially lead the ACC to mistaking a vehicle in the adjacent lane as being directly in front, or a lead vehicle to be in an adjacent lane. Both owner's manuals illustrate the alignment problem and advise drivers to be careful using ACC on curvy roads. Despite this advice, the only effect observed on rated inappropriateness of ACC on curvy roads was associated with vehicle model, as shown in Figure 5-6. Drivers of the Model B vehicle systematically rated ACC use on curvy roads about a full point more inappropriate than drivers of the Model A vehicle ($CI_{.05}$: 0.45 to 1.55). No other effects were observed on ratings.

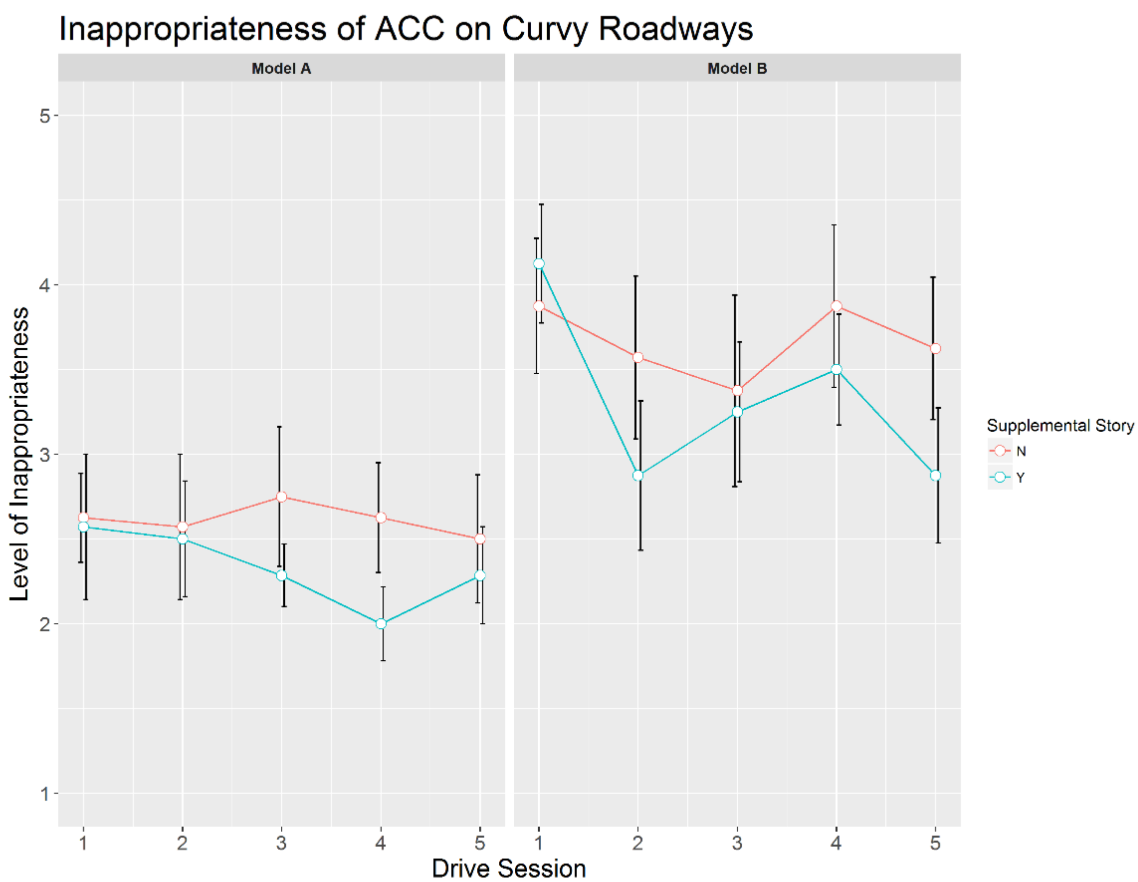

Figure 5-6. Average participant rating of appropriateness of ACC for curvy roadways.

5.3.5 Rated Inappropriateness of ACC on Roadways with Pedestrians and Bicyclists

This question is essentially an alternate way of asking drivers about the ACC's capability to detect small objects on the roadway. In both owner's manuals and in the supplemental story, drivers are advised about the ACC's limitations in detecting small objects. For both vehicles, drivers appear to recognize that the use of ACC on roadways with pedestrians and bicyclists is inappropriate. Scores are generally above the neutral score of 3 (i.e., the fitted model intercept was 3.27), suggesting that drivers appear to understand this (Figure 5-7). No systematic main effects were observed, although there appeared to be marginal effects of vehicle model and gender. Drivers of Model B rated use of ACC more inappropriate compared to drivers of Model A by about 0.5 points on roadways populated with pedestrians and bicyclists ($CI_{.05}$: -0.04 to 1.02). Female drivers rated use of ACC as more inappropriate compared to male drivers, also by about a half-point ($CI_{.05}$: -0.01 to 1.05). This difference is illustrated in Figure 5-7.

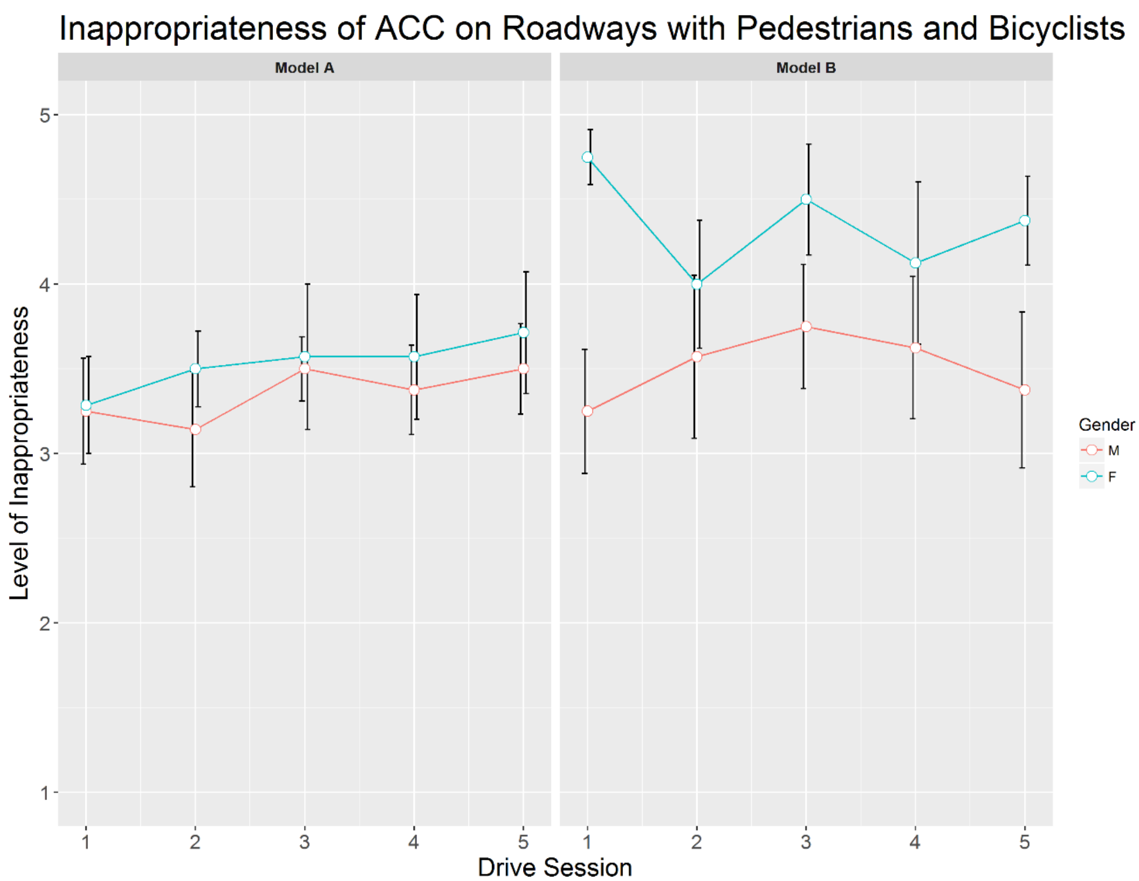

Figure 5-7. Average participant rating of inappropriateness of ACC around pedestrians and cyclists.

5.3.6 Rated Inappropriateness of ACC on Roadways with Active Weather

In this analysis, separate ratings about whether it is appropriate to use ACC in rain and snow were averaged together to produce a more general score related to active weather conditions. The average of this composite score is shown in Figure 5-8. While drivers generally considered it somewhat inappropriate (i.e., the intercept of the fitted model was 3.4), no system effect of session, model, age group, gender, or supplemental story was observed.

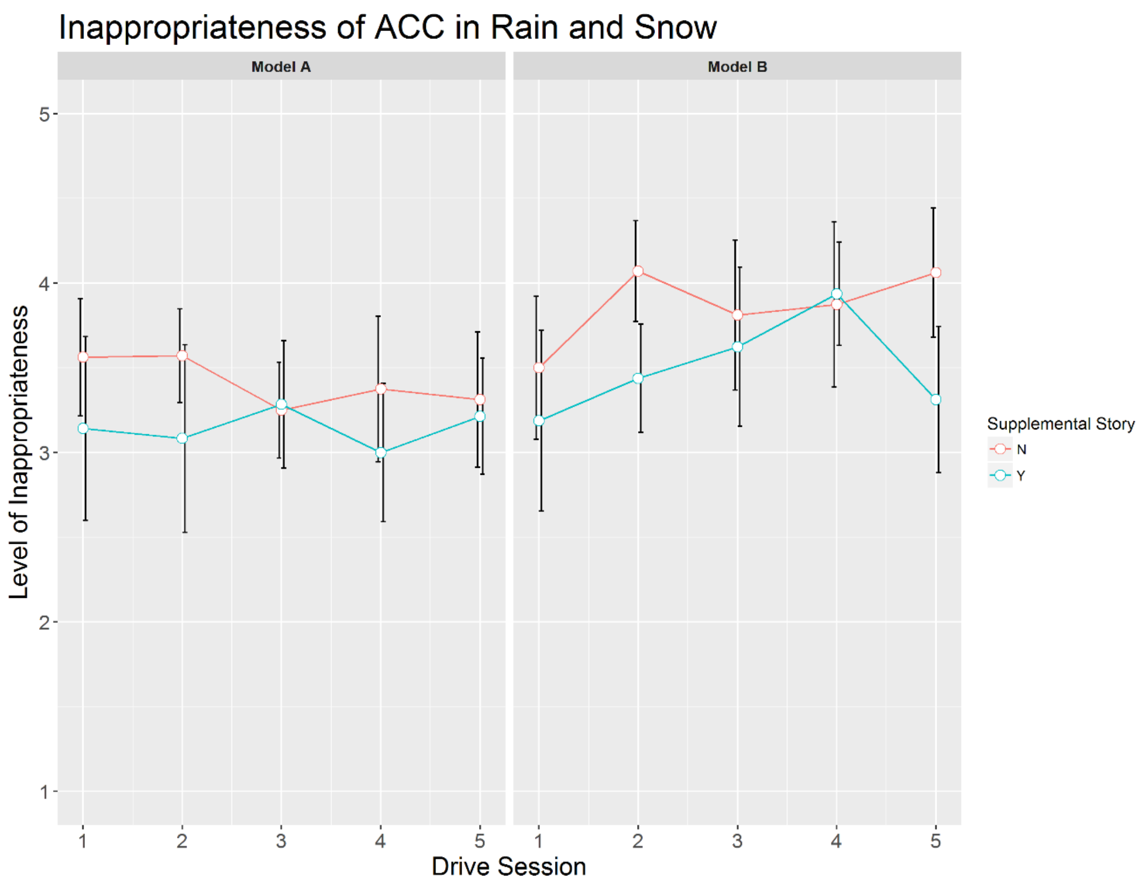

Figure 5-8. Average participant rating of inappropriateness of use of ACC in rain and snow.

5.3.7 ACC Results Summarized

For the ACC results, little change was observed in a participant's understanding of ACC over sessions. One notable exception was in a participant's disagreement that the ACC detects all vehicles on the roadway, which showed a small decline over sessions. While this decline was softened by the supplemental story, it nevertheless represents a decline in the accuracy of the participant's mental model of the ACC. No other session effects or supplemental story effects were observed for ACC.

Differences between the two vehicle models appeared to be more systematic. When a difference was observed, participants appeared more inclined to attribute limitations to the Model B vehicle; conversely, participants may also be characterized as more inclined to misattribute capabilities to Model A. This is summarized in Table 5-2.

Gender differences were also observed such that female participants appeared more inclined than male to disagree that ACC could boost braking in an emergency or find ACC more inappropriate to use around pedestrians.

Table 5-2. Differences in rated disagreement between drivers of Model A and Model B vehicles and driver gender regarding each model's capabilities or appropriateness in different roadway scenarios.

Capability	**Greatest Disagreement or Rated Inappropriateness**	
	Vehicle Model	**Gender**
Detects all vehicles	Model B	-
Boosts braking in emergency	-	Female
Around stopped vehicles	Model B	-
Curvy Roadways	Model B	-
Around pedestrians and bicyclists	Model B	Female
Use in active weather	-	-

5.3.8 Rated Inappropriateness of LKA around Construction Areas

In this analysis, participants were asked to rate the appropriateness of using the LKA system around construction areas. All participants were advised through the owner's manuals and supplemental story that LKA systems required clear and legible lane markings to guide the vehicle along the roadway. Notably, the route used in their drives had no active construction activity present. It is thus unlikely that participants had any opportunity to observe the LKA behavior under this condition. Participant ratings of the appropriateness of using LKA in a construction zone is shown in Figure 5-9. A main effect of session was observed such that participants increased their ratings of inappropriateness by about 0.18 each session ($CI_{.05}$: 0.06 to 0.31). No other main effects were observed.

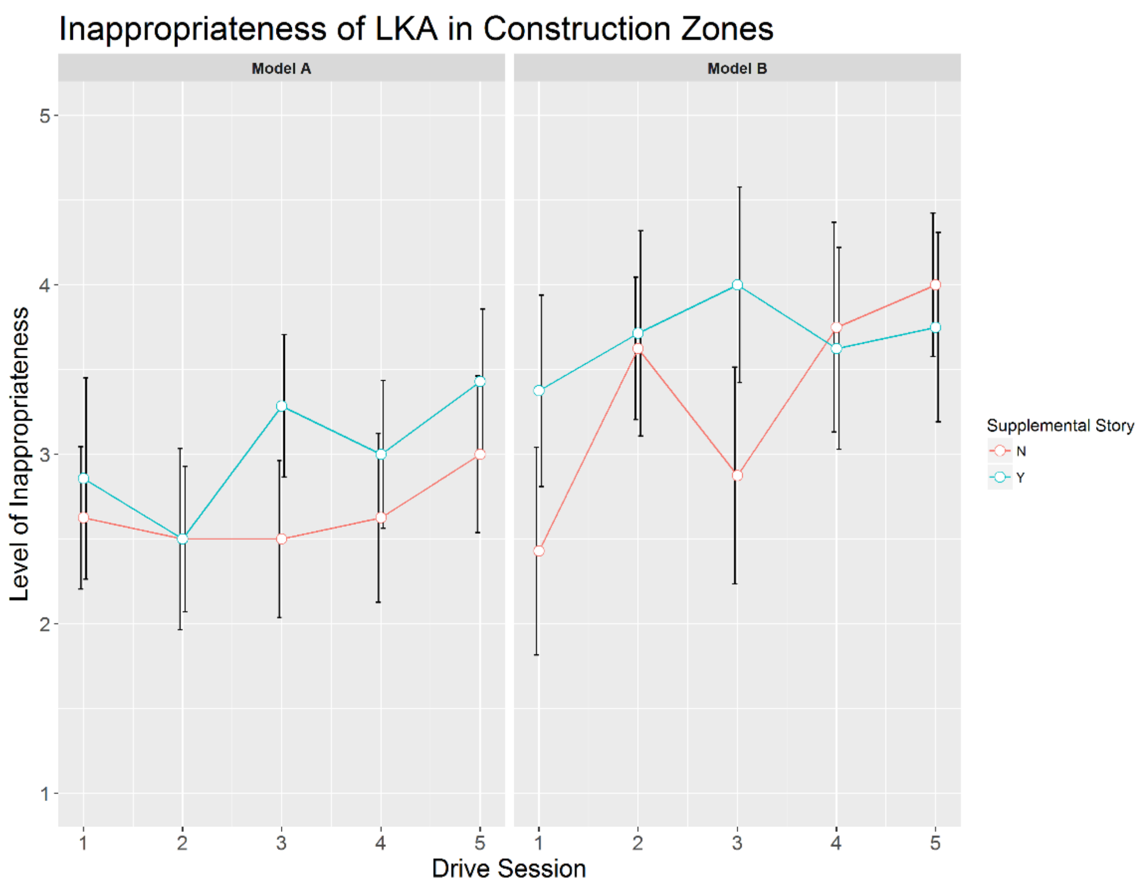

Figure 5-9. Average participant rating of level of inappropriateness of using LKA around construction areas.

5.3.9 Rated Inappropriateness of LKA on Roadways with Active Weather

Participants were generally advised that anything that interfered with the forward view of lane lines would limit the LKA's ability to guide the vehicle along the roadway. This included both rain on the windshield and snow on the roadway. As with ACC, separate ratings about whether it is appropriate to use LKA in rain and snow were averaged together to produce a more general score related to active weather conditions. Indeed, an auxiliary analysis found these answers to be highly correlated (r = 0.74 for ACC and r = 0.65 for LKA). A main effect of gender was found such that female participants found use of LKA about 0.6 points more inappropriate than male participants did (see Figure 5-10). No other effects achieved significance, although drivers of Model B rated LKA as marginally more inappropriate (by 0.51 points) in rain and snow than drivers of Model A (p = 0.103).

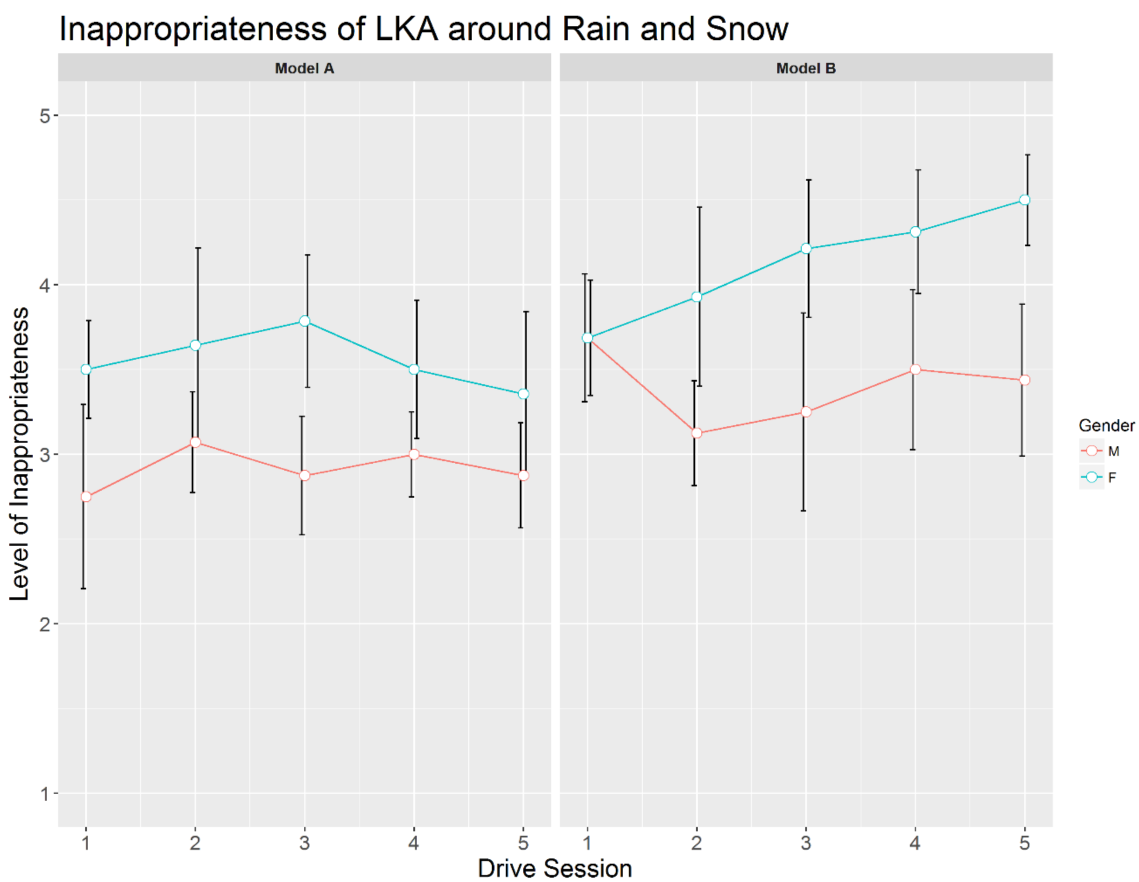

Figure 5-10. Average participant rating of level of inappropriateness of using LKA in rain or snow, illustrating observed differences in rating by gender.

5.3.10 Rated Inappropriateness of LKA around Curvy Roadways

This question asked participants to evaluate the degree to which LKA is suitable for use on curvy segments of roadway. Prior to the drive sessions, participants were advised that LKA might not have sufficient steering authority to maintain the vehicle in a lane if the road curved too much. An analysis of rated responses to the appropriateness of using LKA on curvy roads found a highly significant effect of vehicle model. Model B was, on average, considered 1.17 points more inappropriate on curved segments of road than Model B ($CI_{.05}$: 0.41 to 1.93). This is shown in Figure 5-11. No other effects were observed.

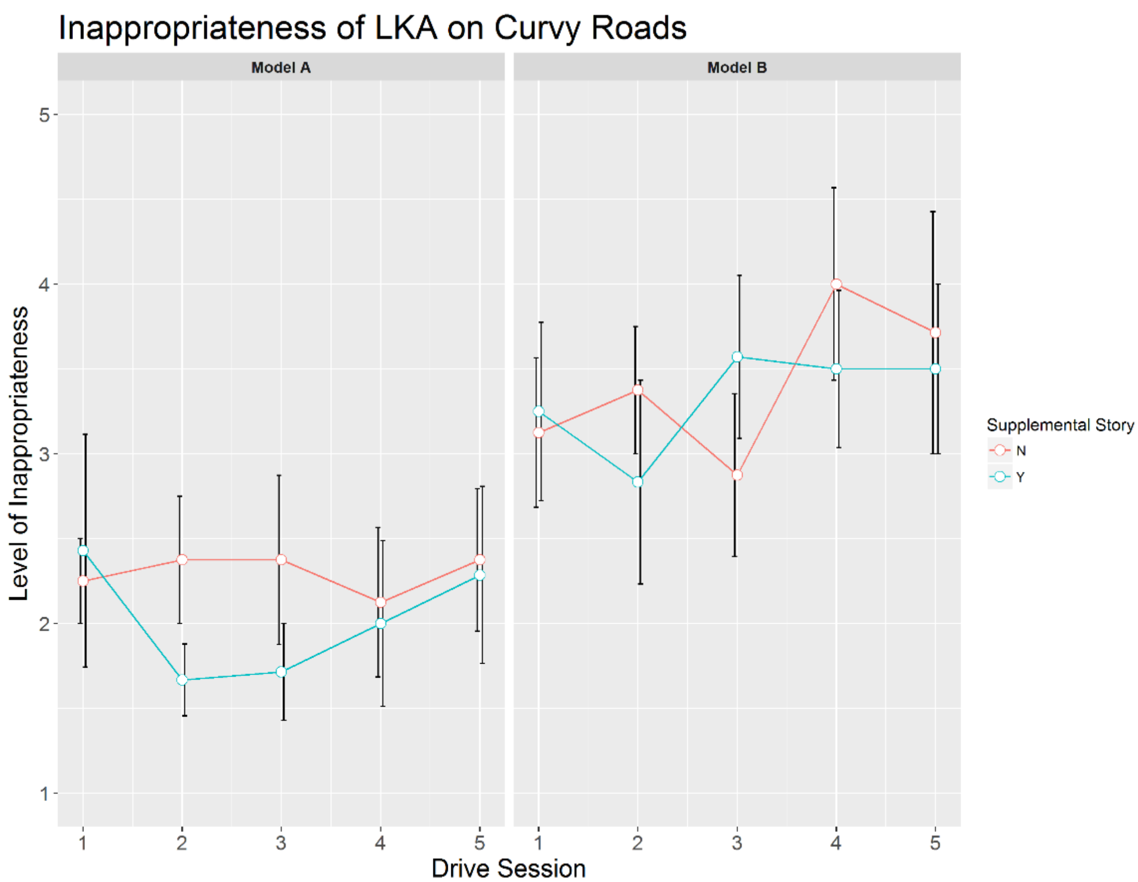

Figure 5-11. Average participant rating of level of inappropriateness of using LKA on curvy roads, illustrating observed differences in rating model vehicle driven.

5.3.11 Rated Inappropriateness of using LKA around Pedestrians and Bicyclists

This question attempts to determine how well participants understand that the LKA is indifferent to other roadway objects that are not lane lines on the road. A main effect of session number was observed in this analysis. In general, rated level of inappropriateness increased by about 0.1 point over successive sessions ($CI_{.05}$: 0.02 to 0.22). This trend can be seen in Figure 5-12. While the effect of vehicle model was marginal ($F_{(1, 25.9)} = 2.21$; $p = 0.15$), on average drivers of Model B rated use of LKA about 0.55 more inappropriate to use around pedestrians and bicyclists compared to drivers of Model A. Similarly, a modest gender effect was also observed such that female participants rated use of LKA about 0.56 more inappropriate to use around pedestrians and bicyclists than did male participants.

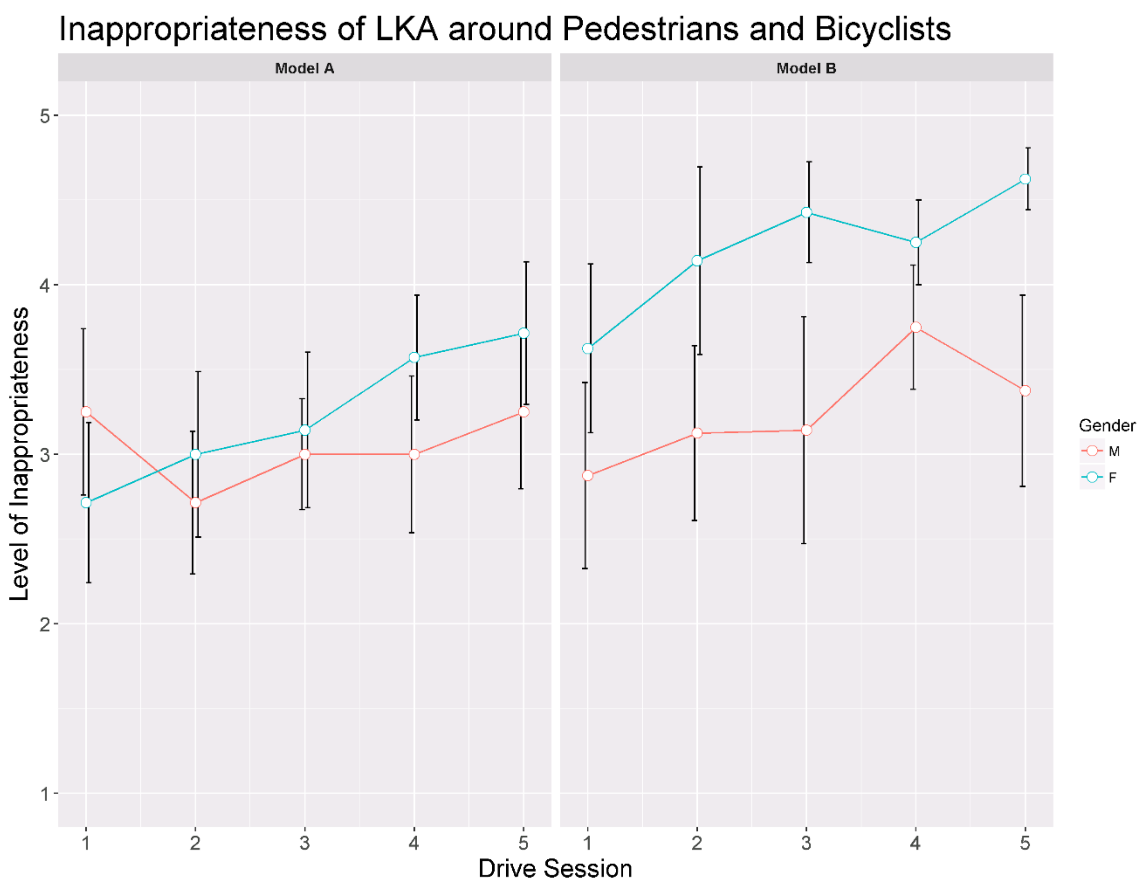

Figure 5-12. Average participant rating of level of inappropriateness of using LKA on roads in which pedestrians and bicyclists are present, illustrating observed session effects.

5.3.12 Rated Inappropriateness of LKA around Deer, Potholes, Small Debris (Combined)

This analysis averaged together survey ratings of inappropriateness for three questions that generally address the same issue: How well is the participant aware that the LKA system does not respond to any animals, potholes, or other objects (like debris) lying in the roadway? The results suggest that participants are generally aware that it is inappropriate to expect that LKA can provide any support for the driver—across sessions, their average rating is above 3 points indicating a rating on the inappropriate side. In addition, there is a main effect of session such that over successive sessions, rated inappropriateness increases by about 0.1 every session ($CI_{.05}$: 0.03 to 0.18). There is also a main effect of vehicle model. Participants who drove Model B systematically rated the LKA on that model more inappropriate to use around deer, potholes, and small roadway objects. Compared to Model A, Model B's LKA was rated as more inappropriate by about 0.74 points ($CI_{.05}$: 0.17 to 1.30). Finally, a marginal gender effect was also observed ($F_{(1, 25)} = 3.3$; $p = 0.08$), similar to the gender effects discussed previously. Female participants appear to regard the LKA as more inappropriate to use in this context than male participants. Female ratings of inappropriate were about 0.55 points higher than the male ratings ($CI_{.05}$: -0.01 to 1.22).

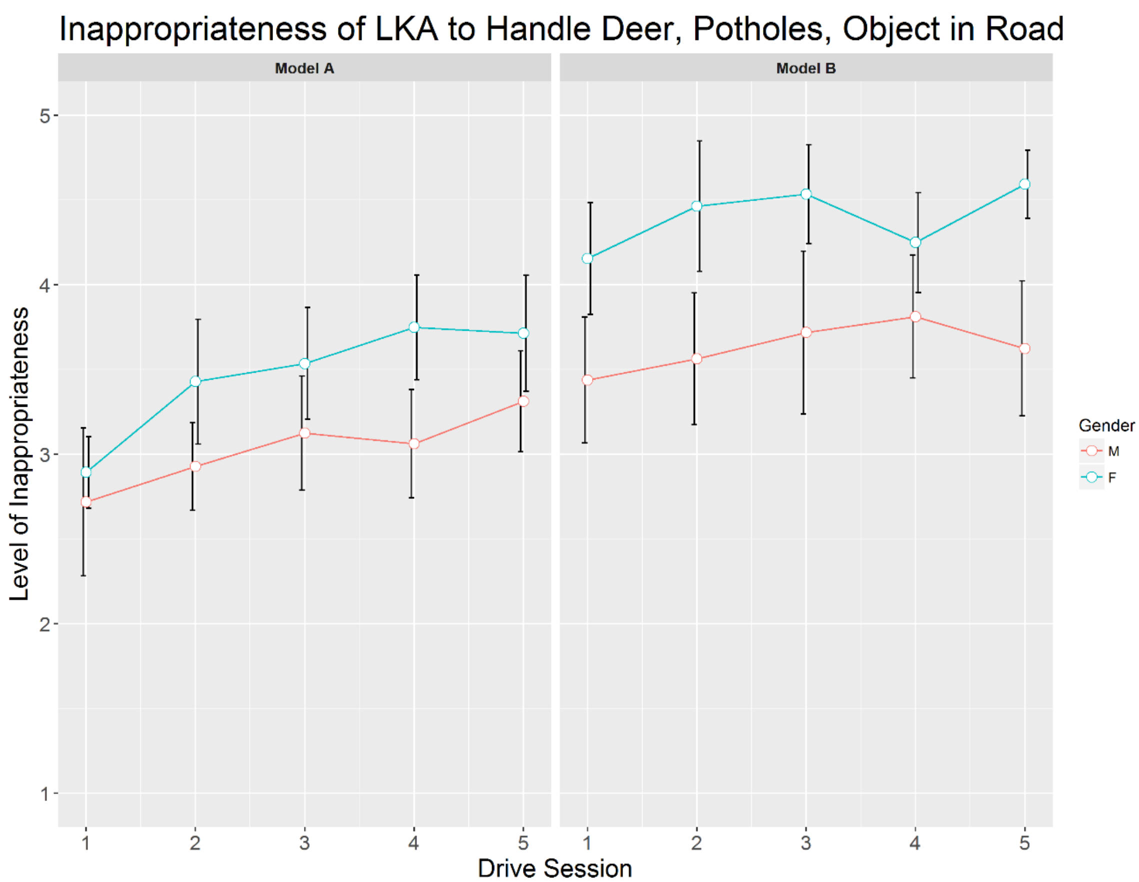

Figure 5-13. Average participant rating of level of inappropriateness of using LKA on roads in which deer, potholes, or other debris might be present. Main effects were observed in session and model; a marginal effect of gender was also observed.

5.3.13 LKA Results Summarized

Unlike the ACC results, there appeared to be more evidence of changes in participants' opinions of the LKA system's capability over the five driving sessions, although not for every area we examined. We also observed differences in the two model vehicles along similar lines observed with the ACC system. In particular, drivers correctly rated Model B more heavily as inappropriate to use in many contexts, compared to Model A. Finally, we also found female participants' ratings on inappropriateness to be systematically greater than male participants' ratings.

Table 5-3. Differences in rated disagreement between drivers of Model A and Model B vehicles and driver gender regarding each model's capabilities or appropriateness in different roadway scenarios.

Capability	**Greatest Disagreement or Rated Inappropriateness**		
	Session	**Vehicle Model**	**Gender**
Construction areas	Increase	-	
Use in active weather	-	*Model B**	Female
Curvy roadways	-	Model B	-
Around pedestrians and bicyclists	Increase	*Model B**	*Female**
Around deer, potholes, debris	Increase	Model B	*Female**

Note: Marginal effects in the above table are indicated in italics and asterisk.

5.4 Discussion/Conclusion

In general, the effort to influence a driver's understanding of the ACC and LKA systems using the supplemental story did not appear to be compellingly successful. Indeed, there appeared to be some influence of the story on the drivers' belief that ACC could detect all objects in the roadway, but this influence does not appear to extend to many other cases. Indeed, for ACC, there was little evidence that driver's understanding changed much over the five drive sessions. For LKA, there appeared to no influence of the supplemental story on drivers' understanding of system limitations, although in three judgments—construction areas, around pedestrians and bicyclists, and other roadway objects—driver ratings of inappropriateness increased systematically. This result indicates that exposure to different ADAS systems over time are likely to affect drivers' understanding differently. We note that, unlike Beggiato et al. (2015) in their study of ACC, we did not see the systematic declines in driver understanding over sessions. This may be a consequence of providing drivers with two ADAS systems to review, and fielding two different vehicle models.

We also note that participant ratings of the two vehicle models used in this study often differed markedly, with drivers of Model B often rating their ACC and LKA systems more strongly inappropriate in driving contexts in which they are indeed inappropriate. Since the two models differed in many dimensions, the exact basis of this difference is unclear. We suggest that one compelling difference is that Model A featured a lane-centering LKA system in which the vehicle's steering interventions were continuous and obvious to drivers. It is possible that these continuous interventions created a strong sense in drivers that the vehicle was actively providing guidance throughout their drive. While some drivers found this characteristic potentially annoying, others may have found this to inspire some level of comfort or confidence that the system was on the job. Systematic measures of driver attitudes regarding these differences were not taken. In any case, it is likely that the Model A drivers observed many more LKA interventions than did Model B drivers. Indeed, Model B LKA interventions occurred only when the vehicle was near or over the lane edge. Consequently, over a given drive such interventions did not occur frequently. One possible result of this might be that Model A drivers trusted (or maybe over trusted) their vehicle's ADAS capabilities more than Model B drivers. This could perhaps lead Model A drivers to overestimate the capabilities of these systems.

Finally, we note that the observed gender effect suggests that female drivers are less inclined to rate ACC and LKA systems as appropriate to use in a variety of inappropriate contexts than their male counterparts. Conversely, male drivers may be more inclined to believe ADAS technologies are more capable than they may actually be.

6 Task 5: Lateral Assist Systems – Effectiveness and Benefits Estimation

Task 5 addresses lane and road departure crashes, and consists of a set of activities to estimate the effectiveness and potential safety benefits of lateral assist systems, particularly LDW and LKA. This section begins with studying crash types and mechanisms that are associated with lane- or road-departure events and possibly amenable to LDW and/or LKA. Subsequent sections select key scenarios and develop simulation approaches to support the subsequent analysis of effectiveness. These results are implemented in UTMOST. An extra consideration regarding the authority level of LKA is made, using naturalistic driving data to study the question of whether a high-authority LKA would possibly encounter driver acceptance issues.

6.1 Characteristics of Lane- and Road-Departure Crashes

This section addresses the characteristics of lane- and road-departure crashes involving light vehicles that may be remedied by LDW and/or LKA. Light vehicles (LTVs) include all passenger cars as well as light trucks and vans, using the same definitions used by NHTSA (NHTSA 2014). LTVs include automobiles (convertibles, coupes, sedans), sport utility vehicles (SUVs), minivans, standard vans, and light-duty pickup trucks.

Lane- or road-departure (L/RD) crashes were defined as crashes initiated by an LTV departing a lane or roadway. Such lane departure crashes can result in a number of different crash types, including run-off road crashes in which vehicles ran off roads under control[1] and either collided with objects off road or rolled over; same-direction sideswipes, in which vehicles struck another vehicle going in the same direction in another lane; or opposite-direction sideswipes and head-on collisions. In each of these crash types, the initiating event of collisions was departing a lane, with some sort of collision or other harmful event (e.g., rollover) ensuing subsequently. In some of the crashes, departing the lane also resulted in departing the road, without an intervening collision with another vehicle. The combination of lane departure and road departure crashes, which are the target of the analysis, will be referred to as L/RDs. The defining commonality of the crash types evaluated was going out of lane as the initiating event.

The goal of the crash analysis was to classify L/RD crashes into distinct categories that would support identifying the *mechanisms* that produced lane/road departures, to identify and evaluate *interventions* with the potential of reducing these lane/road departures.

Not all L/RD crashes are considered here. Some L/RD crashes were initiated by mechanical failures, such as tire blowouts, or by environmental conditions, such as icy or snow-covered roads. These conditions produced loss of control (yaw or skid) that resulted in going out of lane and crashing.

[1] Meaning the vehicles were tracking at the lane departure, without any skidding or yaw coded in the crash data, prior to departing the lane.

However, the focus here is on *driver-related* interventions, interventions that address driver error or failure to control the vehicle, rather than addressing vehicle-related failures or environmental conditions, which might be addressed by more durable tires or better low-friction traction. Therefore, L/RD crashes that were initiated by loss of control prior to crossing the lane lines were excluded.

For an analogous reason, lane/road crashes precipitated by drivers using drugs or driving under the influence of alcohol were also excluded. The interventions considered in this project attempt to aid drivers to stay safely in lanes through warnings or gentle guidance back into lane. The research team excluded drugged or drunk drivers because the range of their responses to the warnings and alerts was unknown and likely to be significantly variable, related to the degree of intoxication.

The effect of excluding alcohol/drugs was to reduce the total crash population (all types of crashes) by about 2.9%. But the effect on L/RD crashes was much greater: About 14.7% of all LTV involvements in L/RDs were related to alcohol and drugs. This is because certain crash types tend to be related to driver use of alcohol or drugs. For example, about 25% of road departures were related to alcohol or drugs, and about 15% of opposite-direction crashes (head-on crashes and sideswipes) involved alcohol or drugs. But L/RD crashes with drugged or drunk drivers were excluded because they fall outside of the interventions being considered currently.

Table 6-1 specifies the L/RD crash types developed, along with hypothesized causal mechanisms. The first three types are all road departures, in which vehicles departed a road, while stable, not yawing or skidding, but still tracking. The crashes were further divided between departures while going straight, while negotiating a curve, and in other situations. Drivers going straight or negotiating a curve were simply lane-keeping, that is, not engaging in other maneuvers. Road departures during such a simple driving task suggest the drivers were not engaged in the driving process for some reason, and allowed the vehicles to drift off the road. Road departures while steering through a curve may include disengaged drivers as well, but may also be the result of excessive speed—entering the curve too fast to be able to stay on the road. The final road departure crash category combines all other crash situations in which vehicles departed the road, while still under control. Many of these occurred when the vehicles were turning at an intersection, left or right. The vehicles were still tracking but the drivers were unable to stay on the road.

Same-direction sideswipes included all cases where vehicles departed their lanes and collided with another vehicle, often in the adjacent lane, going in the same direction. Geometrically, many were simple lane-changes. They could have resulted from drivers failing to look before changing lanes, or, in some cases, disengaged drivers drifting into adjacent lanes.

Opposite-direction lane-departure crashes were classified by whether they occurred while the driver was just going straight, negotiating a curve, or some other action—paralleling the classification of road departure crashes. The driving task in going straight or negotiating a curve was simply lane-keeping; departures out of the lane may have been due to distraction or disengagement from the driving task, and in curves, again, a possible additional explanation could have been excessive speed.

The final set included all other opposite-direction crashes, where the vehicles were engaged in maneuvers other than just lane-keeping. These included errors in overtaking and passing.

Table 6-1 Lane/road departure crash types, with description and hypothesized mechanisms

L/RD taxonomy	Description	Candidate mechanism/interventions
Drove off, going straight	Departed road under control, pre-crash maneuver was going straight.	Distraction, disengagement. Probably most susceptible to LDW or LDP.
Drove off, negotiating a curve	Departed road under control, pre-crash maneuver was negotiating a curve.	Some likely from distraction or disengagement, but others may be related to excessive speed in a curve, so curve speed warning or autonomous braking might address.
Other drove off (maneuvering)	Departed road under control, pre-crash maneuver was other than going straight or negotiating a curve. Many were turning left or right.	Many are preceded by turns at intersection; these could be excessive speed or other vehicle control issues.
Same direction sideswipe	Includes all cases of same direction sideswipe.	Presumed mechanism is mainly lack of surveillance prior to lane change; some could be disengagement.
Drove into opposite direction, going straight	Cross into on-coming lane, pre-crash maneuver was going straight.	Distraction, disengagement. Some could be judgment errors while passing.
Drove into opposite direction, negotiating a curve	Cross into on-coming lane, pre-crash maneuver was negotiating a curve.	Two primary mechanisms hypothesized: Disengagement/distraction and excessive speed in a curve.
Drove into opposite direction, other maneuver	Cross into on-coming lane, pre-crash maneuver was other than going straight or negotiating a curve.	This is a miscellaneous type, but errors in passing/overtaking likely.

Table 6-2 shows the annual average frequencies of the L/RD crash types just described. In addition, estimates of all other single-vehicle crash involvements, other two-vehicle crash involvements, and all other involvements are shown for perspective and comparison. The other single-vehicle involvements group included crashes with pedestrians and other nonmotorists, as well as road departure crashes precipitated by loss-of-control and others that did not fit in with the types described above. The other two-vehicle crash involvements group included all crashes in which an LTV was one of the first two vehicles in a crash. The other crash category include mainly LTVs involved in a crash after the first two vehicles, or other miscellaneous crashes, such as U-turns and on-road rollovers.

L/RD crashes accounted for about 6.7% of LTV crash involvements annually **(Table 6-2**). Same-direction sideswipes were the most frequent L/RD crash type, accounting for about 48.1% of the involvements. Drove off, going straight was the second most common, with about 155,746 crashes, 1.8% of all crashes, but 26.4% of L/RD crash involvements. As a group, the opposite-direction crash types were the least frequent, yet they tended to be the most severe, because the vehicles were moving in opposite directions.

Table 6-2 Average annual involvements of LTVs in L/RD crashes and other crash types

Crash type		N	%
Lane/road departure crashes	Drove off, go straight	155,746	1.8
	Drove off, neg. curve	53,513	0.6
	Other drove off	46,016	0.5
	Same direction	283,704	3.2
	Opp. dir., go straight	31,488	0.4
	Opp. dir., neg. curve	15,706	0.2
	Opp. dir., other	4,134	0.0
All lane/road departure		*590,307*	*6.7*
Other single-vehicle		1,001,323	11.4
Other two-vehicle		6,543,333	74.4
Other/unknown		657,746	7.5
Total		8,793,333	100.0

Further characterization of L/RD crash types is presented in Appendix E. Many additional details are presented there, but the highlights include:

- The seven L/RD crash types can be categorized into three general types: ran-off-road, same-direction sideswipes, and opposite-direction sideswipe and head-on collisions.
- The three types varied in terms of severity. Only 0.6% of same-direction sideswipes resulted in a fatality, compared with 5% of ran-off-road types, and 8% of opposite-direction crashes.
- Younger drivers (25 or younger) tended to be overinvolved in run-off-road crashes, while older drivers (65 and over) were overinvolved in same-direction sideswipes.
- Younger drivers were identified as fatigued or distracted at higher rates than older drivers.
- Younger drivers had higher involvement in L/RD crashes that involved turning or steering through curves.
- Electronic stability control clearly reduced ran-off-road crashes, but younger drivers tended to have higher rates nonetheless.

Case review of L/RD crashes

Case materials from the National Motor Vehicle Crash Causation Study (NMVCCS) were used to provide an enriched understanding of the L/RD crashes. NMVCCS information available for review includes crash scene diagrams; photos of crash scenes, often including the vehicles in their final positions; photos of each vehicle interior and exterior, showing damage; and the researcher's narrative of crash events and causes. Together, this material provides a significantly enhanced understanding of how the crashes occurred.

NMVCCS cases from each L/RD crash type were sampled for the review. The cases were reviewed for a number of purposes. The first purpose was to confirm or reject the general understanding of how the crashes occurred. For example, our understanding of the drove-off-road while going straight crashes was that the vehicles departed the road at a shallow angle with no driver intervention. The second purpose was to attempt to identify causal mechanisms for the different crash type, to determine the reasons for the specific crash types. The fundamental L/RD crash types were developed around a set of hypotheses for how they occurred. In the case of same direction sideswipes, one possible mechanism was disengaged drivers drifting out of lane into a vehicle in the adjacent lane. Another was a deliberate lane change but the driver failed to see the other vehicle. Case review of a set of crashes allowed us to confirm the fundamental understanding of how the crashes occurred as well as to determine specific mechanisms.

The classification rules developed in the GES data to identify L/RD crashes were applied to NMVCCS cases to identify a sets of crashes that fell into each category. Crashes in which the driver was coded as fatigued were excluded to focus on mechanisms with alert drivers. A total of 201 crashes with nonzero weights[2] were sampled. NMVCCS case materials were reviewed for each crash.[3]

Information about each crash was reviewed separately by two coders, who compared results and reconciled any differences in coding. Data collected for each case included crash mechanism, whether drivers overcorrected prior to the collision, presence of shoulders, type of shoulders, the start lane for the vehicle, the lane (or off road) into which the vehicle moved, the presence and condition of lane markings, and a brief description of the crash.

Table 6-3 shows the percentage distribution of top-level mechanisms identified for the NMVCCS L/RD crashes. Avoidance was coded when a driver made a maneuver to avoid another vehicle, but the maneuver resulted in a lane departure and collision with another vehicle.[4] Disengaged refers to drivers who were not actively engaged in piloting their vehicles; instead their attention was directed elsewhere or they were not paying attention at all. Physical control was used for crashes where drivers were unskilled and failed to maneuver safely. These drivers were often younger and likely inexperienced. Cases were coded "too fast" if excessive speed was noted as a factor, such as entering a curve at an unsafe speed. Surveillance was used for crashes in which drivers were intentionally changing lanes but failed to see the other vehicles. The "other" category includes a variety of situations, primarily hit-and-run cases where no causal mechanism could be inferred, vehicle failures, or medical emergencies. Note that if avoidance and the "other" crashes are outside the bounds of currently-contemplated interventions, then about 70% of lane/road departure crashes could be addressed, based on this review.

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[2] NMVCCS is a sample file, with case weights that are used to compute population estimates. The data files include cases with zero values for the case weight. These cases were either from the pilot phase of the project or it was later determined that they did not meet the selection criteria.

[3] Case materials may be accessed at http://www-nass.nhtsa.dot.gov/nass/nmvccs/SearchForm.aspx.

[4] Note that pre-crash avoidance maneuvers should have been filtered out because one of the criteria for L/RD crashes was that the vehicles were just lane keeping (i.e., going straight or negotiating a curve). However, in 11.4% of the L/RD crashes, the researcher's narrative recorded that the driver leaving the lane was reacting to the movement of another vehicle on the road.

Table 6-3 Top-level L/RD crash mechanisms, weighted

Mechanism	%
Avoidance maneuver	11.4
Disengaged	30.4
Physical control	13.8
Too fast	8.7
Surveillance	17.0
Other/unknown	18.7
Total	100.0

The distribution of causal mechanisms for the L/RD crash types were reasonably consistent with expectations. Table 6-4 shows the distribution of mechanisms for each L/RD crash type. Drivers were coded as disengaged in about half of the road departure crashes in which the vehicle went off road while going straight or negotiating a curve. About 13-15% were precipitated by poor physical control, and about 27% of the crashes in which a vehicle drove off the road while negotiating a curve were related to speed. It was expected that run-off-road crashes on curves would be more likely related to speed than on straight roads. Opposite-direction crashes were related more often to physical control or going too fast, with an elevated proportion of opposite-direction crashes in curves related to speed or physical control. The same-direction cases were largely related to surveillance failures, though in 27.6% of the cases, the crash was precipitated by an avoidance maneuver. Only 5.2% of these same-direction crashes were related to driver disengagement. In fact, if avoidance and the other category are excluded, same-direction sideswipes were almost all related to surveillance failures.

Table 6-4 Percent distribution of mechanism by L/RD crash type

L/RD type	Avoidance maneuver	Dis-engaged	Physical control	Too fast	Adj Traffic Surveillance	Other (specify)	Total
Drove off go straight	0.8%	58.0%	12.9%	1.2%	0.0%	27.1%	100.0%
Drove off neg. curve	0.0%	49.0%	15.0%	27.6%	0.0%	8.4%	100.0%
Other drove off	16.3%	19.1%	23.0%	34.1%	0.0%	7.5%	100.0%
Same direction	27.6%	5.2%	2.3%	0.0%	53.7%	11.2%	100.0%
Opp. dir., go straight	5.1%	25.0%	9.5%	13.0%	0.0%	47.5%	100.0%
Opp. dir. neg. curve	1.4%	18.6%	46.7%	7.6%	0.0%	25.7%	100.0%
Opp. dir. other	25.6%	50.8%	9.8%	3.1%	10.0%	0.7%	100.0%
Total	11.4%	30.4%	13.8%	8.7%	17.0%	18.7%	100.0%

Coders also classified the rate, in terms of lateral velocity, of lane departure into general categories. The purpose was to obtain a general understanding of the available time for interventions. If lane departures were gradual, with a low lateral velocity, there would be more opportunity to alert a driver than if lateral velocity was high. Three broad categories were coded: gradual drift out of lane; a more abrupt departure, consistent with a deliberate lane change; and a lane departure with a large angle (>20 degrees) of departure.

Crashes in which vehicles departed the road while going straight or negotiating curves were primarily classified as a gradual drift off road. (See Table 6-5.) However, about half of the other drove off road category were more abrupt and 24.9% were coded large angle. The other drove off road category consisted largely of road departures at turns; for example, crashes in which a vehicle attempted to turn a corner going too fast to stay on the road. About three-quarters of the same-direction sideswipes were more gradual lane departures, which is consistent with the characterization of these crashes as intentional lane changes. The opposite direction crashes were similar to the drove-off-road crashes, in that the lane crossings were largely gradual events.

Table 6-5 Percent distribution of lane departure type by L/RD crash type

L/RD crash type	Lane departure type				Total
	Gradual, drift	More abrupt	Large angle (>20 deg.)	Unknown	
Drove off go straight	84.0%	8.2%	6.1%	1.7%	100.0%
Drove off neg. curve	92.3%	0.5%	5.7%	1.5%	100.0%
Other drove off	24.0%	48.6%	24.9%	2.6%	100.0%
Same direction	12.8%	75.1%	11.2%	0.9%	100.0%
Opp. dir., go straight	70.4%	18.1%	11.1%	0.5%	100.0%
Opp. dir. neg. curve	85.5%	14.5%	0.0%	0.0%	100.0%
Opp. dir. other	5.0%	85.8%	9.2%	0.0%	100.0%
Total	52.5%	37.5%	8.9%	1.1%	100.0%

Once vehicles went out of lane, about 61.9% entered another lane, which would provide some recovery opportunity. (Overall in these lane/road departure involvements, 52.9% departed the lane to the left and 47.1% to the right.) However, when vehicles went off the road, in almost 60% of the crashes, there was no paved or other engineered shoulder, which would provide a much more challenging surface on which to recover. Paved shoulders were present in only 24.2% of departures off road. In 16.0%, the departures were into curbs.

Table 6-6 Distribution of shoulder type for run-off-road crash involvements

Shoulder presence/type	%
None	59.1%
Paved	24.2%
Curb	16.0%
Gravel	0.1%
Other/unknown	0.6%
Total	100.0%

Summary

Defined as crashes that might be addressed by LDW and LKA interventions, L/RD crash types accounted for about 6.7% of the crash involvements of LTVs. About 48.1% of L/RD involvements were same-direction sideswipes, 43.2% were run-off-road (under control), and 8.7% were opposite-direction collisions. In terms of crash severity, the three general types varied widely. Further characterization is presented in Appendix E.

A sample L/RD crashes that had been the subject of in-depth investigations as part of NHTSA's NMVCCS program showed that the events of the L/RD crash types were generally consistent with hypothesized mechanisms. Most of the drove-off-road crash types were related to driver disengagement, with drivers either distracted or otherwise not fully engaged in driving. Poor driving skills, especially entering curves at speeds too fast to be safe, were also identified in a significant percentage, particularly among younger drivers. Same-direction sideswipes were largely related to surveillance, i.e., drivers not noticing conflict vehicles when changing lanes. However, over a quarter of same-direction sideswipes were precipitated by avoidance maneuvers. Drivers responding to other vehicles went out of lane to avoid and collided with another vehicle. About a quarter of opposite-direction crashes were related to disengaged drivers drifting into the opposing lanes, but a significant percentage were related to poor driving skills and excessive speed, particularly in curves. Drivers entered curves at high rates of speed and allowed their vehicles to go into opposing lanes.

Overall, the review of L/RD crashes suggested that up to 70% could be addressed by driver interventions, such as lane change/departure warning, blind-spot warning, lane departure prevention, or even possibly ESC for vehicles going too fast into curves.

6.2 Scenarios, Mechanisms, and Countermeasures for Lane- and Road-Departure Crashes

Table 6-7 shows a simplified set of relationships between the crash type, the mechanism of crash causation, and key countermeasures. The top part of the figure is an incomplete illustration of the work reported in the previous subsection that links common crash mechanisms with lane- and road-departure crash types. Two asterisks (**) indicates a very strong relationship and a single asterisk (*) indicates a moderately strong relationship. The bottom part of the figure shows the crash mechanisms that are addressed by various crash countermeasures. Two countermeasures in the figure have not been discussed much in this report, and are not addressed within this project:

- Curve speed system – a driver alert and/or a reduction in cruise control speed when approaching a curve quickly.
- Evasive steering damping – a system that helps the driver from applying excessive and possibly destabilizing amounts of steering in evasive maneuver situations (such as a road departure) or in evasive maneuvering. (Whether such a system can be effective and not activate at inappropriate times is not known.)

Overall, the figure is intended to show that the lateral assist systems being addressed most directly in this project (LDW and LKA) focus on driver errors that include distraction, drowsiness, or other "temporary" driver disengagements from driving.

Table 6-7 Key relationships between crash causation, crash types, and countermeasures for lane- and road-departure crashes

	Distraction / inattention	Drowsiness	Speed	Evasive maneuvering	Failure of surveillance
Crash types					
Run-off-road, straight	**	**			
Run-off-road, curve	*	*	**		
Sideswipe	*			*	**
Head-on	**	**		*	
Countermeasure					
LDW	**	**			
LKA	**	**			
Lane change warning					**
Blind spot indicator					**
Curve speed system			**		
Evasive steering damping				**	

* Moderately strong relationship

** Very strong relationship

To estimate effectiveness and safety benefits for these systems, the team focused the remaining analysis on the mechanisms, conditions, and crash attributes summarized in Table 6-8.

Table 6-8 Crash mechanisms and crash attributes addressed in analysis

	Addressed	Not Addressed
Mechanisms	• Drifting out of lane due to driver disengagement (drowsiness, distraction, inattention)	• Evasive maneuvering • Poor driving skill • Loss of control (including weather related) • Lane change error • Passing in opposing lane error • High speed including curve overspend • Alcohol or drugs involved • Incapacitation due to illness • Poor vehicle maintenance or tire failure
Roadway attributes	• Straight sections, curves • All speeds • Freeways, surface streets, ramps, all paved roads • Paved shoulder or adjacent lane	• Unpaved roads • Movement onto unpaved shoulders • Navigating intersections
Harmful events	• Striking roadside object • Rollover • Head-on collision • Sideswiping same-direction vehicle	• Crashes caused by over-correction

6.3 Simulation Description

To study the effectiveness of LDW and LKA, the team conducted a large-scale time-domain simulation effort similar to the one described for assessing FCAM system, with modifications to address unique aspects of the lane- and road-departure cases. An overview is given here, with details in Appendix C. The output of this simulation activity is passed to the second stage of analysis, described in Section 6.4, which consists of the development and application of a harm model for the individual simulated departure events, weighting of events based on scenario conditions, and computation of effectiveness measures.

Conceptually, a similar approach was taken for both FCAM and LKA simulations and an outline of the methodology is given in Figure 6-1. The simulations were conducted with inputs from a variety of models and algorithms and initial conditions. For a given set of conditions, the simulations were repeated with the driver response input (braking or steering) delayed in 0.1 s time steps. Algorithms were used to calculate when a warning was issued and when the countermeasure technology was triggered. The output of each simulation is a time-series measures of vehicle kinematics. From the time-series data summary results were aggregated and used in a statistical model to compare baseline with warning and countermeasure results.

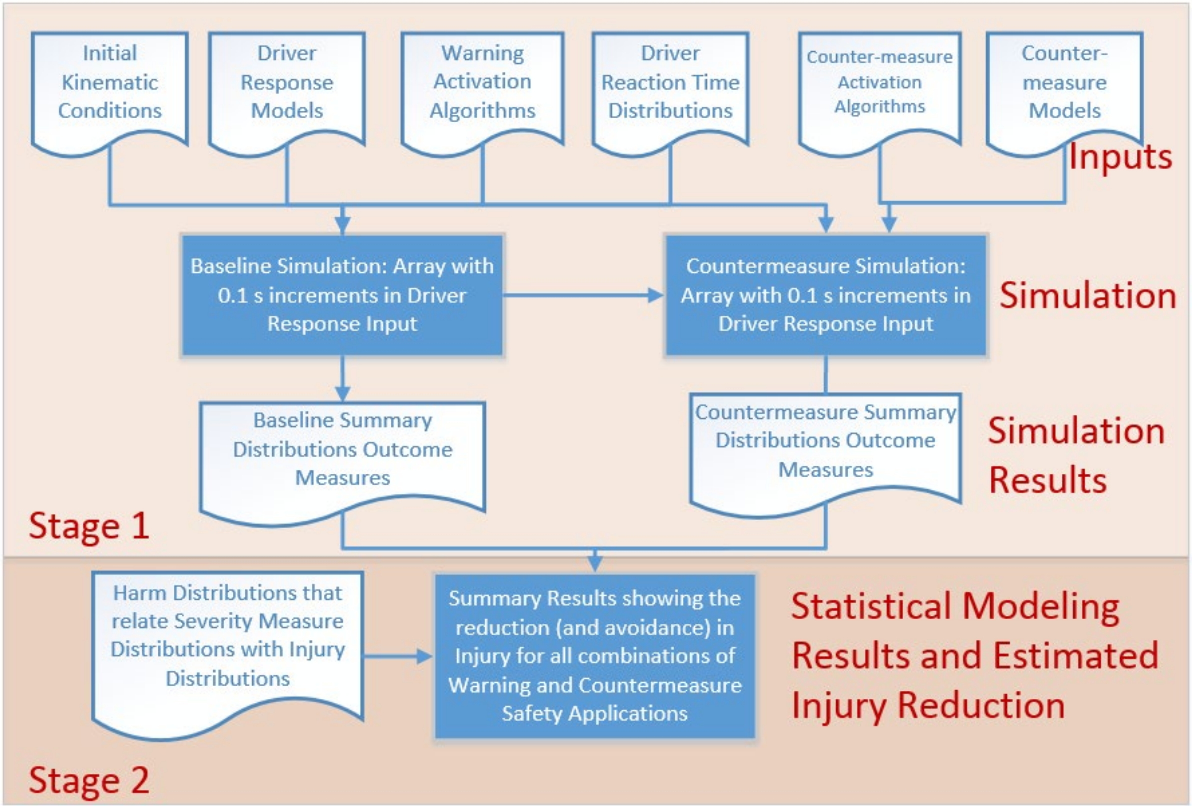

Figure 6-1 Simulation approach to support crash avoidance effectiveness estimates

The analysis was conducted in two stages. In the first stage, described in this section, simulations were conducted for drifting out of lane events, including unassisted cases and assisted cases, in which LDW and/or LKA effects were modeled. The trajectories outside the lane were simulated and characterized. In the second stage, described in the following section, those trajectories were used in conjunction with harm models that mapped the trajectories into the probability of crash severity. The second stage also applied weighting of scenarios to compute effectiveness and potential benefits.

In this manner, the first stage needs only to simulate variations of a basic scenario: a vehicle leaves the lane, and a driver recovery follows – some with LDW/LKA assistance, and others without. Three levels of LKA control authority are simulated, as detailed in Appendix C.

To create these trajectories, a set of kinematic initial conditions were developed using naturalistic driving road departures as seed events to create departure events. These initial conditions consist of speed and departure angle at the time of departure, as well as the road curvature. Appendix C describes how sets of baseline and countermeasure-assisted trajectories are computed, to provide a data set that supports efficient and flexible calculations of effectiveness (described in the following subsection).

The outcome of the simulation activity includes simple statistics about the trajectory outside the lane, including the time spent within different ranges of distance outside the lane, e.g., between 0 and 3+ meters outside the lane. A harm model is later applied to use these statistics for estimating the number and severity of crashes. Details of both the FCAM and LKA simulation inputs and methodology can be found in Appendix C.

Table 6-9 Simulation activity outputs to the post-simulation analysis stage

Simulated event inputs	Simulated event outputs
• Kinematic conditions of departure (forward speed, lateral speed, road curvature) • Type of countermeasure set (none (baseline), LDW, LKA, or LDW/LKA--3 levels of LKA steering response were used) • Driver delay increments of 0.1 s • Driver steering response (2 levels of steering response were used).	• Average lateral speed departing and returning to the lane • Bins of forward distance when lateral distance was between 0 and 1; 1 and 2; 2 and 3 and more than 3 meters outside the lane. • Maximum lateral distance from the lane • The time of maximum lateral distance

This information, as shown Table 6-9, is passed on to the second stage of analysis for lateral crashes, which includes the weighting of scenarios, and application of a harm model.

6.4 Analysis of Lateral Assist System Simulation Data

Each row in the simulated dataset has the vehicle's speed, the distance traveled outside the lane (in 1m lateral bins), the maximum distance from the lane, and when the LDW system would trigger under baseline conditions and with each Lane Keeping Assist (LKA) system. The speed is constant over interventions and is used as a proxy for the functional class of the road, while the other variables are used to calculate the risk.

Figure 6-2 illustrates the basic approach to applying a harm model to the simulation data and from that, obtaining a benefits estimate. The two diagrams represent a road with two lanes and a shoulder with pavement edge indicated by a gray line. The rightmost solid black line is the lane-edge boundary. The dotted gray lines indicated bins of specific widths (0-10 ft, 11-30 ft, 31+ ft).

From the simulation, the vehicle path (red line) cuts a swath (orange colored area) off the road. This area swept is the entire period of risk for the event. If the swath extends beyond the pavement edge, like the example on the right, the event is considered a run-off-road ending off the pavement edge (often rolling over). If the swath does not extend beyond the pavement edge, like the example on the left, the vehicle may hit either a hard or soft object at some distance from the road edge.

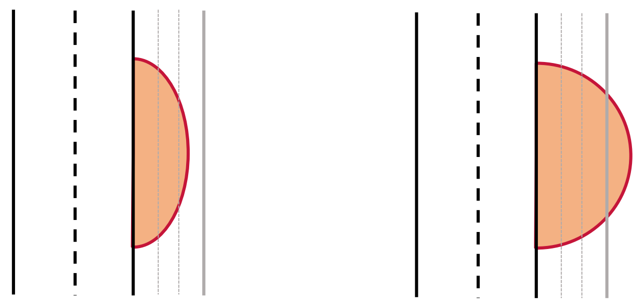

Figure 6-2 Illustration of evaluation of lane departures

To calculate effectiveness, the following steps are required:

1. Run-off-road Risk: For each type of road (based on speed limit), an average distance from the lane boundary to the pavement edge (i.e., shoulder width) was selected using available state data and road design guidelines. For any baseline or intervention crash in which the maximum distance from the lane boundary is larger than the shoulder width for that road type, the crash is classified as run-off-road.
2. Risk of Hitting an object by Object Type and Road Class: Data from North Carolina were used to determine the distribution of the distance from the lane to the object hit by object type (hard/soft) and the roadway functional class. Since the North Carolina data uses very coarse bins (0-10 ft., 11-30 ft., and greater than 30 ft.), we fit a Gamma distribution to each object type and functional class pair so that the 1m bins from the simulation could be imputed. This allowed us to create a unit-less risk metric for hitting an object by multiplying the distance traveled in each out-of-lane bin by the estimated probability of an object being in that bin and summing the resulting values.
3. Risk of Injury by Object Type and Road Class: Using the North Carolina data, we defined the probability of injury given a crash as a function of the distance from the road, the object type, and the functional class of the road. The estimated probability of injury in each out-of-lane bin was multiplied by the distance traveled in that bin and the probability of an object being in that bin (see above) and then summed, to obtain a unit-less risk of injury for that bin. This is described in Appendix F.

After performing the above calculations, each row of the simulated dataset has five risk measures for the baseline crash and each lateral assist system: risk of off road crash, risk of hitting a soft object, risk of hitting a hard object, risk of injury in a soft object crash, and risk of injury in a hard object crash.

To estimate the effectiveness of the LDW system, a driver reaction time distribution was needed. This was created by fitting a Gamma distribution to observed response times from events found in existing naturalistic driving data with kinematics similar to those in the simulation. This produced a distribution of 10 possible reaction times starting at 0.3 seconds and incrementing by 0.5 seconds.

For each row in the simulated data, if the driver delay is less than the LDW trigger time plus the reaction time, the risk for that reaction time is the same as the baseline risk. Otherwise, the LDW risk is the baseline risk from an earlier row, such that the delay for that row is equal to the LDW trigger time plus the reaction time. The overall risk is defined to be the expected value of the risk across the reaction times. This process is repeated for each lateral system, with the system risks replacing the baseline risks as needed.

For each row, we calculated the ratio of the intervention risk and the baseline risk and defined the intervention effect as the proportion of the baseline risk removed. The reduction in risk of off-road crashes is calculated for all rows, but the other risk reductions are only calculated for rows in which the baseline off-road crash risk is not 1. This is because the object hit and injury risks assume that the vehicle does not leave the road.

With the risk reductions calculated for all rows, the estimated overall effect size is the weighted average of the risk reductions with the weight for each row determined by the duration of the event in seconds. This weighting is intended to correct for the fact that the simulated lane departures tend to be longer than what is seen in naturalistic driving data. To correct for this, we fit an exponential distribution to the observed event durations and the simulated data was weighted to match that target distribution.

Finally, the hard object, soft object, and run-off-road results for each system were combined using a weighted average. The weights on the three outcomes were based on crash data showing that run-off-road (generally resulting in rollover) were 3.6% of lateral crashes. The relative proportion of soft and hard objects depends on the road type.

6.5 Results for Lateral Assist Effectiveness

The results of the simulations are shown in Table 6-10. Each section includes a complete analysis of three LKA algorithms with and without LDW for a given driver response profile. The reduction in component crash types are separated by off-road, soft object and hard object. Although the injury models indicate somewhat different injury risks for these objects, the reductions for the two object types are relatively similar. In general, the injury reductions came more from avoidance than mitigation since both avoidance and mitigation are similar percentages for each system.

Table 6-10 Estimated benefits of lateral systems from simulation

Steering response	Intervention	Percent reductions: Off road	Hit soft object	Hit hard object	Injuries from soft object	Injuries from hard object	Overall percent crashes avoided
Driver response 1	LKA 1	82.8%	26.3%	27.4%	27.0%	28.2%	28.7%
	LKA 2	88.1%	32.2%	33.2%	32.9%	33.9%	34.2%
	LKA 3	94.6%	37.4%	38.2%	38.0%	38.7%	39.5%
	LDW	69.9%	6.5%	7.3%	7.0%	7.8%	8.7%
	LDW + LKA 1	88.1%	27.1%	28.1%	27.8%	28.8%	29.3%
	LDW + LKA 2	90.6%	32.6%	33.5%	33.3%	34.2%	34.7%
	LDW + LKA 3	94.6%	37.4%	38.2%	38.0%	38.7%	39.5%
Driver response 2	LKA 1	82.8%	28.3%	29.1%	28.8%	29.6%	30.5%
	LKA 2	88.1%	35.6%	36.3%	36.1%	36.7%	37.7%
	LKA 3	94.6%	43.0%	43.4%	43.3%	43.8%	44.9%
	LDW	69.9%	3.8%	4.4%	4.2%	4.8%	6.1%
	LDW + LKA 1	88.1%	28.5%	29.2%	29.0%	29.7%	30.7%
	LDW + LKA 2	90.6%	35.7%	36.3%	36.1%	36.8%	37.7%
	LDW + LKA 3	94.6%	43.0%	43.4%	43.3%	43.8%	44.9%

Driver response 2 was slightly more aggressive, but the two profiles produced fairly similar reductions in crashes and injuries for each system. In addition, benefits of LKA were the primary driver of all benefits for lateral systems. The improvements in response time due to warnings do not substantially reduce the time spent out of the lane compared to LKA systems, which respond quickly upon crossing the lane boundary.

6.6 Implementation in UTMOST

Of the various system algorithms, we consider LKA2 to be the closest to current production systems. Driver response profile 1 is the most similar to how drivers likely steer in panic situations on average, and it produces slightly conservative benefits estimates.

In UTMOST, the percent effectiveness assigned to LDW affects all drifting crashes and 61% of run-off-road crashes. The remaining 39% of run-off-road crashes occur when speed is too great for a curve or turn. Those crashes cannot be addressed by an LDW or LKA system. The reduction for LDW, 8.7%, is only applied if alcohol is not involved. For LKA, the reduction of 34.7% is applied if the alcohol is involved, since the system operates independent of driver response.

Other systems implemented in UTMOST include blind spot warning and curve-speed warning. Blind-spot warning reductions apply to lane-change crashes and curve-speed warning reductions apply to the 39% of run-off-road crashes in which speed was a factor.

Lane centering systems would, in our simulations, eliminate all drifting and run-off-road crashes because they do now allow lane departure without driver action. This was not implemented as a default in UTMOST because it is unrealistic. The results of the video review are not implemented in UTMOST explicitly, but specific implementations of lane-centering and LKA systems will be influenced by the need to avoid strong lateral movements towards hazards the driver may be trying to avoid.

6.7 Intentional Lane Departure Circumstances

The results above addressed LKA systems at different levels of corrective lateral acceleration authority. Automakers need to balance their systems between providing firm responses to bring the vehicle back toward the lane in a risk situation and not being too strong in response when the departure is intentional or desirable. Lane departures —either running out of lane on the roadway or off the road—were examined in naturalistic driving study (NDS) data. The purpose was to better understand the circumstances under which LDW/LKA devices would operate, with particular attention to “safety-positive” lane departures, where safety-positive means that the lane departure was an intentional maneuver by the driver to increase a perceived margin of safety. Examples of safety-positive maneuvers include moving away from pedestrians or bicyclists in lane, from parked vehicles, or from other vehicles in adjacent lanes when overtaking.

A set of lane departure epochs were identified in NDS data that had been collected as part of UMTRI’s Safety Pilot project (Bezzina and Sayer 2015). The epochs were defined by:

- Excursions over a solid or double boundary line or road edge;
- Minimum departure distances of 0.25m perpendicular to the boundary of interest;
- Minimum departure time of 1s;
- Return to the original lane.

Lane departure detection was based on the internal lane position estimates of a production tracking system from Mobileye. As defined, the set of lane departure epochs was intended to capture events in which the driver did not intend to change lanes, but instead went outside the lane briefly and then returned. Accordingly, at least kinematically, the events were potential candidates for an LDW or LKA.

Cases were sampled from approximately 164,000 lane departure events that met the criteria in the NDS data. Sample lane departures were drawn from six “bins”, defined by three speed categories and left or right moves. The speed categories were 25 to 45 mph, 45 to 62 mph, and speeds greater than 62 mph. The 25 to 45 mph range generally corresponded to local city streets; 45 to 62 mph covered mostly 2-lane, 2-way roads of moderate speeds; and, 62+mph covered typically high-speed and limited access roads. The categories were defined by the travel speeds, and the travel speeds corresponded to the general road types described.

A total of 540 lane departures were reviewed independently by two coders. The coders captured data on road type, number of lanes, start lane (numbered from the road edge), start lane type (through-lane, center-turn lane, ramp, etc.), new lane type (same direction through lane, opposite direction, turn lane, bike lane, road edge, etc.), presence and type of shoulder, reason for leaving the lane, and whether there was a hazard in the new lane. Coders reviewed video of the events, including of the driver, forward view, lateral view to each side, as well as maps of the roadway where the event occurred. Each coder reviewed each case, the coding for each case was compared to identify differences, and then all differences were reviewed jointly by the coders and reconciled. Sampling weights were computed so the results for completed cases to be weighted to the original population of lane departures.

None of the lane departures resulted in a crash or even a near-crash. Thus, the departures captured situations in which LDW/LKA technologies would operate, rather than events leading to lane-departure crashes, which were described in the Section 6.1 and Appendix E describing those crashes. As such, they illuminate circumstances in which warnings or lane-keeping assistance would be helpful as well as those in which LDW/LKA might be considered by drivers as unnecessary or even problematic.

Table 6-9 shows the distribution of lane departure events by speed category (road type) and direction. Most of the departures were to the right, with almost 60% moving over the right lane line. The right/left balance varied by speed category, with the balance almost even for the low-speed and high-speed sets, but shifted toward the right in the middle speed group. The middle group may be preponderantly to the right because the roads were primarily 2-lane, 2-way so a move to the left would be into an opposite direction lane. Thus, the overrepresentation of right-going moves have reflected a tendency to move away from potential collision danger. Likewise, low-speed roads may have been more balanced because of parked vehicles, pedestrians, and bicyclists to the right, while higher speed roads tend to have at least two same-direction travel lanes.

Table 6-11 Lane departures by speed and direction

Speed category	Direction of departure		
	Left	Right	Total
25 to 45mph	36,183	39,958	76,141
45 to 62mph	12,686	40,116	52,802
62+mph	17,681	17,340	35,021
Total	66,550	97,414	163,964
	Left	Right	Total
25 to 45mph	47.5%	52.5%	100.0%
45 to 62mph	24.0%	76.0%	100.0%
62+mph	50.5%	49.5%	100.0%
Total	40.6%	59.4%	100.0%

Almost 60% of the lane departures were over the road edge line or onto the shoulder (Figure 6-3). An estimated 18.7% were into an opposite direction lane, but only 1.8% were into a same-direction through lane (though this result may be an artifact of the requirement to pass over a solid lane line or double boundary line; cases were selected to identify lane boundary crossings associated with serious crashes). Another 9.4% were into a bike lane, and a total of 10.4% were into a ramp, right or left turn flare[5], or center turn lane. Excursions into same- or opposite-direction lanes, turn flares, ramps, bike lanes, and so on were all onto paved surfaces. Paved surfaces provide sufficient and reasonably uniform friction for technologies that could return the vehicles to the original lane. Of the almost 60% of departures that were over the road edge boundary line, almost 90% were onto a paved shoulder. Thus, almost 93% of these lane departures were onto a paved surface.

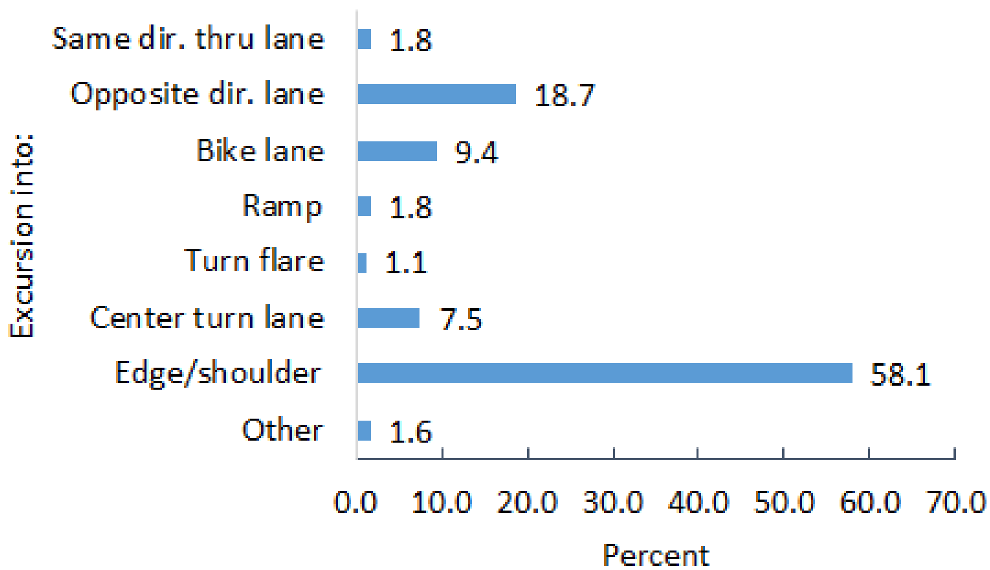

Figure 6-3 Roadway area of lane departures

Table 6-10 shows the distribution of the immediate explanations or reasons for the lane departures. All of these reasons were based on the joint judgment of the two reviewers, after reviewing video and drawing inferences from the appearance and actions of the driver, as well as the surrounding circumstances.

The most common reason for the lane departures was "cutting the curve". These represent cases where drivers intentionally or indifferently went over lane lines or road edges, essentially because it was convenient to do so. The drivers appeared to be aware of that they were going out of lane and apparently judged it to be safe. Cutting curves accounted for about half (50.7%) of the departures.

About a quarter (24.9%) of the departures might be considered unsafe, or at least unintentional. These include cases where the drivers were judged to be distracted (22.6%) or not paying attention to the driving task (2.0%). Of the distraction/inattention cases, about 13% were related to phone

[5] "Turn flare" was defined as a dedicated right or left turn lane.

use; 6.4% eating; 6.7% texting; about 14% personal grooming; and 13.4% looking around, out the window, or searching for something in the car. There was no dominant distraction activity, but a variety of distractions, both internal and external.

About 18.0% of the lane departures might be deemed "safety-positive", in that crossing the lane line was apparently related to avoiding other road users. In these events, the vehicles were passing (or being passed by) other vehicles on the road and the drivers steered away to separation on the road. Most of these maneuvers were to avoid other vehicles, predominantly light vehicles but also some trucks. Vulnerable road users—bikes and pedestrians—were the object of avoidance in only 1.6% of the cases.

Table 6-12 Reasons for lane departures

Why leave lane?	N	%
Distracted	37,102	22.6
Not paying attention	3,360	2.0
Lane change/turn	913	0.6
Pothole/object	6,046	3.7
Truck	7,657	4.7
Light vehicle	13,175	8.0
Bike in lane	651	0.4
Bike in bike lane	381	0.2
Pedestrian etc.	1,658	1.0
Cutting curve	83,103	50.7
Poor vehicle control	365	0.2
Other	1,271	0.8
Unknown	8,282	5.1
Total	163,964	100.0

In summary, only about a quarter of these cases where drivers went out of lane would be usefully the target of a warning or a lane-keep assist. These are the cases where lane departures were due to inattention or distraction. In these situations, drivers would be most likely to benefit from LDW/LKA. About 70% of the lane departures were intentional or at least knowing—including cutting curves and the safety-positive cases. In most of these cases, drivers were aware of the lane departure and did so intentionally or indifferently. In cases of curve-cutting, drivers may regard as annoying and unnecessary the actions of LDW or LKA. On straight roads, drivers may appreciate LKA keeping them in lane in circumstances when they have allowed the vehicle to cross a lane boundary. However, in curves, drivers might prefer to reduce lateral acceleration by cutting the curve, rather than experiencing the higher lateral acceleration by keeping within the lane boundaries. In addition, where the boundary-crossing was apparently safety-positive, drivers may regard an automatic intervention to prevent the departures as actually unsafe.

7 Effect of Teen Passengers on Teen Driver Behaviors

7.1 Introduction

The goal of this study was to utilize the Teen IVBSS FOT naturalistic driving data to more closely examine aspects of teen crash risk and to ultimately identify opportunities to reduce teen crash risk. Background information is useful in motivating the work described in this section.

On a per population basis, motor vehicle crash rates are higher for teen drivers than for any other age group (NHTSA, 2011). Their elevated risk is attributable to individual developmental factors, driving inexperience/lacking skill, and propensity toward risky behavior (Williams, 2003). Crash risk is greatest during the first six months of driving, but remains significantly elevated compared to experienced drivers for the first five to 10 years (Mayhew et al., 2003). The most widely available prevention approach for new drivers under age 18 in the U.S. is Graduated Driver Licensing (GDL). GDL typically includes two phases: extended supervised practice driving, and intermediate/restricted licensure with limits on unsupervised driving (e.g., at night or with teen passengers). GDL programs vary by state, but most have modest requirements with none as strict as recommended (IIHS, 2011). Nevertheless, evaluations have demonstrated GDL's effectiveness in reducing teen crashes (Shope, 2007; Williams and Shults, 2010; Williams et al., 2012). Despite the effectiveness of GDL, the high crash risk during the early months of licensure has persisted even after adoption (Masten and Foss, 2011), suggesting additional approaches are needed to further reduce teen crash risk.

Research examining the use of crash avoidance technologies by teen drivers is still in the early stages. The Teen Integrated Vehicle-Based Safety System Field Operational Test (Teen IVBSS FOT) conducted at UMTRI included 40 teens driving instrumented cars for 14 weeks with and without the assistance of an integrated vehicle-based safety system (Buonarosa, Bao, & Sayer, 2013). The system had been previously tested with adults and included forward collision warning, curve speed warning, lane departure warning, and lane change/merge warning. In general, minimal effects of the IVBSS were found for teens, either between experimental and control groups or across the pretreatment, treatment, and post-treatment phases of the study. The naturalistic driving data collected during the Teen IVBSS FOT provided a unique opportunity to utilize objectively collected data on the driving environment, driver behavior, and vehicle kinematics to examine aspects of teen crash risk.

7.2 Methodology

<u>Development of the research question</u>

The investigators conducted a review of the literature on teen crash characteristics, three risk factors for teen motor vehicle injury (driving with teen passengers, nighttime driving, and low safety belt usage), and safety technology for teen drivers. Based on the literature review, the investigators developed a broad list of research topics that had not been sufficiently addressed, as of that time, in the literature. The investigators narrowed the list of research topics to those that could be addressed using naturalistic driving data collected during the Teen IVBSS FOT. The investigators sought the input of investigators from the Teen IVBSS FOT to eliminate research topics that had already been examined or were not feasible to examine using Teen IVBSS FOT data. Specifically, the Teen IVBSS FOT team helped the investigators weigh the benefits and limitations of those data to address the research topics. The investigators identified the following research questions:

How much does teens' safety-related behavior (seat belt use, following distance, closing rate, speed, and distraction) change:

1) With and without passengers (compared to driving alone)?
2) During daytime compared to nighttime?
3) With the same compared with opposite sex front seat teen passengers present?
4) On different road types and in different weather conditions?

Measures and sources of data

Two types of data from the Teen IVBSS study were included in the current study: 1) variables created by systematically viewing the video segments recorded during driving (video coding); and, 2) data collected via the Teen IVBSS FOT data acquisition system during driving.

Video data measures had been coded for a subset of driving segments as part of the Teen IVBSS FOT evaluation (Buonarosa, Bao, Sayer, 2013). The subset consisted of 32 five-second video segments per driver (n = 1,279 video segments; one driver had 31 segments). Each video segment met the following criteria: the minimum driving speed was 11.18 m/s (25 mph); the road type was either a surface street or a highway; no crash avoidance warning was given within five seconds before or after the segment; and, video segments were at least five minutes apart from one another. The measures coded in the original study included if the driver glanced away from forward, secondary tasks the driver engaged in, the total number of passengers in the vehicle, the total number of teen passengers in the vehicle, if there was a teen passenger in the front seat, the sex of the teen front seat passenger, the road type (major arterial, freeway, residential), time of day (daytime, nighttime), and the weather conditions (none, precipitation, snowy road, precipitation and snowy road, wet road).

Additional video coding was completed as part of the current study: driver hand position (both hands on steering wheel, left hand only on steering wheel, right hand only on steering wheel, or no hands on steering wheel); attention to the forward roadway (driver appeared to be focused on the road or driver did not appear to be focused on the road); and, passenger activities (activities engaged in by the front seat passenger). The investigators considered adding front seat passenger's seat belt use to the set of new variables; however, coders were not able to determine if front seat passengers were wearing seat belts and this variable was not added. The new coding provided a broader range of measures of driver distraction. From the literature to date a definition of driver distraction has emerged as: 1) hands off the steering wheel; and/or 2) eyes off the road; and/or 3) attention off the road. The new coding, when paired with the 'eyes off road' variable coded previously as part of the Teen IVBSS FOT, allowed all three markers of distraction to be measured with these naturalistic data. Additionally, the new coding of passenger activities provided a measure of observed potential contributors to driver distraction.

The new video coding was completed by a team of four student video coders. One student video coder was initially hired and worked with the investigators to develop and test the coding protocol and train the other student video coders. To establish inter-rater agreement, coders were assigned video clips/segments in batches of 50-100 segments and independently coded the segments in each batch. Batch assignment was structured to ensure that each video segment was independently coded by three coders. Coding was compared and discrepancies between coders were discussed and resolved. Reliability assessment and additional training were continued until the inter-rater agreement of all coders reached a Kappa score of 0.80.

Data collected via the data acquisition system provided driver seat belt use, vehicle speed (m/s), distance between the driver's vehicle and a lead vehicle (following distance; m), and closing rate range between the driver's vehicle and a lead vehicle (closing rate; m/s). Speed, following distance, and closing rate data were collected at 10 tens/second yielding 51 records for each five-second segment. Those records were averaged to create a mean value for speed, following distance, and closing rate for each video segment.

Data analysis

The data analysis included a combination of descriptive and inferential techniques. Frequency distributions and means were used to summarize measures. Differences between groups were tested for statistical significance using chi-squared tests or analyses of covariance, depending on the nature of the variable (e.g., dichotomous or continuous). All analyses were performed using SAS 9.4.

7.3 Results

Characteristics of the sample of video segments

Frequency distributions of the descriptive characteristics the research question comparisons were based on are presented in Table 7-1 .

Table 7-1 Basic description of the 5-second segments (n = 1,279).

	n (%)
Driver's Sex	
Male	639 (50.0)
Female	640 (50.0)
Was there a teen passenger in the front seat?	
No	767 (60.0)
Yes	518 (40.0)
Distribution of driver's sex and teen front passenger's sex (n=518)	
Female driver-Female passenger	219 (42.3)
Female driver-Male passenger	88 (17.0)
Male driver-Female passenger	72 (13.9)
Male driver-Male passenger	139 (26.8)
Driver and Passenger opposite sex	160 (30.9)
Driver and Passenger same sex	358 (69.1)
Road type	
Major arterial	820 (64.1)
Freeway	286 (22.4)
Residential	173 (13.5)
Weather	
None	1171 (91.6)
Precipitation	26 (2.0)
Snowy road	18 (1.4)
Precipitation and snowy road	3 (0.2)
Wet road	61 (4.8)
Time of day	
Daytime	918 (71.8)
Nighttime	361 (28.2)

<u>Outcome measures: safety-related behaviors</u>

Seat belt use. Driver seat belt use was 99.9% so seat belt use was eliminated as an outcome measure.

Driving measures. Means and standard deviations for the driving outcomes measures are presented in Table 7-2. Following distance and closing rate to lead vehicle are only presented where a lead vehicle was present.

Distracted driving. Frequency distributions for observed distracted driving behavior and the newly coded markers of distraction are presented in Table 3. The mean number of markers demonstrated by drivers was 1.21 ± 0.7.

Table 7-2 Means and standard deviations for the driving outcomes

	n	Minimum	Maximum	Mean (SD)
Speed (m/s)	1279	11.5	39.5	20.5 (6.4)
Following Distance/Distance to lead vehicle (m)	668	0.49	106.08	34.82 (21.3)
Closing rate to lead vehicle (m/s)	668	-13.86	3.86	-0.55 (1.8)

Table 7-3 Frequency of distracted driving

Driver engaged in secondary task	
No	673 (52.6)
Yes	606 (47.4)
Distraction Marker 1: Did the driver glance away from forward during the segment?	
No	550 (43.0)
Yes	649 (50.7)
Distraction Marker 2: Did the driver have one or both hands off the steering wheel during the segment?	
No	422 (33.0)
Yes	856 (66.9)
Distraction Marker 3: Did the driver's focus appear to be away from the road during the segment?	
No	1,241 (97.0)
Yes	38 (3.0)
Number of distraction markers demonstrated by the driver in each segment	
Zero	209 (16.3)
One	627 (49.0)
Two	413 (32.3)
Three	30 (2.4)

<u>Comparison of teens' safety-related behaviors with and without passengers</u>

Drivers with teen passengers were marginally more likely to drive closer to the vehicle in front of them (following distance) (DF = 666, t = 1.67, p = .0955). There were no differences for speed or closing rate.

Comparisons were made of the distraction markers by presence or absence of a teen passenger in the front seat. Drivers with a teen passenger in the front seat were more likely to take their eyes off the road (DF = 1, x^2 = 11.80, p = .0006), but less likely to take one or both hands off the steering wheel (DF = 1, x^2 = 15.66, p = <.0001). With respect to focus off the road, there was no difference between drivers with and without teen passenger(s) in the front seat. And there was no significant difference in the number of distraction markers by presence/absence of a teen passenger in the front seat. Drivers with a teen passenger were more likely to engage in a secondary task (DF=1, x^2=82.38, p<.0001) than drivers without teen passengers.

The investigators had considered examining teen drivers' safety behaviors with and without at least one adult passenger present in addition to examining teen passengers; that analysis was not possible because the teen drivers rarely drove with adult passengers (only 1.5% of the segments with a front seat passenger)

Comparison of teens' safety-related behaviors during daytime and nighttime

In terms of teen drivers' daytime compared to nighttime driving, there was no difference for speed or closing rate. Drivers were more likely to drive closer to the vehicle in front of them during the daytime (DF = 207, t = 2.38, p = .0180) and were more likely to take their eyes off the road during the daytime (DF = 1, x^2 = 8.30, p = 0040) then the nighttime.

Comparison of teens' safety-related behaviors with same sex and opposite sex front seat teen passengers

Most (69.1%) of the teen drivers with passengers had front seat passengers of the same sex (42.3% of female teens and 26.8% of male teens). Comparing drivers with same-sex teen passengers to those with opposite-sex teen passengers showed no differences in following distance, closing rate, or speed. Teen drivers, however, with a same-sex compared to an opposite-sex teen passenger in the front seat were more likely to glance away from forward/take their eyes off the road (DF = 1, x^2 = 4.87, p = .0273).

The most common driver-passenger combination was female driver-female passenger. Female drivers with female teen front passengers were the driver-passenger combination most likely to glance away from forward (DF = 10, x^2 = 44.06, p<.0001). Vehicles with a teen passenger and where either the driver or passenger was female were more likely to have a driver engaged in a secondary task (DF = 5, x^2 = 98.55, p<.0001).

Comparison of teens' safety-related behaviors for different road types and weather conditions

In terms of road type, there was no difference among major arterial, freeway, or residential roads in teen drivers' following distance or closing rate. Not surprising, teens drove faster on freeways than on major arterials and residential streets, and faster on major arterials than on residential streets (Df = 2, F = 692.34, p< 0001). Teen drivers were marginally more likely to glance away from forward/take their eyes off the road on freeways and on major arterials than on residential streets (DF = 2, x^2 = 5.03, p = 0808). There were no differences between weather conditions for any of the outcome measures.

Markers of driver distraction and driving outcomes

T-tests were conducted to compare those who demonstrated distraction markers versus those who did not speed, following distance, and closing rate. There was no difference in speed between those who took their eyes off the road or not, but drivers with hands off the steering wheel (DF = 777, t = 3.72, p = .0002) and focus off the road (DF = 42, t = 3.29, p = .0020) drove at slower speeds. There was no difference in following distance between those with eyes off road or hands off the steering, but drivers with their focus off the road were marginally more likely to be driving closer to the vehicle ahead of them (DF = 15, t = 2.02, p = .0610). The closing rate to the lead vehicle was less for drivers with their eyes off the road (DF = 645, t = 2.19, p = .0288), but not different for those with hands off the steering wheel or focus off the road.

Passenger activities

One of the new coding measures added as part of this study was a description of the activities teen passengers in the front seat engaged in. In 56.8% of the video segments, the front seat passengers were engaged in some activity. The most frequently observed activities are presented in Table 7-4.

Table 7-4 Frequency distribution of the leading activities demonstrated by teen passenger in the front seat

	n	%
No activity (just sitting)	224	43.2
Talking with driver only	92	17.8
Talking with driver and at least one additional activity	42	8.1
Listening/singing/dancing to music	40	7.7
Viewing cellphone	30	5.8
Texting	19	3.7

7.4 Summary and Future Directions

Viewing and coding recorded video segments was a satisfactory method for observing teen drivers' safety behaviors and factors both in and outside the vehicle that might relate to those behaviors. In general, the drivers in the study behaved reasonably safely, with only a few significant differences found in the analyses run to address the research questions. In daylight compared to nighttime, teen drivers were more likely to drive closer to a lead vehicle and to have their eyes off the road. When teen passengers were present, drivers' eyes were off the road more and they were more likely to be engaged in a secondary task, both behaviors known to increase crash risk. When teen drivers and passengers were the same sex, drivers' eyes were off the road more than when they were opposite sex; this was especially true for female-female combinations, where the drivers also engaged more in secondary tasks. When drivers had their eyes off the road or one or both hands off the wheel, they were driving slower. However, the closing rate to a lead vehicle was less for drivers with their eyes off the road. Overall, among the teen drivers studied, the presence of teen passengers seems related to increased crash risk as shown by more time with eyes off the road and engagement in secondary tasks.

This research utilized naturalistic driving data to examine several safety-related behaviors among teen drivers and added new video coding measures to enrichen those data and provide a clearer picture of teen driver and teen passenger behaviors and distractions. Even among a relatively safe group of teen drivers, these initial analyses suggested relationship between teen passengers and safety-related behaviors associated with increased crash risk. Future work with these data could examine within-driver comparisons and further exploration of the newly coded passenger activity measure to examine how various combinations of driver behavior and passenger behavior relate to driving outcomes. Additionally, data from the Adult IVBSS and Teen IVBSS FOTs have been combined to compare seat belt use between adult and teen drivers (Bao et al., 2015). Future analyses could be conducted to similarly compare teens and adults for the safety-related outcome measures examined in this study.

8 Task 7: UTMOST Comprehensive Benefits

For this project, the UTMOST web tool was substantially redesigned and enhanced. The URL is http://utmost.umtri.umich.edu/. A tutorial for the web tool can be found in Appendix G, and online instructions are also available.

The UTMOST tool was exercised to illustrate comprehensive benefits to address teen-driver issues.

Figure 8-1 shows the child restraint law countermeasure panel as implemented in UTMOST. Users can change the population proportion that are covered by laws including best-practice language.

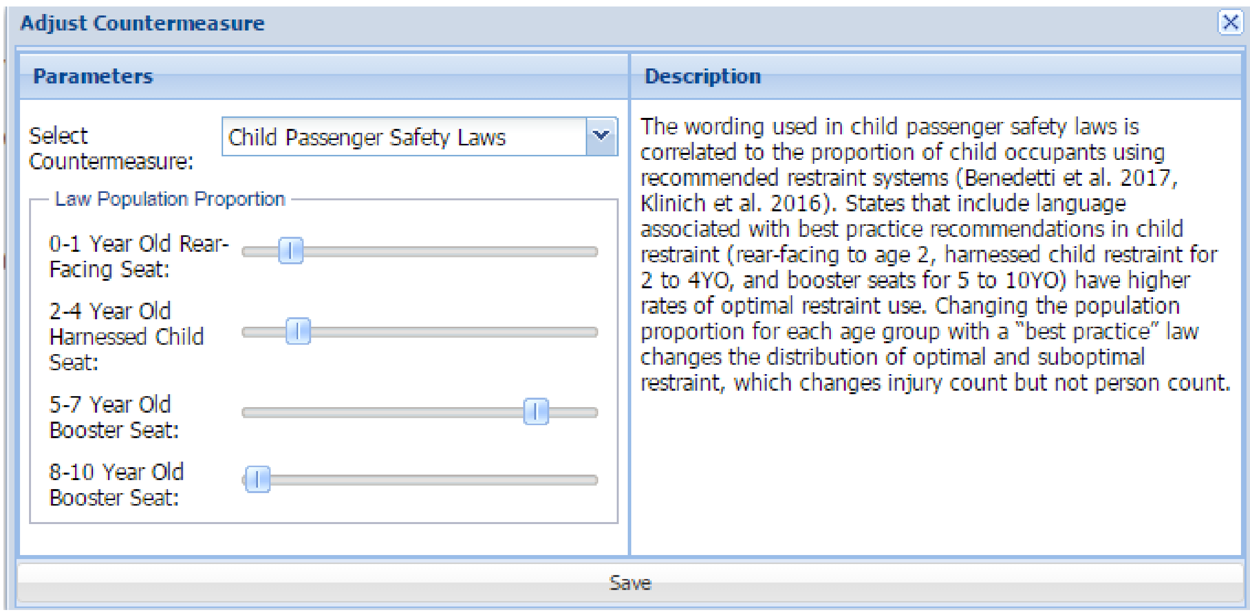

Figure 8-1 Example of a law countermeasure as implemented in UTMOST.

8.1.1 Effects of Restraint Use

Another key comparison element implemented in UTMOST is the effect of different levels of seat belt use across the population. Seat belts do not prevent crashes, but are very effective at preventing injury in all kinds of crashes (particularly rollover and frontal crashes). We implemented a "restraint override" to allow users to envision the benefits of, for example, 100% belt use in the occupant population. The user interface for this countermeasure is shown in Figure 8-2.

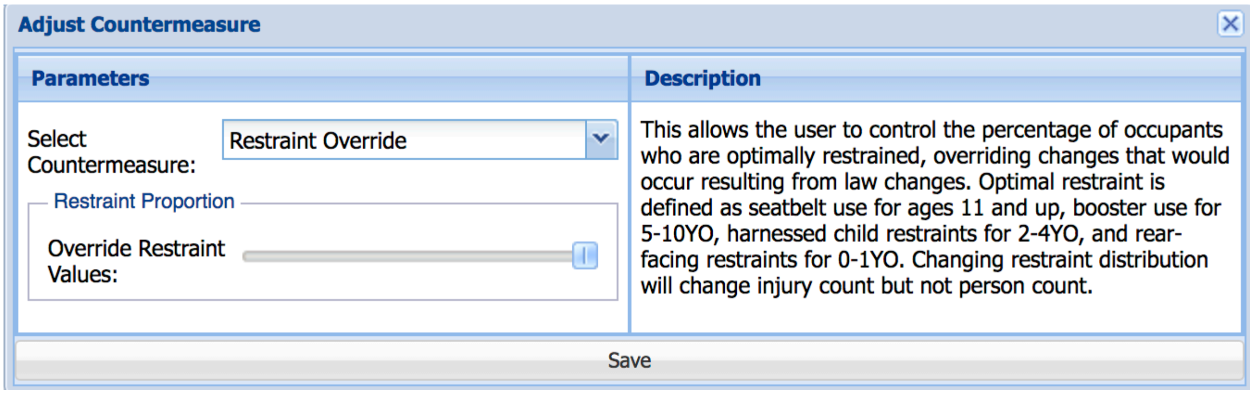

Figure 8-2 Restraint override user interface in UTMOST

8.2 Effects of Countermeasures on Teen Safety

UTMOST was used to analyze the effect of different countermeasures relative to teen crash involvement. Figure 8-3 shows the number of 16-17 year-old (YO) teenagers involved in crashes. In this section, teen involvement means that the teen may be either the driver or the passenger. The first column indicates the baseline count, then the reduced number of crashes as different countermeasures are applied. When the countermeasures are applied, they were used at their baseline rate of effectiveness and at 100% penetration of the fleet or population.

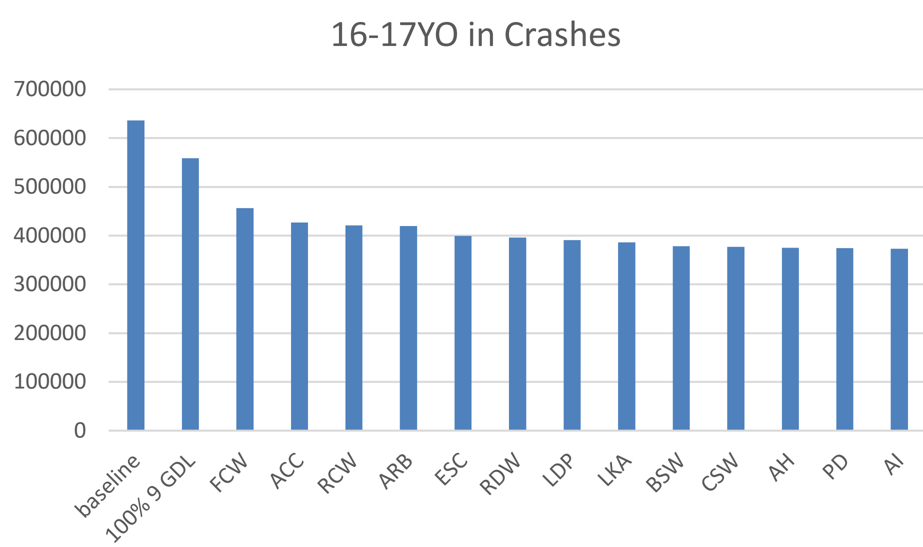

Figure 8-3. Effect of different countermeasures on number of 16-17YO teens in crashes.

Figure 8-4 shows the baseline and reduced counts of teens in crashes for the three different age groups 14-15YO, 16-17YO, and 18-20YO. The first reduction shows the reduced count when all fourteen of these countermeasures are applied, and the second reduction shows the reduced count when the five most effective countermeasures are applied. The five most effective countermeasures were frontal collision warning, 100% strong GDL laws, adaptive cruise control, electronic stability control, and blind spot warning.

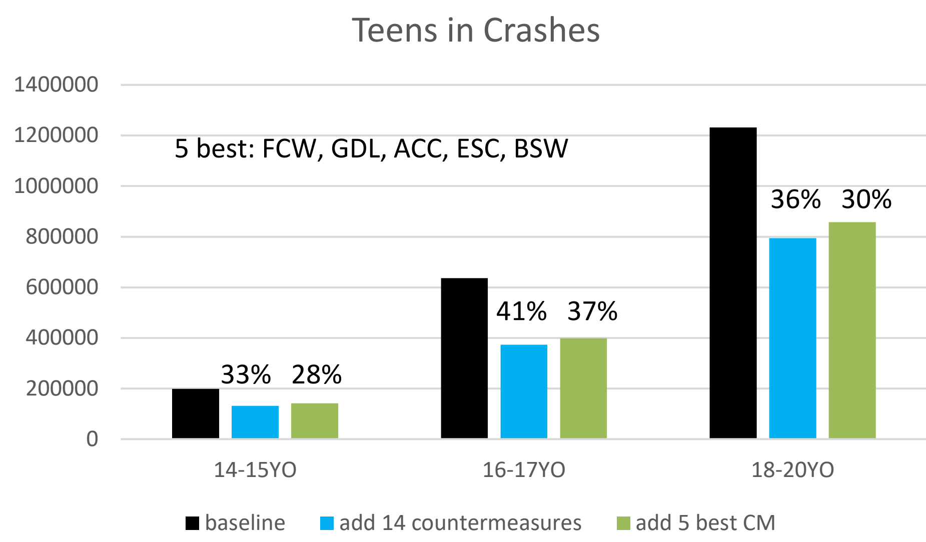

Figure 8-4. Number of teenagers in crashes by age group, baseline, and when 14 or 5 countermeasures are applied.

Next, the effect of countermeasures and restraint use on injured teens was tabulated. Figure 8-5 shows the baseline counts of injured teens for each age group, the reduced counts when the five best countermeasures were added to 100% of vehicles, when all teens were considered restrained by a three-point belt, and when both the countermeasures and restraint conditions were applied. The number of teens injured in crashes could be reduced between 28% and 40% if teens had 100% belt use and the five most effective countermeasures were implemented in all vehicles and states.

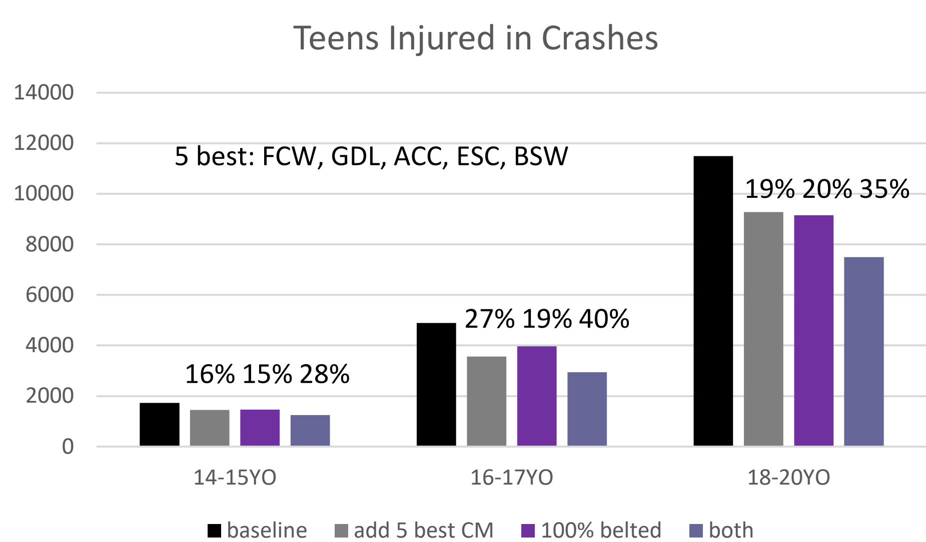

Figure 8-5 Effect of countermeasures on teens injured in crashes

9 Dissemination of Research

In addition to conducting this research, the project team sought to publish results in peer-review journals and conferences. Table 9-1 shows the peer-review publications at the time of this final reporting. In addition, three more submissions have been made, with no feedback yet, and several are underway or planned. The final administrative report provides information on those.

Table 9-1 Project research publications

Type	Citation	Status
Journal	Bao, S, Zizheng Guo, Carol Flannagan, John Sullivan, Sayer JR, Dave LeBlanc (2015), "Distracted driving measures: A spectral power analysis." Journal of the Transportation Research Record, 5592.	published
Journal	Klinich, K. D., Benedetti, M., Manary, M. A., and Flannagan, C. A. (2016). "Rating child passenger safety laws relative to best practice recommendations for occupant protection." *Traffic Injury Prevention, August 2016, pp.1-6*.	published
Journal	Benedetti M, Klinich KD, Manary MA Flannagan CA (accepted) Predictors of Restraint Use among Child Occupants, *Traffic Injury Prevention*	accepted
Conference	Bao, S., Guo, Z., Flannagan, C. A., Sullivan, J., Sayer, J., and LeBlanc, D. (2015): "Distracted Driving Performance Measures: A Spectral Power Analysis." Proc. Transportation Research Board: 94thAnnual Meeting, Washington, D.C	published

10 Summary

This UMTRI project, supported by a grant from the Toyota Class Action Settlement Safety Research and Education Program, pursued a multi-pronged approach to develop and demonstrate methods to assess the safety impacts of crash avoidance systems – individually, and in combination with other technologies and factors. Quantitative results from each of the research threads are included within Sections 4, 5, 6, 7, and 8. The UTMOST framework was greatly expanded to provide comprehensive safety outcomes for sets of countermeasures. This tool is online and usable by safety professionals and the general public. Thus the online UTMOST user can further generate more results and findings beyond those in this report.

To populate UTMOST with effectiveness estimates for forward crash avoidance and mitigation systems and lateral assist systems, a unique and flexible approach to large-scale simulation of events, seeded by UMTRI naturalistic driving data, was created. The approach allows for flexible weighting of simulation runs to reflect the known crash data. Approximately one million simulations were used to compute effectiveness estimates for implementation into UTMOST.

Because driver understanding of new active safety systems is coupled with eventual acceptance and proper usage of these systems, an experiment was conducted in which dozens of drivers were exposed repeatedly to full-speed ACC and lane-keeping assist to understand how driver training and driving experience shapes the driver's understanding of these system. This can then be used as driver usage input into UTMOST.

Teen driver behavior was also studied, including a study using coding of naturalistic driving data from teen drivers to understand the effects of teen passengers on teen driver behaviors related to safety. UTMOST was also used to look at how teen safety in vehicles could be improved by the selection of countermeasures, including the crash avoidance systems, laws, and other effects.

Other related research (as indicated in the research dissemination section) addressed driver performance with and without crash avoidance systems, and advanced evaluation of semi-automated lane departure corrections.

Overall, this project aims to help the vehicle safety community acquire the ability to study sets of safety technologies, laws, and behaviors, instead of single technologies. The online, no-cost tool UTMOST is now available for any user to explore the possibilities on their own.

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Appendix A UTMOST Legislation Modules

Overview

As part of this project, we have added legislation modules to UTMOST to allow users to compare the effect of laws on crash outcomes alongside advanced technologies. Five legislative areas were addressed: child passenger safety, seat belts, impaired driving, teen driver laws, and motorcycle helmets.

For the first four areas, we began with a comprehensive review of each state's laws from 2000 to 2014 using the Lexis Nexus database available through the University of Michigan. Elements of the laws were summarized and tabulated, accounting for changes in the laws over the time periods of interest. A quantitative scheme for ranking the strength of each component of the laws was developed, and the coding was merged with the NASS-GES database from 2000 to 2014 using the zip code of the driver to link the appropriate law for each state. Statistical analysis was performed to identify elements of the laws that effected restraint use or crash outcomes. Analysis of motorcycle helmet legislation focused on the current distribution of laws.

The legislation modules led us to split the crashing population into children aged 0-13, teens aged 14-20, and adults 21 and over. States were categorized as having better or worse categories of each law. Choices allow the user to simulate the effect on outcomes if all states had laws as good as the states with the best laws. Details regarding the law coding, statistical analysis, and UTMOST implementation for each type of law follow.

Child Passenger Safety

Text of each state's child passenger safety law was reviewed and compared to current best practice recommendations for child occupant protection for each age of child (Klinich et al. 2016). A 0-4 scale was developed to rate the strength of the state law relative to current best practice recommendations. A rating of 3 corresponds to a law that requires a restraint that is sufficient to meet best practice, while a rating of 4 is given to a law that specifies several options that would meet best practice. Scores of 0, 1, or 2 are given to laws requiring less than best practice to different degrees. The same scale is used for each age of child despite different restraint recommendations for each age. Legislation that receives a score of 3 requires rear-facing child restraints for children under age 2, forward-facing harnessed child restraints for children aged 2 to 4, booster seats for children 5 to 10, and primary enforcement of seatbelt use in all positions for children aged 11-13. Legislation requiring use of a "child restraint system according to instructions" would receive a score of 1 for children under age 2 and a 2 for children aged 2-4 because it would allow premature use of a booster for children weighing more than 30 lbs. A total rating for each state was developed that sums the scores for each age. Figure A-1 shows the distribution of total scores for each state on a hexagonal map, while Figure A-2 shows the trends in number of states meeting best practice over time.

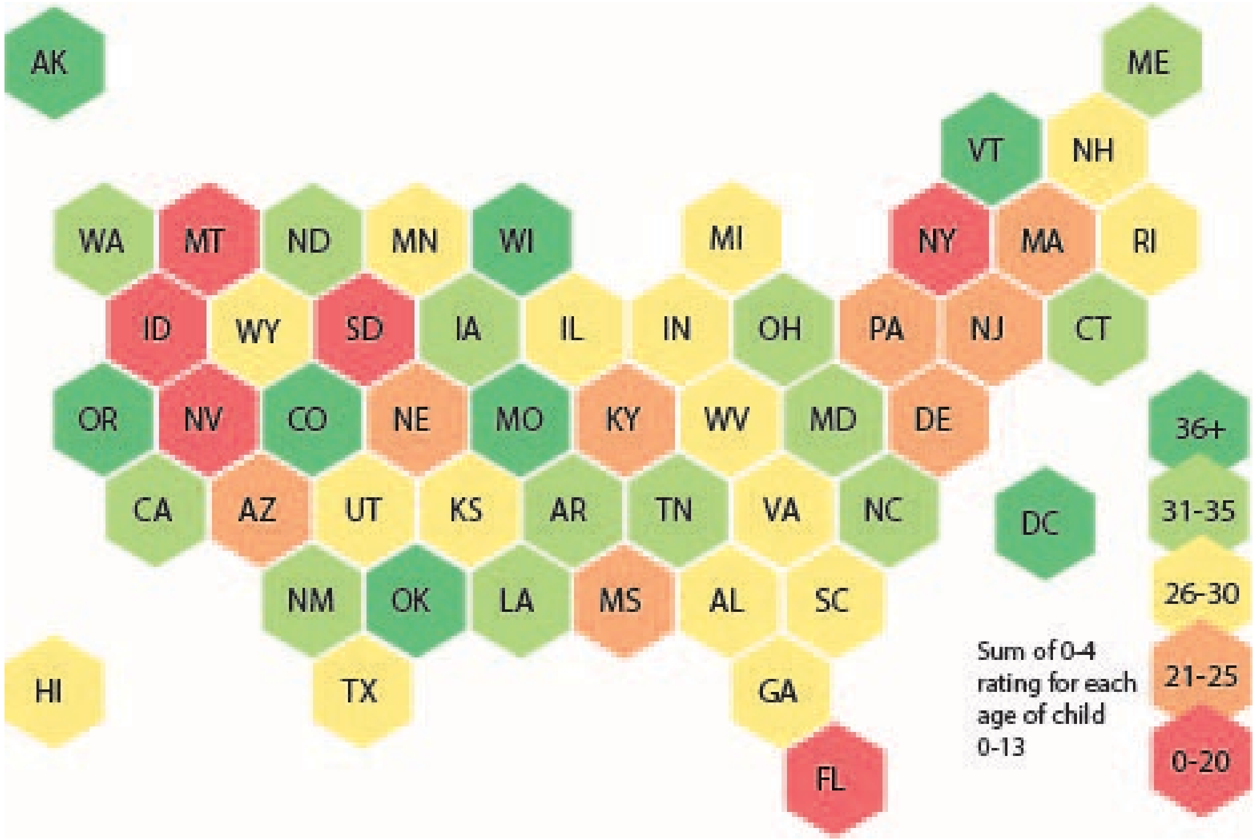


Figure A-1 Total score of state ratings of child passenger safety laws relative to best practice recommendations for each age of child in 2015.

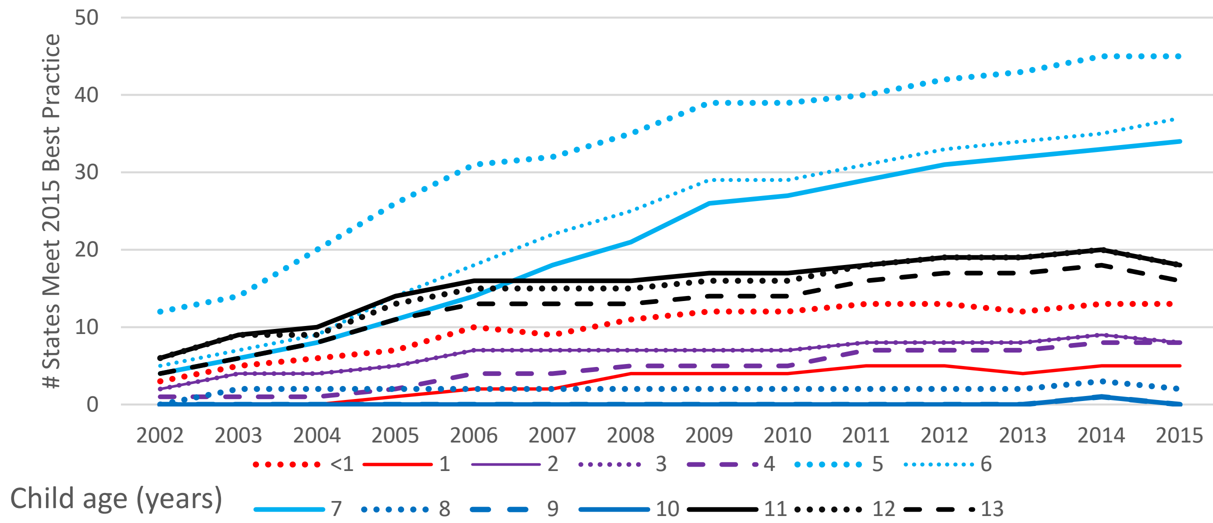


Figure A-2 Number of states meeting/exceeding current best practice recommendations by child age for years 2002-2015. Best practice by age group= Rear-facing, forward-facing (or RF), child restraint system, child restraint system, seatbelt or child restraint system.

The scoring system was merged with the NASS-GES dataset for inclusion as a predictor in mathematical models to predict restraint use and optimal restraint use. The rating scale was condensed to states with laws meeting best practice (3+) or not meeting best practice (0-2). The dataset was also supplemented with demographic census data linked by driver zip code. Analysis used multinomial linear regression techniques.

The strongest predictor of unrestrained child occupants was the presence of an unrestrained driver. Among restrained children, children had 1.92 (95% CI: 1.03, 3.57) times higher odds of using the recommended type of restraint system if the state law at the time of the crash included wording based on best practice recommendations. Figure A-3 shows the rate of optimal restraint use in states that do and do not meet best practice. Children under two are 58% more likely to ride rear-facing in states with better child restraint laws, and children aged 2 to 4 are 30% more likely to use a harnessed child restraint. Male drivers are 0.75 (0.59, 0.97) times as likely to optimally restraint their child passengers than female drivers. Children in the front seat tend to be optimally restrained less often than those sitting in the rear seat [OR 0.75 (0.54, 1.03)].

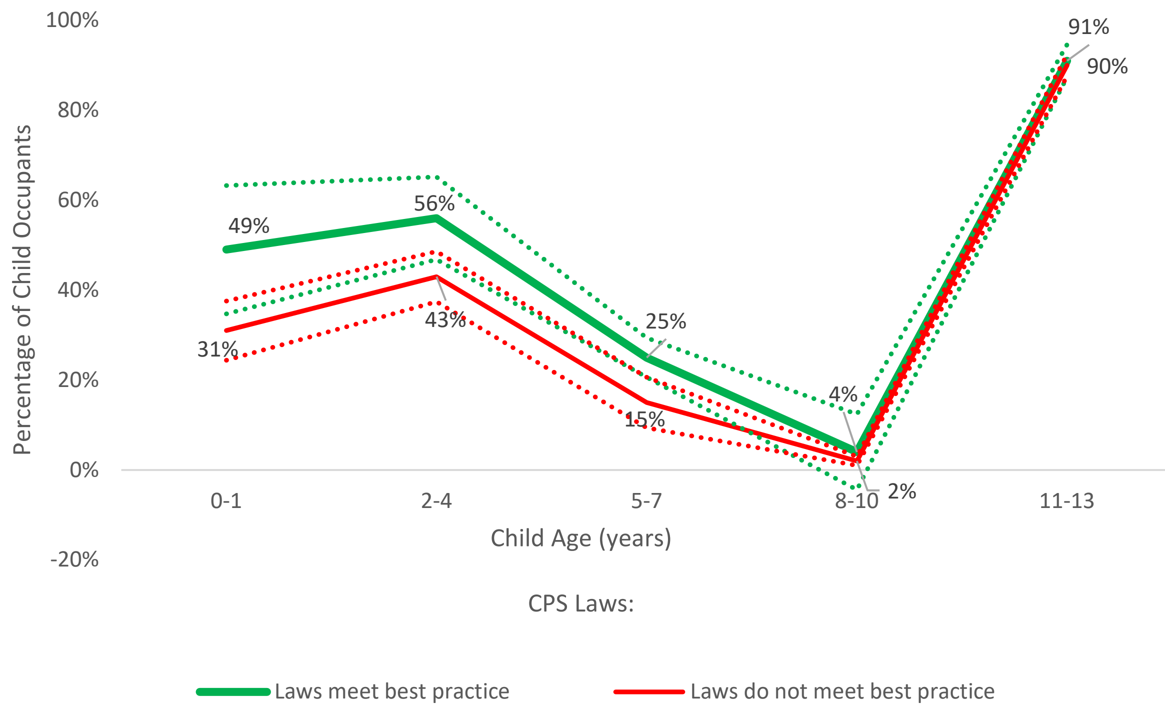


Figure A-3 Predictions of child restraint use by age group and state law strength. Dotted lines indicate 95% confidence intervals.

To implement these results in UTMOST, for each state, we obtained the 2015 population of each age child from 0 to 13. Each state was tagged as meeting best practice for each age or not meeting best practice for each age based on the 2014 state law. For each age, the number of kids living in states with and without best practice laws was summed. So for each year of age, we know the population living in states with and without best practice (BP) CPS laws for their age.

The next step is to estimate the number of kids who are unrestrained (U), optimally restrained (O), and suboptimally (S) restrained for each age, according to whether their laws do or do not meet best practice. The NASS-GES data was used to calculate the ratio of optimal restraint use by type of law. However, the NSUBS observational study was used to approximate the percentage of children who were U, O, or S for each age because of inconsistencies with distribution of reported restraint type in NASS-GES.

The NASS-GES dataset was used to explore the relationship between injury and restraint type. Risk of KAB injury for children was modeled as a function of age, restraint type (optimal, suboptimal, unrestrained), driver age, driver alcohol use, driver injury, crash direction, driver restraint, and child seat location (front, rear). The resulting model was used in UTMOST as the injury risk function for children.

Figure A-4 shows the child restraint law countermeasure panel as implemented in UTMOST. Users can change the population proportion that are covered by laws including best-practice language.

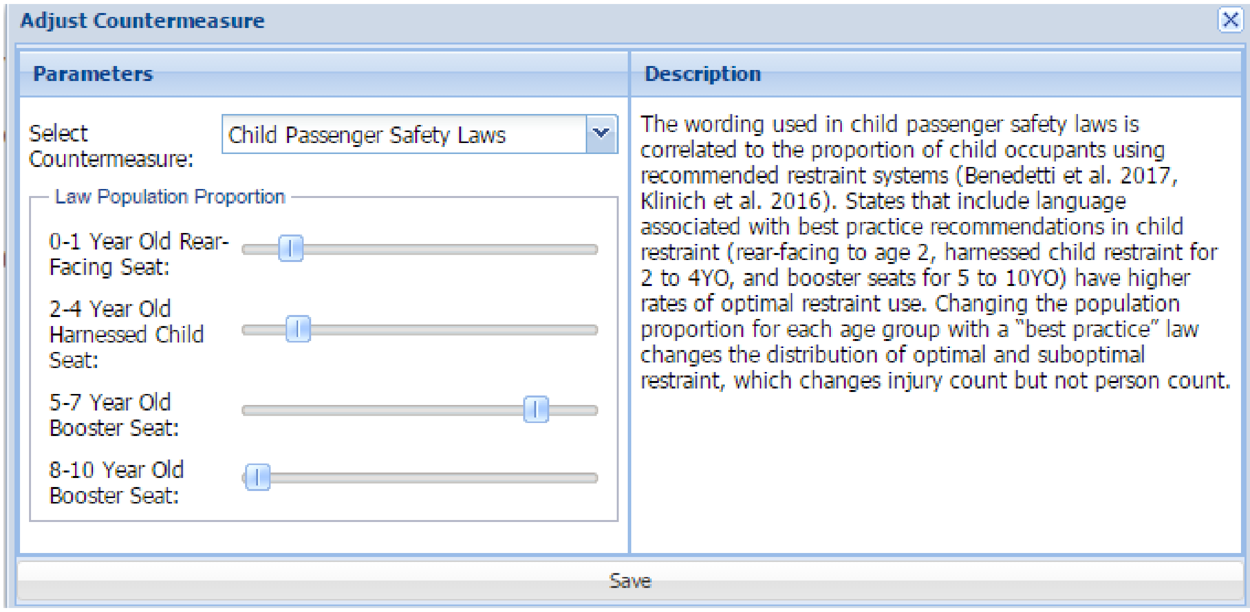


Figure A-4 Child restraint law countermeasure as implemented in UTMOST.

Seat belts

While several past studies demonstrate that a primary seatbelt law is associated with higher rates of observed belt use, other elements of seatbelt legislation have not been comprehensively evaluated. In addition, many analyses have focused only on a single state or on fatal crashes.

Initial analysis of the NASS-GES dataset indicated that the reports of belt use rates were extremely high, with less than 1% of occupants as unbelted. Therefore, instead of using the NASS-GES dataset to track belt use rates, the observed rate of seat belt use in each state from 2000-2014 was extracted from published reports of the National Occupant Protection Use Survey (Chen et al. 2014).

State seat belt laws from 2000-2014 were reviewed, focusing on laws for adults aged 18 and older, as some states have stricter laws for teenagers. For each year and state, the components of each seat belt law were documented as follows:

- Is seat belt use required for adults in the front seat?
- Is seat belt use required for adults in the back seat?
- Is primary enforcement allowed for front seat occupants?
- Is primary enforcement allowed for back seat occupants?
- What is the fine for a seat belt infraction?
- Does the fine increase for a subsequent infraction?
- Is someone penalized with points on their driver's license for not wearing their seat belt?

For subsequent analysis, the amount of the fine was categorized either as none, $1-$25, $26-$50, $51-$75, $76-$100, and >$100.

Results indicate that seat belt use rates increase by 1% per year independent of law. The presence of a seat belt law for front-seat occupants increased belt use rates on average by 12.6%, and a primary law for front-seat occupants increased seat belt use rates by another 6.1%. States that either added points to a driver's license or increased seatbelt fines after the first violation had belt use rates that are 3.2% higher than states that did not. Once these elements were included in a model predicting seatbelt use rate as a function of law components, the amount of fine or the presence of a back seat belt law were not significant. Figure A-5 shows a hex map of the United States according to the type of law in 2014. Although 19 states (37%) do not have primary seatbelt laws, Figure A-6 shows that 75% of the adult population is covered by primary laws because states with secondary laws tend to have fewer people. Results are consistent with an earlier study by Nicholls et al. (2014).

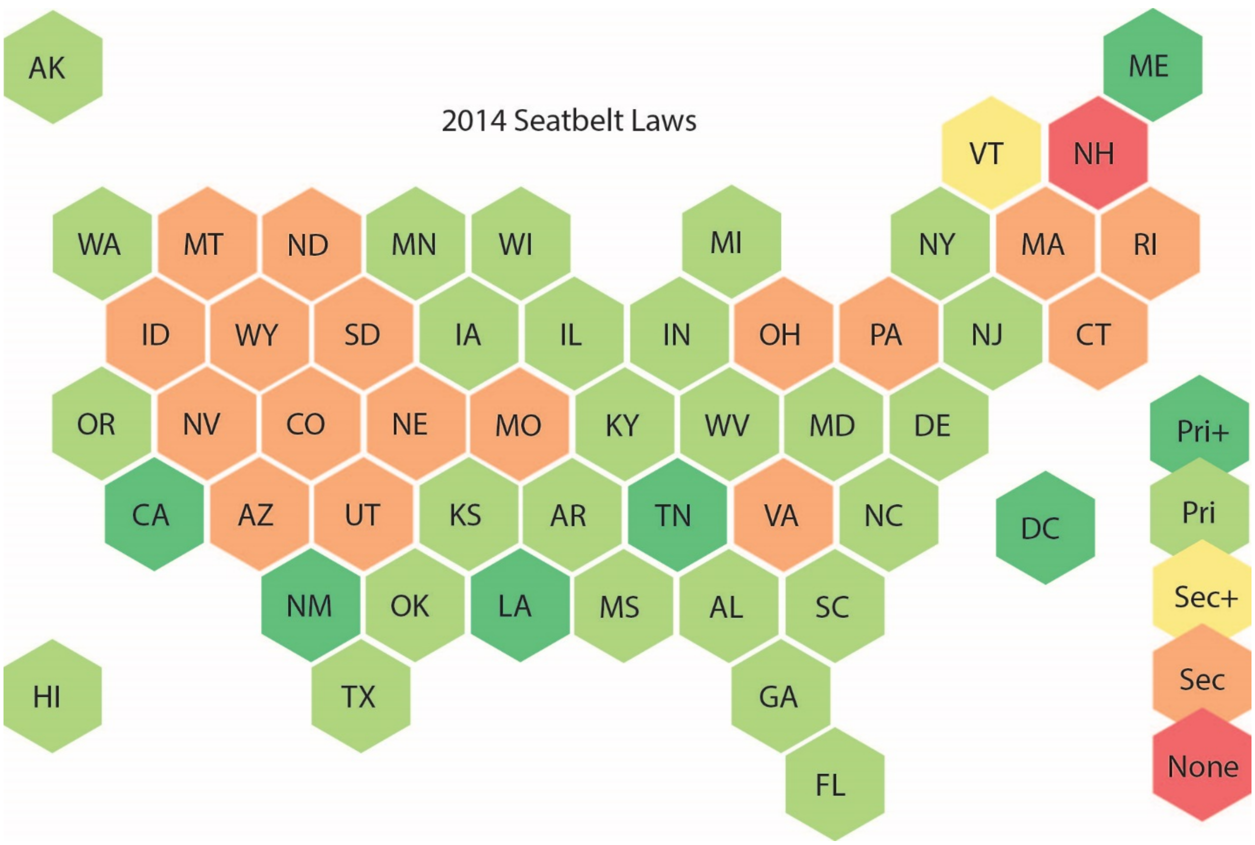


Figure A-5 Distribution of states by type of seatbelt law.

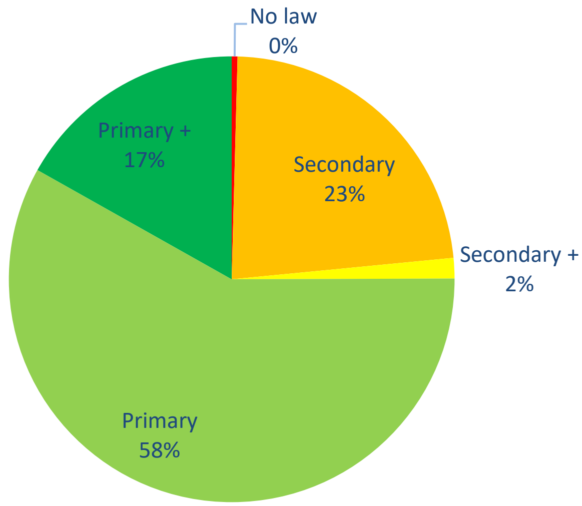


Figure A-6 Distribution of population by type of seatbelt law.

To implement the seat belt legislation module in UTMOST, we provide a table showing the distribution of the US adult population by type of seatbelt law. Table A-1 shows the adult population distribution for 21-65YO, the proportion of unbelted and belted occupants based on type of law, current rate of belt use, and adjusted rates of belt use if all states had primary laws or all states had primary laws plus increased fines or points. The last row estimates the total overall belt use with law changes weighted to consider the populations for each type of seatbelt law. The user can redistribute the population to examine the effects of having stronger seatbelt laws.

Table A-1 Distribution of population by type of seat belt laws and current and predicted belt use rates.

	Population%	Unbelted	Belted	Current Belt use	All primary	All primary +
None	0.4%	1.2%	0.3%	70%	89%	92%
Secondary	23.3%	38.6%	21.5%	82%	88%	92%
Secondary+	0.2%	0.3%	0.2%	84%	90%	93%
Primary	59.0%	50.9%	59.9%	91%	91%	94%
Primary +	17.1%	9.0%	18.0%	94%	94%	94%
Overall				89%	91%	93%

Figure 2-1 shows how this table has been implemented in UTMOST. The user can adjust the population proportion that are covered by primary vs. secondary laws, with and without higher fines for second offenses.

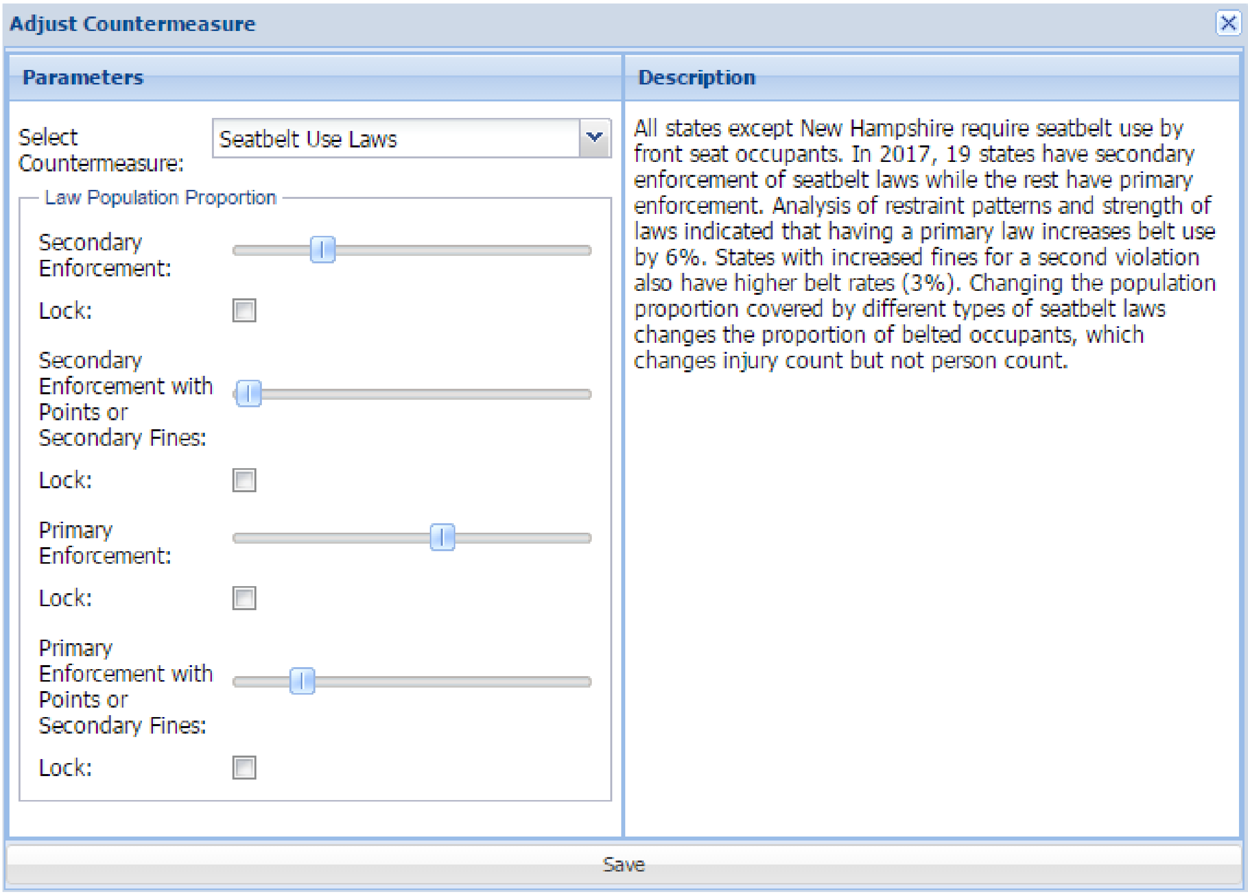


Figure A-7 Seat belt law countermeasure as implemented in UTMOST.

For each type of unbelted or belted driver in the UTMOST dataset, we assign a likelihood of being in a state with a particular type of law based on the distributions shown in the unbelted and belted columns of Table A-1. Drivers without primary laws are flagged as being affected by primary law changes, and drivers without increased fines or points are flagged as being affected by these types of changes.

Drunk Driving Laws

Similar to studies of seatbelt legislation effectiveness, most published studies have focused on individual elements of drunk driving laws using data from a single state or from fatalities. Most have not examined elements of the law simultaneously using a national crash dataset.

Driving under the influence (DUI) laws from 2000-2015 were reviewed, focusing on laws for adults aged 18 and older, as some states have stricter laws for teenagers. For each year and state, the components of each seat belt law were documented as listed in Table A-2, considering penalties for the first, second, and third infraction. In addition, a 0 to 5 scale was used to code the range of penalties for each category as indicated. Two other factors that were documented are whether a treatment program is an option for reduced penalties and whether victim impact panels are held.

Table A-2 Scoring method for elements of impaired driving laws.

Item	Unit	0	1	2	3	4	5
BAC	BAC	NA	.10	.08	NA	NA	NA
Fine	Dollars		<500	500 - < 1000	1000 - < 5000	5000 - < 10000	10000+
Jail time	Years		.01 - < .5	.5 - < 1	1 - 2	3 - 4	5+
License suspension	Years		.01 - < .5	.5 - < 1	1 - < 2	2 - 4	5+
Felony?	NA	No	NA	NA	NA	NA	Yes
Ignition Interlock device (IID) optional?	Years	Not indicated	.01 - < .5	.5 - < 1	1 - 2	3 – 4	5+
IID required?	Years	Not indicated		.01 - < .5	.5 - < 1	1 – 2	3+
Lookback period	Years		3 -5	6-7	10	12-15	Lifetime
Penalty for elevated BAC	BAC		.1	.15	.16	.17-.18	.2

The scores for different elements of DUI laws were linked with the NASS-GES dataset for 2000-2014, matching the state and year for each case and law. The VEH_ALCH variable, which indicates if there was alcohol use by the vehicle driver, was used as the outcome variable. Using general linear models and backwards selection, all of the drunk driving law elements were considered potential predictors. Various strategies considering the predictors as categorical or linear were implemented. In most models, the elements related to third offenses dropped out first, followed by the second. Modeling efforts were unable to identify which elements of impaired driving laws were consistently associated with reduced rates of impaired crashes across states. As a result, specific models of impaired driving laws are not currently included in UTMOST. Instead, we consider previously published data that focused on the use of alcohol interlock devices to prevent impaired driving crashes.

Motorcycle Helmet Laws

Pickrell and Choi (2015) report that 64% of motorcyclists use DOT-compliant helmets. They also report that helmet use varies between states that require universal helmet use (89%) and those that do not (49%). The online database of motorcycle helmet laws by state maintained by the Insurance Institute for Highway Safety (IIHS, 2016) was used to characterize whether each state currently has a universal motorcycle helmet law. Data on motorcycle registrations by state in 2014 (Statista 2016) were used to estimate the proportions of the motorcycle-riding population that live in states with and without a universal motorcycle helmet law. These calculations indicate that 39% of motorcycle registrations are in states with universal helmet laws, while 61% are not. For UTMOST implementation shown in Figure A-8, the user can adjust the percentage of the motor-cycle riding population (based on registrations) that are covered by universal helmet laws.

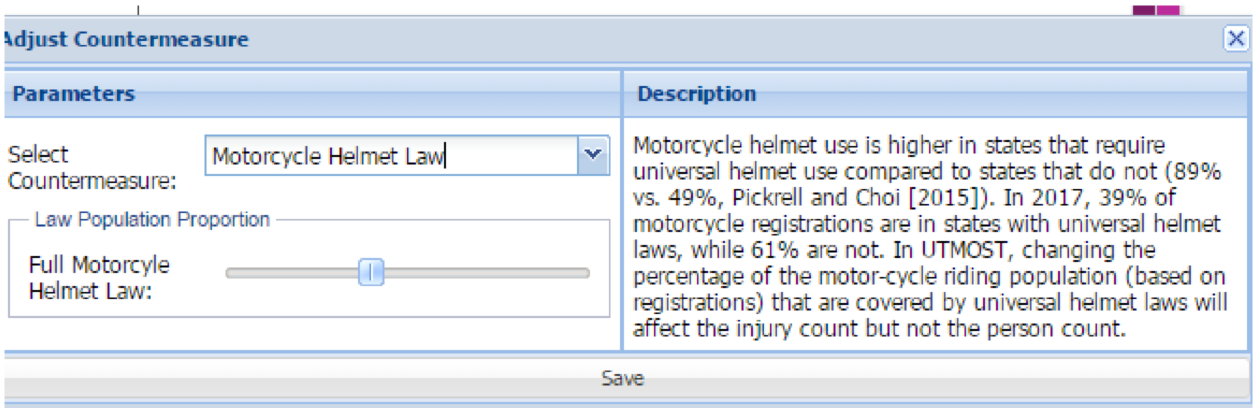


Figure A-8 Motorcycle helmet law countermeasure as implemented in UTMOST.

Graduated Driver's Licensing

The NASS-GES dataset from 2000-2014 was the basis for analysis. To determine the effect on teen crash rates of different elements of teen driving laws, we considered as our outcome variable the population-weighted rate of teen crashes relative to the population-weighted rate of adult crashes. We obtained from 2015 census estimates the number of people by US state in the following age groups: 14 to 15 years old, 16 to 17 years old, 18 to 20 years old, and 21 to 65 years old. For each crash year, state, and age group, we divided the weighted number of crashes by the 2015 population. We then calculated crash ratios by dividing each teen crash rate by the adult crash rate for each state and year.

Initial review of the ratios indicated issues related to low sample size for many states. To avoid these problems, we reviewed the unweighted number of crashes in the dataset for each state and year. Twenty-four states had at least one year where the raw crash count in the dataset ranged from one to 90; the other 26 states had minimum annual raw case counts ranging from 387 to 5581. Consequently, we restricted our analysis to the 26 states with higher raw case counts that cover 80% of the U.S. teen population. These are indicated by outlined states in the hexagonal representation map of the United States shown in Figure A-9.

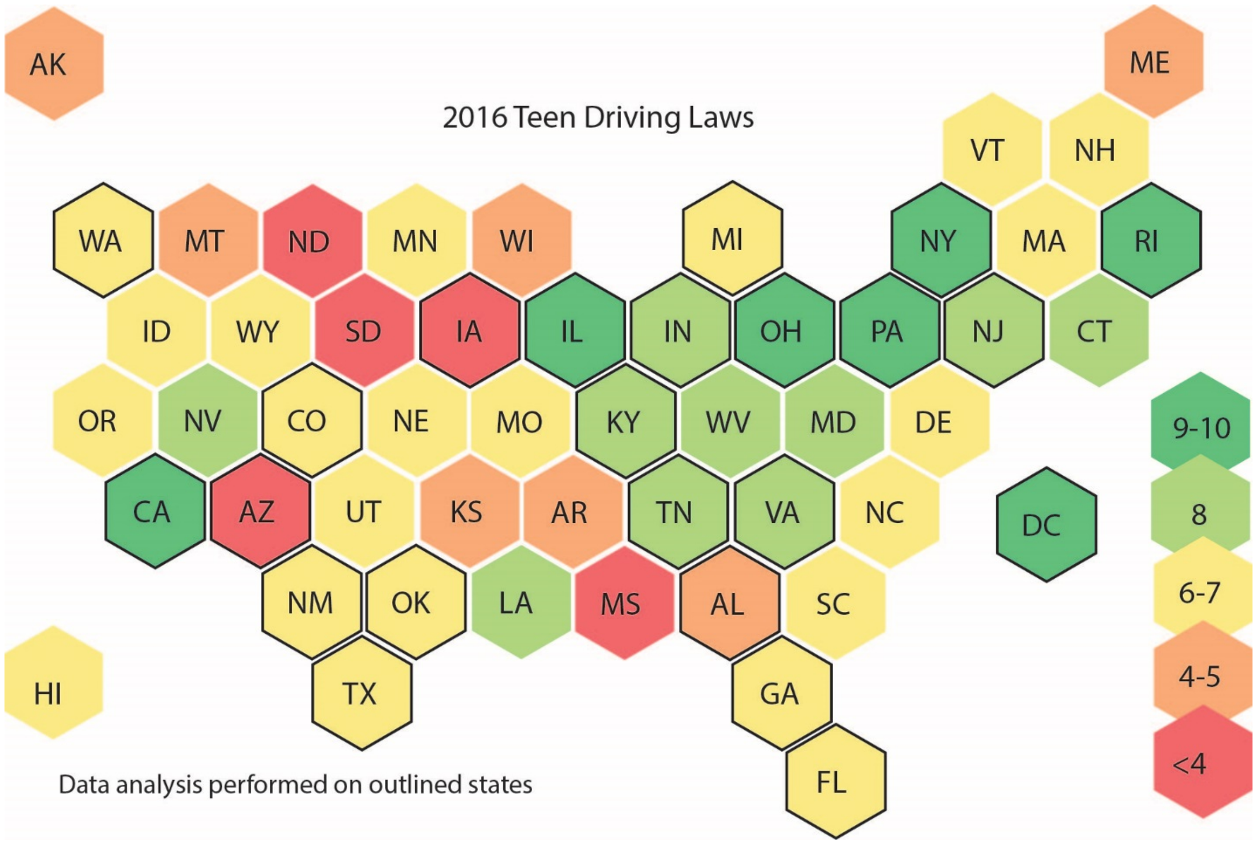


Figure A-9 Hexagonal US map showing number of strong graduated licensing laws for each state, as well as the states used in analysis (outlined).

The laws governing licensing of teen drivers were reviewed using the LexisNexis database available at the University of Michigan. The following elements of each law were assessed for each state and year from 2000-2014:

- Minimum age to obtain learner's permit
- Minimum duration to hold learner's permit
- Number of supervised driving hours required
- Number of supervised driving hours required at night or inclement conditions
- Age for required driver education
- Minimum age for obtaining intermediate/probationary license
- Number of hours of restricted nighttime driving for intermediate license holders
- Age/period when nighttime restrictions end
- Restrictions on passengers
- Age/period when passenger restrictions end

For each of these elements of teen driving laws, a zero-to-five score was assigned based on the range of values found in laws across all states and years. Table A-3 shows the scores corresponding to each element and value. For coding the passenger restrictions, we considered the maximum number of passengers under age 18 possible in the first and second phase of the restriction, even though specific age restrictions may vary.

Table A-3 Scoring method for strength of graduated drivers licensing law components.

Score	Min age learner (yr)	Learner duration (months)	# hours		# harder hours	Age drivers ed (years)	Min age intermediate	# hours restricted nighttime	Nighttime restrictions end	Passenger restrictions	Passenger restrictions end
0		0	0-12		0	NA	≤15	0	NA	No limits	NA
1	14	1-3	20-25		2-5	< 15.5	>15 to <16	3, 4 or 4.5	6M/16.5YO Or 6M or 16YO	2 or 3	6M/16.5YO Or 6M or 16YO
2	> 14 to < 15	4-5	30		10	< 16	16	5	12M/16.5YO or 6M/17YO or 9M/16.75	1 then 3	12M/16.5YO or 6M/17YO or 9M/16.75
3	15	6	40-45		15	< 17 or 17.25	> 16 to < 16.5	6	12M/17YO Or 17YO	1	12M/17YO Or 17YO
4	15.5 or 15.75	9	50		NA	< 18	16.5	7	18YO	0 then 1 or 3	18YO
5	16	12	60-72		NA	all	17	8+	(12M+18YO or 21YO) or 24M+18YO or (6M+18YO) or 21YO)	0	(12M+18YO or 21YO) or 24M+18YO or (6M+18YO) or 21YO)

The law scores were merged with the dataset of teen crash ratios by crash year and state. Univariate analysis was initially performed to identify potential predictors with significance at $p<0.05$. A composite teen driving score was constructed by adding up the number of “strong” laws for each state, defined as those receiving a rating in the upper half of the scoring scale (2-3 for harder hours and 3-5 for all other components).

Figure A-10 shows the relationship between number of strong laws and the teen/adult crash risk ratio described. A greater number of strong laws reduces the crash risk ratio for all three age groups, with the greatest effect seen on 16-17YO drivers.

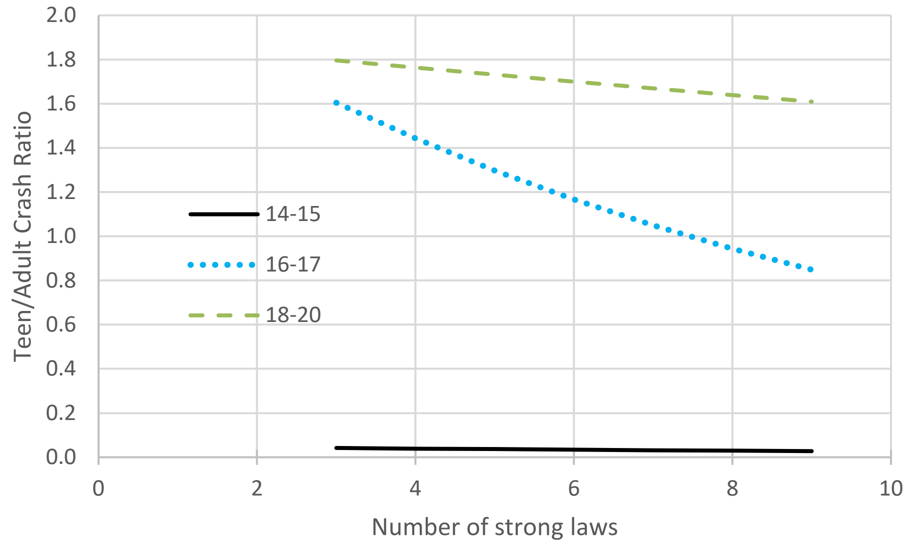


Figure A-10 Ratio of teen/adult crashes as a function of number of strong GDL laws.

For the teen driver legislation module in UTMOST, users are presented with the current distribution of teen population by the number of strong GDL laws, shown in Figure A-11. Users can adjust the population distribution to examine the effect of more states having more strong laws. Laws apply to all three teen population groups in the same way.

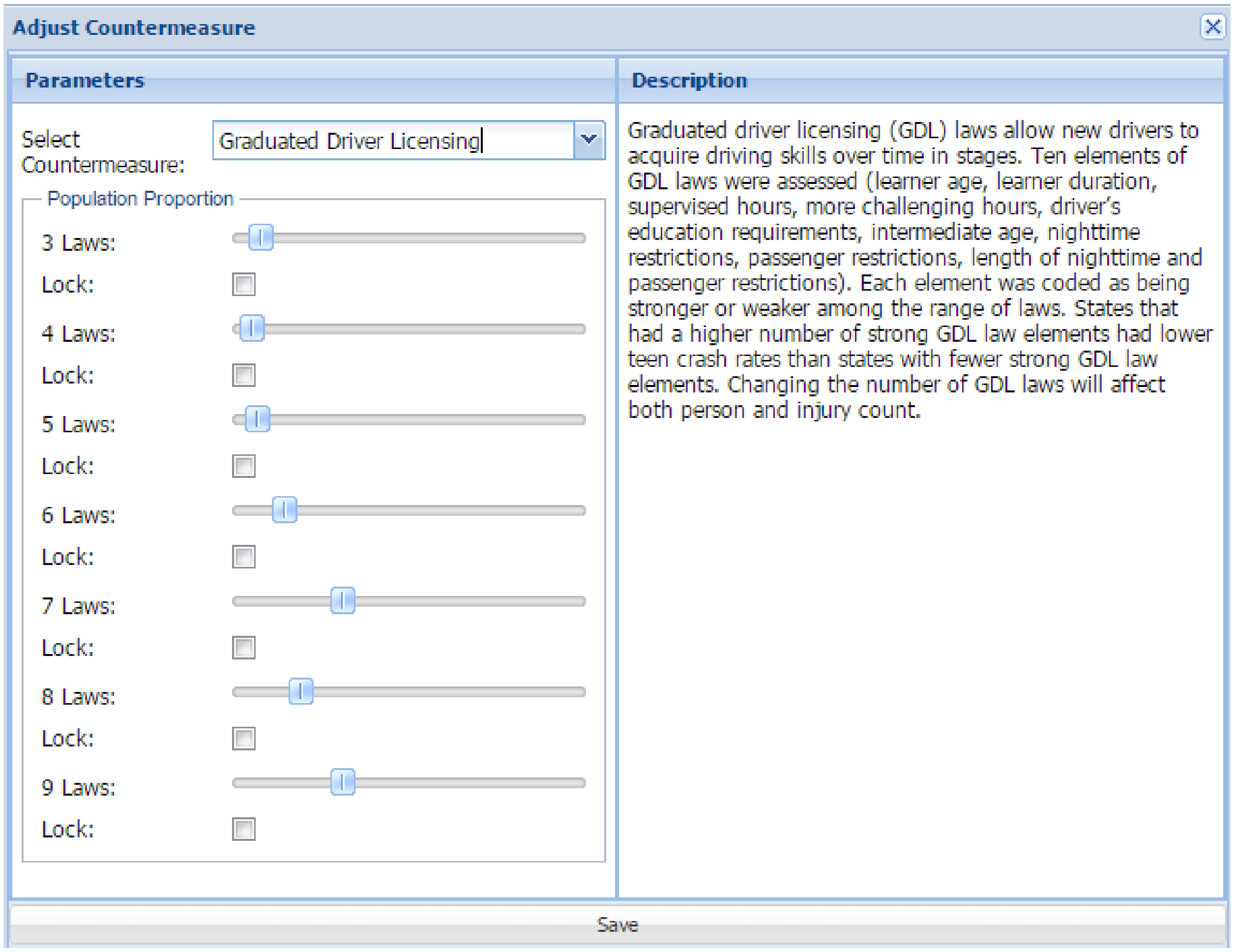


Figure A-11 GDL law countermeasure as implemented in UTMOST.

Appendix B Further Characterization of Forward Crashes

The following pages further characterize the forward crashes that are used as the baseline for estimating the FCAM systems' potential benefits. This appendix extends the discussion of Section 4.1.

Crash severity

Although annually about 828 persons were killed and 18,752 were seriously injured (i.e., suffered incapacitating injuries), FC crashes tend to be less severe than other crash types. **Figure B-1** compares the severity of FC and all other crash types, measured by the most severe injury in the crash. Only 0.05% of FC crashes involved a fatality and only 1.0% involved an incapacitating injury, compared with 0.5% and 2.8% respectively for the aggregate of all other crash types. In FC crashes, both vehicles were going in the same direction, which would reduce impact speeds in comparison with head-on collisions or crashes in which the vehicles were crossing paths. Non-FC crashes also included run-off road crashes and rollovers, which can be very severe.

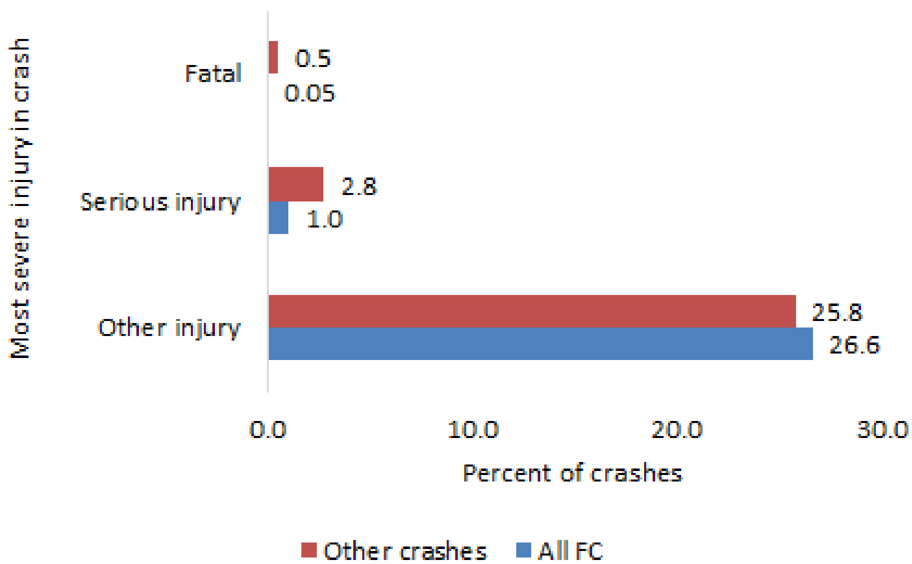


Figure B-1 Crash severity of LTV FC and other crash types

Pre-crash maneuver (scenarios) associated with FC crashes

Table B-1 shows the distribution of the pre-crash maneuver of striking vehicles for each FC crash type. In over three-quarters of FC crash involvements, the striking vehicles were simply going straight. Decelerating in lane and starting in lane were the next most common pre-crash maneuvers—but in both cases, the LVs would have been in front of the striking vehicles. Crashes in which LVs suddenly cut into the lane in front of striking vehicles were rare. LV cut-in-front of the striking vehicles occurred in only 0.1% of all LTV crash involvements, and only 0.6% of FC crashes (**Figure 4-1**). Striking vehicles changed lanes just prior to impact in 1.7% of FC crashes overall, but in

5.0% where the LVs were going slower at a steady speed. In most cases, the LVs were in front of the striking vehicles for the period prior to collision and the striking vehicles were simply going straight. There were few crashes where one vehicle or the other maneuvered prior to put the vehicles on a collision path.

Table B-1 Pre-crash maneuver of striking vehicle by FC crash type

Pre-crash maneuver	LV stopped	LV slower	LV decel.	LV cut-in	All FC
Going straight	75.1%	80.1%	83.1%	85.8%	77.5%
Negotiating a curve	2.8%	2.4%	3.5%	1.6%	2.9%
Decelerating in lane	7.9%	3.6%	9.3%	0.3%	7.7%
Starting in lane	7.6%	4.0%	1.0%	0.9%	5.7%
Change lanes/merge	1.1%	5.0%	1.8%	9.6%	1.7%
Avoidance maneuver	0.0%	0.1%	0.0%	0.0%	0.0%
Other	4.7%	4.1%	0.9%	0.8%	3.7%
Unknown	0.7%	0.6%	0.3%	0.9%	0.6%
Total	100.0%	100.0%	100.0%	100.0%	100.0%

Driver age

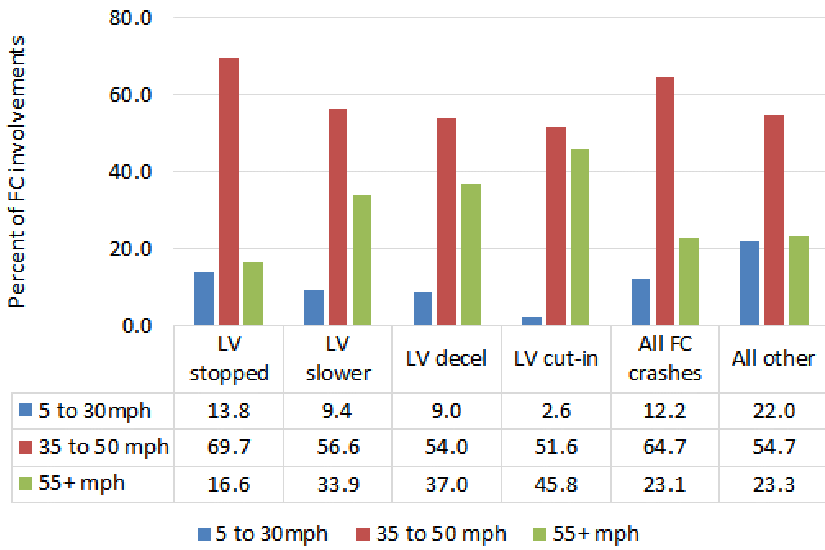
Younger drivers tended to be overinvolved in FC crashes, compared with other drivers (Table B-2). Overall, FC crashes accounted for almost a quarter of crash involvements for drivers up to 17 years of age and 23.1% of involvements of drivers 18-25, compared with 15.6% of drivers 26-64, and 12.5% of drivers 65 and over. FC crashes in which the LVs were stopped or decelerating were particularly overinvolved for younger drivers, while older drivers were under-involved for each FC crash type. Younger drivers may tend to leave shorter gaps to the LVs and may tend to be distracted more than older drivers (see Figure B-4 for distraction).

Table B-2 Distribution of FC crash types by driver age

FC crash type	Driver age				Total
	0-17	18-25	26-64	65+	
LV stopped	17.5%	15.0%	10.4%	8.8%	11.6%
LV slower	1.7%	2.2%	1.5%	1.2%	1.7%
LV decelerating	5.5%	5.9%	3.6%	2.5%	4.1%
LV cut-in	0.2%	0.1%	0.1%	0.0%	0.1%
All FC	24.9%	23.1%	15.6%	12.5%	17.5%
All other crash types	75.1%	76.9%	84.4%	87.5%	82.5%

Speed limits

Most FC crashes occurred on roads with speed limits between 35 and 50 mph, but the distribution differed by individual crash type (Figure B-2). LV slower, LV decelerating, and LV cut-in crashes all occurred significantly more often on higher speed roads (55+ mph) than the LV stopped type. This makes some sense, because roads signed for lower speed limits tend to have more stop-and-go traffic. Table B-2 above showed that the LV stopped type was the only FC type with a significant percentage of starting in traffic as the pre-crash maneuver. Roads with speed limits 55 mph and over are high speed, and many are limited access. Rear-end crashes on such roads suggest coming upon traffic that was unexpectedly slow, due to congestion work zones, or other reasons.

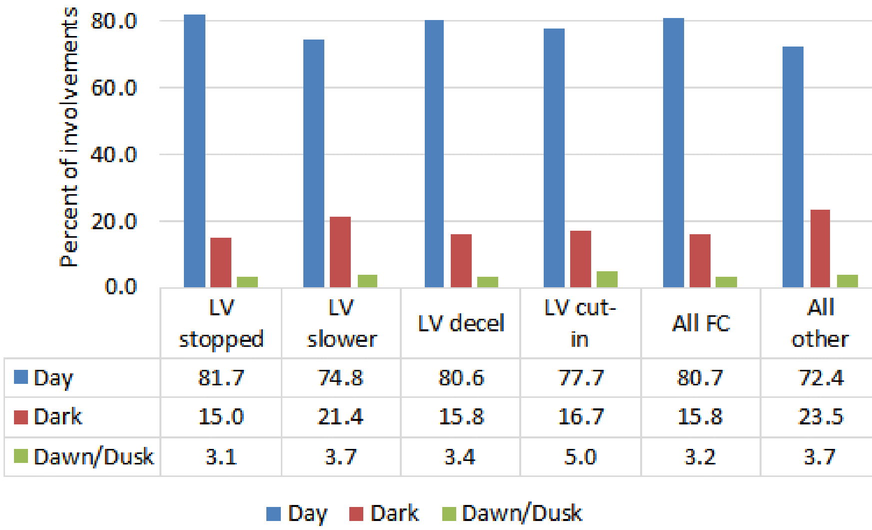


	LV stopped	LV slower	LV decel	LV cut-in	All FC crashes	All other
5 to 30mph	13.8	9.4	9.0	2.6	12.2	22.0
35 to 50 mph	69.7	56.6	54.0	51.6	64.7	54.7
55+ mph	16.6	33.9	37.0	45.8	23.1	23.3

Figure B-2 Distribution of speed limit for FC crash types and other crashes

Ambient lighting

Most FC crashes occurred in daylight (Figure B-3). In fact, FC crashes as a whole were more likely in daylight than other crash types. Daylight accounted for over 80% of FC involvements, light condition was dark in 15.8%, and 3.2% occurred in dawn or dusk conditions. In contrast, 72.4% of all other crash involvements of LTVs occurred in daylight, 23.5% in darkness, and 3.7% at dawn or dusk. Again, there were some differences between FC types. Over 21% of the LV slower type occurred in darkness, which was the highest percentage among FC types. These may be crash involvements on rural roads at night, where the striking vehicles came upon slower vehicles unexpectedly because of sight distance restrictions due to darkness. But again, most FC crashes occurred during daylight hours, when the drivers' ability to see should have been good.

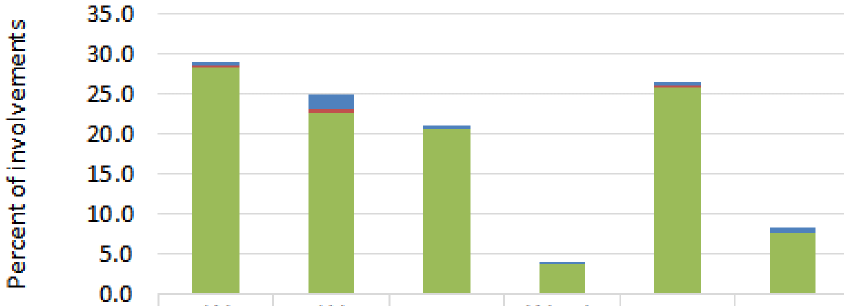


	LV stopped	LV slower	LV decel	LV cut-in	All FC	All other
Day	81.7	74.8	80.6	77.7	80.7	72.4
Dark	15.0	21.4	15.8	16.7	15.8	23.5
Dawn/Dusk	3.1	3.7	3.4	5.0	3.2	3.7

Figure B-3 Distribution of light condition for FC types and other crashes

Driver state

FC crash types were significantly associated with driver distraction, much more so than other crash types. Figure B-4 shows the distribution of fatigue and distraction among drivers in FC crashes and in all other crashes (right-most column). Overall, 26.0% of FC-involved LTV drivers were coded as distracted, compared with 7.8% of LTV drivers in all other crash types. Distraction was identified most commonly for the LV stopped type of FC crash, which likely occurred somewhat more on low speed roads in stop-and-go traffic. Distraction was coded least often for the LV cut-in type, but comparatively few FC crashes fell into that type. Fatigue was less relevant, except for the LV slower type, where a total of 2.4% of involvements were related to fatigue, compared with 0.7% for all FC involvements and 0.8% for all other types of crash involvements.



	LV stopped	LV slower	LV decel	LV cut-in	All FC	All other
Fatigued	0.4	2.0	0.4	0.2	0.6	0.7
Both	0.1	0.4	0.0	0.0	0.1	0.1
Distracted	28.4	22.7	20.7	3.7	25.9	7.7

Distracted Both Fatigued

Figure B-4 Distribution of fatigue and distraction for FC types and other crashes

Appendix C Models and Methods for Crash Avoidance System Effectiveness Simulation

General Simulation Approach and Concept

Conceptually, a similar approach was taken for both AEB and LKA simulations and an outline of the methodology is given in Figure C-1. The simulations were conducted with inputs from a variety of models and algorithms and initial conditions. For a given set of conditions, the simulations were repeated with the driver response input (braking or steering) delayed in 0.1 s time steps. Algorithms were used to calculate when a warning was issued and when the countermeasure technology was triggered. The output of each simulation is a time-series measures of vehicle kinematics. From the time series data summary results were aggregated and used in a statistical model to compare baseline with warning and countermeasure results. The details of simulation inputs are given the sections below.

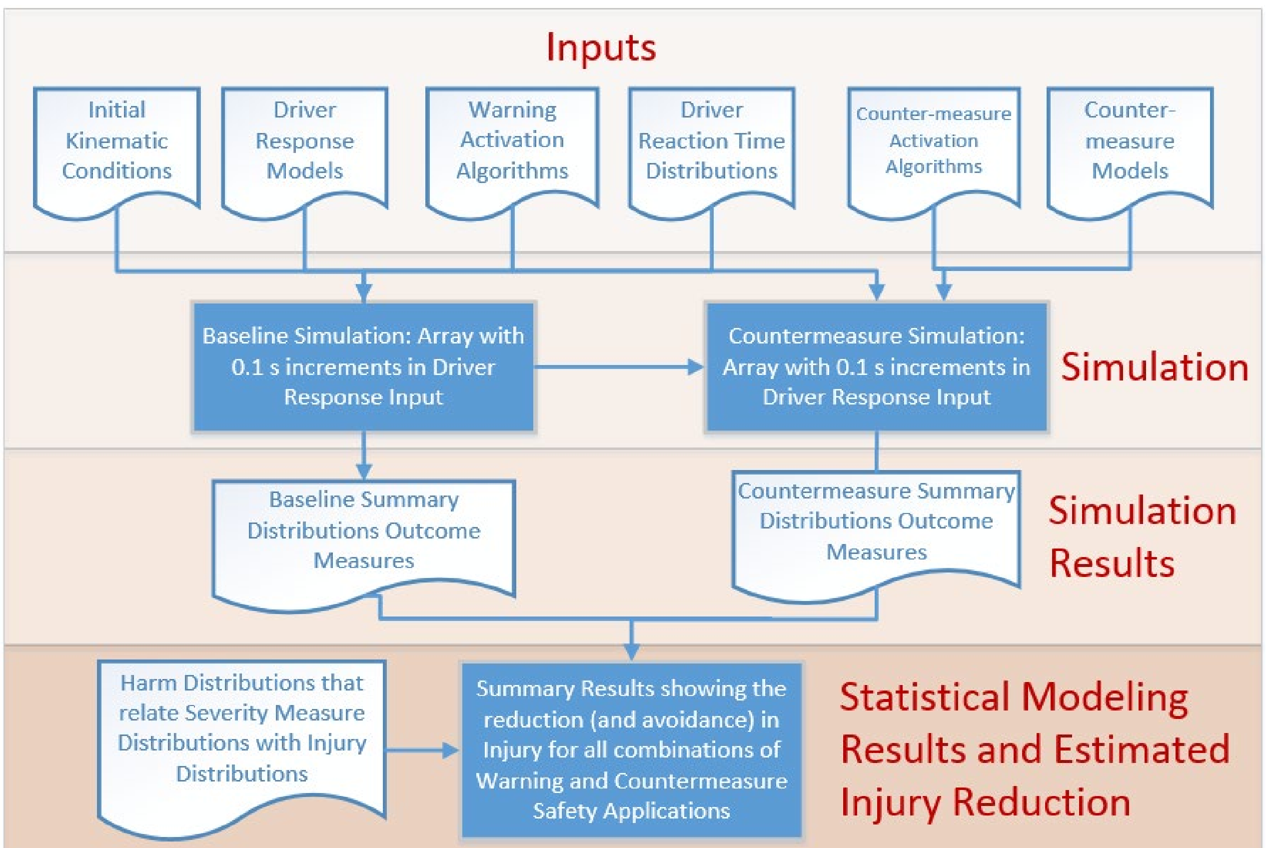


Figure C-1 Simulation Approach for AEB and LKA simulations.

Initial Kinematic Conditions (IC)

All IC were derived from UMTRI naturalistic driving databases with millions of miles of driving. For the AEB simulation these included measures of host speed, remote speed and distance between vehicles. For simulations that involved a slowing lead vehicle, actual braking profiles were derived measures in these datasets. For LKA, values of lane offset and boundary type from a lane-tracking vision sensor were used to calculate lateral speed for lane departures. The number of IC for AEB were:

- 6501 for Slowing Lead Vehicle
- 3041 for Slower Lead Vehicle
- 6001 for Stopped Lead Vehicle
- 656 for Cut-in by Lead Vehicle

The seed events for the LKA simulation were selected from the SPMD dataset. Vehicles in SPMD were equipped with a forward camera module capable of measuring vehicle lane position (distance to boundary left and right), lane boundary type (solid, dashed, missing, double solid, etc.) and lane boundary curvature. These measures, and other pertinent vehicle data were recorded at 0.1 s intervals for all ignition on time. A table of lane departure events was generated for all driving during SPMD. These events were related to forward speed, event duration, lane position confidence, and vehicle type (passenger vehicles only) to create the final set of 2,384 events used in the simulation analysis. Figure C-2 shows the distribution of lateral lane departure speed used in the simulation.

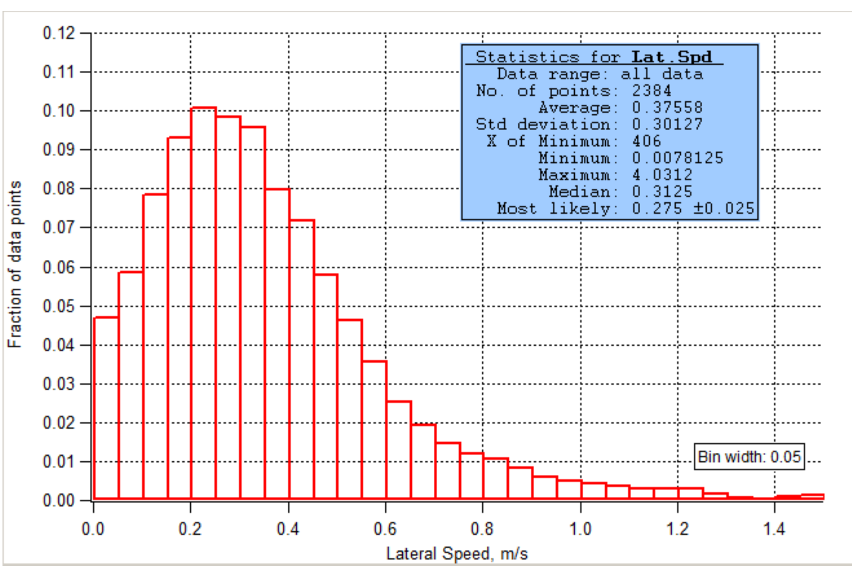


Figure C-2 Distribution of Lateral Lane Departure Speed for the Simulation of Lateral Assist System Effects

Driver Response Models

All simulations used models intended to represent what a driver would have done to avoid or mitigate a rear-end crash or lane departure. For AEB the response was modelled as a longitudinal deceleration profile, while in LKA, the response was modeled as lateral acceleration profile both as function of time. Two driver response models were used in the AEB simulations and are shown in Figure C-3.

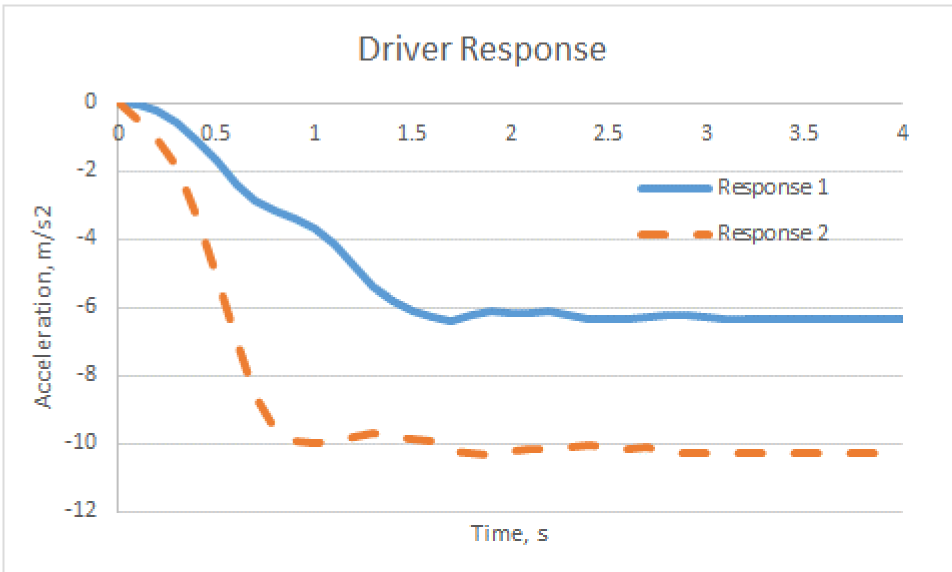


Figure C-3 Driver Response Profiles for AEB Simulation

For the simulation to reflect the kinematics of real-world rear-end crashes, the driver of the host vehicle must apply the brakes in a realistic manner that is consistent with an imminent rear-end crash. In normal driving the host vehicle applies an appropriate amount of deceleration to manage the distance between the two vehicles, taking into account the level of deceleration of the lead vehicle and a rear-end crash is avoided. The assumption for this simulation effort is the driver will always respond to the current situation with a host vehicle deceleration profile that is representative of what happens in actual rear-end crashes. Analysis of 46 rear-end crashes from the SHRPII naturalistic data show the deceleration profile of the striking vehicle takes two different profiles, namely:

a) Ramp and Hold: the driver does not brake aggressively at first but then increases deceleration in a controlled manner until a maximum level is reached. This level is then maintained until impact occurs. An example illustration of a Ramp and Hold profile is shown in Figure C-4 below. The figure contains three traces. The top trace show vehicle speed, the center is acceleration, the bottom is range. All traces are a function of time which is shown across the bottom of the figure (in seconds). In this illustration, it takes approximately 2 seconds for the deceleration to reach a maximum value of almost -0.6 g. This braking level is then held 1.5 seconds before impact with the lead vehicle.

b) Plunge and Hold: The driver applies the brake very aggressively to reach a maximum deceleration and that level is held until impact with the lead vehicle. An example of Plunge and Hold is shown in Figure C-5. Braking is very aggressive and quick, reaching a peak level of -1.0 g in 0.5 s. The peak value is then held constant until impact with the lead vehicle.

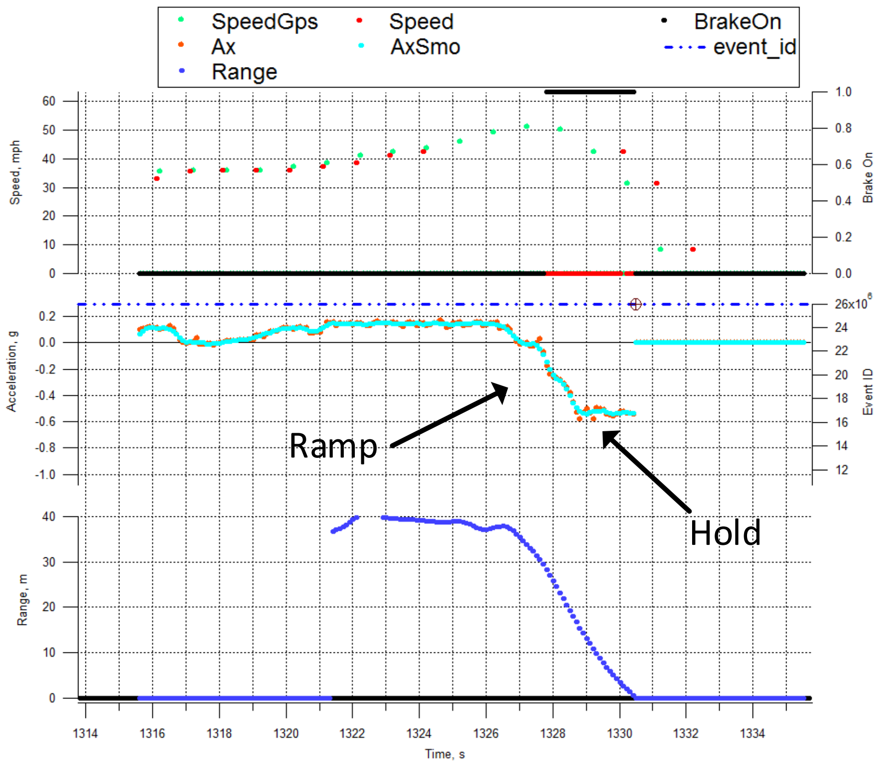


Figure C-4 Example of Ramp and Hold host vehicle braking profile.

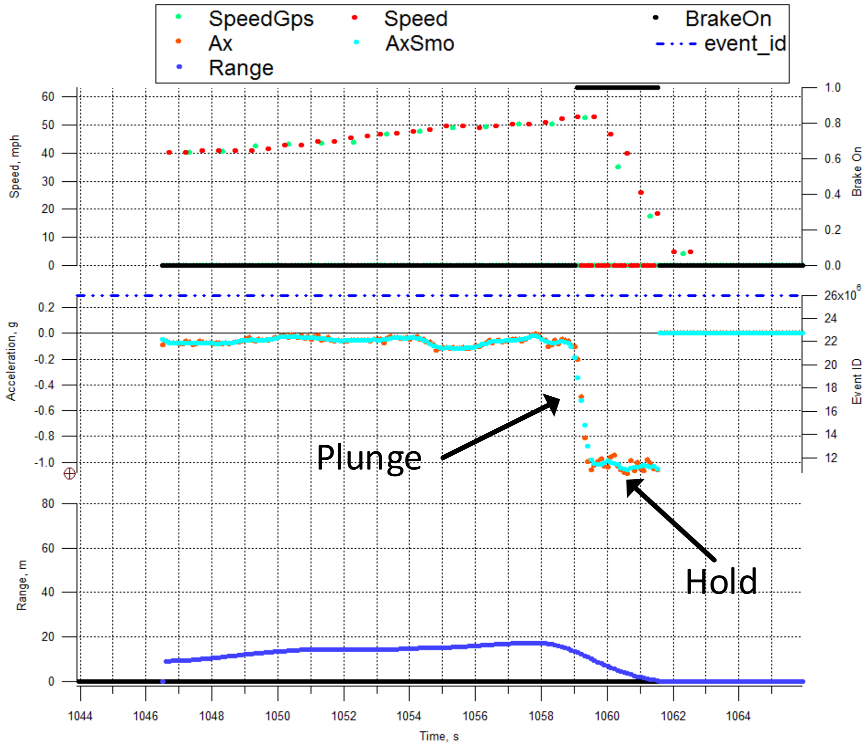


Figure C-5. Example of Plunge and Hold host vehicle braking profile.

For LKA two driver response models were used in the simulation and are shown in Figure C-6. Both models are based on actual steering corrections from naturalistic data for drivers on a variety of road types. The cases where selected because they all represent significant lane departure and correction by the driver and all involve a distracted driver reading or texting before making the correction. For the simulation, lateral acceleration is used as the response measure for three reasons:

a) it was measured onboard each vehicle by an independent 50 Hz accelerometer;
b) hand/steering wheel angle was not always available on all vehicles in SPMD; and
c) the relationship between steering wheel input and vehicle response depends on steering, suspension and tire design characteristics which are outside the modeling scope for this effort. That is, without a clear understanding of the relationship between steering wheel input and lateral acceleration output for each of these vehicles, performing the simulation with a driver steer input makes the modeling unduly complicated.

Another assumption in the driver response model is a sustained maximum lateral acceleration. In normal driving, the input by the driver would reach a maximum value and not be sustained indefinitely as it is in the simulation. The lateral simulation model simply ramps up and maintains a maximum correction input until the departure distance returns to zero (vehicle back in the lane) at which point the simulation ends. This assumption is analogous to a rear-end crash scenario where the driver applies and sustains a maximum deceleration level until the relative speed between the vehicles is zero regardless of the final range between the vehicles. In actual lateral and longitudinal scenarios, driver control is 'closed-loop' with dynamics of the scenario applying only enough correction/input to mitigate the conflict.

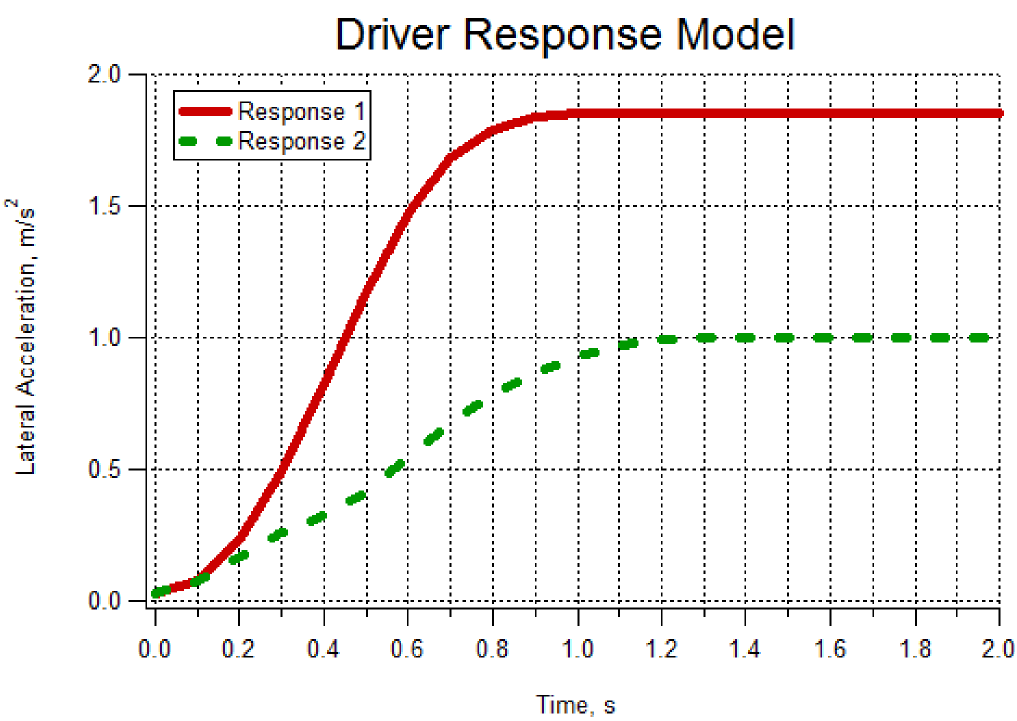


Figure C-6 Driver Response Models for the Simulation of Lateral Assist System Effects

Warning Activation Algorithms

Both AEB and LKA simulations include the effect/benefit of a warning to the driver.

Lane Departure Warning (LDW)—for the LKA simulation an LDW activation algorithm used was a lane departure distance of more than 0.15 (6 inches).

Forward Collision Warning (FCW)—it was assumed that an active safety technology, like AEB will have an audible (and perhaps visual) warning that is issued before automatic intervention and control of the vehicle occurs. It was the intent of this study to estimate the potential benefit of this warning function on crash severity assuming that drivers react to it. One set of simulations will measure the change in crash severity given an FCW is issued and the driver reacts by braking according to a predefined set of driver brake reaction times. The algorithm for the FCW was defined using measure of forward conflict such as time-to-collision, required deceleration to avoid a crash and closing speed and is given in Table C-1.

Table C-1. Rule used to initiate FCW in AEB simulations

Range-rate < -2.2 m/s and (DecelAvoid <=-2.5 m/s^2 or TTC <= 2.5 s)

Driver Reaction Time Distributions

The Lateral countermeasure models consisted of LDW and LKA. LDW does not involve any direct control of the vehicle and is modeled using a distribution of driver steer reaction time to a lane departure warning. The distribution used in the simulation is given below in Figure C-7. This distribution was derived from 53 vetted lane departure events in the IVBSS naturalistic FOT. A video review processes was used to verify drivers in this set responded to the LDW warning with a significant steer correction and appeared to be distracted in the video when the warning was issued by the LDW system.

Although the estimate of safety benefits for LDW are determined in the benefits analysis section below, the simulation determined when the LDW would have been issued to the driver for each set of initial conditions and driver delay time. The LDW activation algorithm used was a lane departure distance of more than 0.15 (6 inches). The data summary simulation results used in the benefits analysis included a distinct indication of which element of the simulation array corresponds to the driver reacting after a delay given by the distribution shown in Figure C-7. Since the simulation effort includes all possible delays by the driver, to include the LDW countermeasure in the simulation results was just a matter of pointing to the correct simulation that corresponds to a the delay bin the driver reaction time distribution.

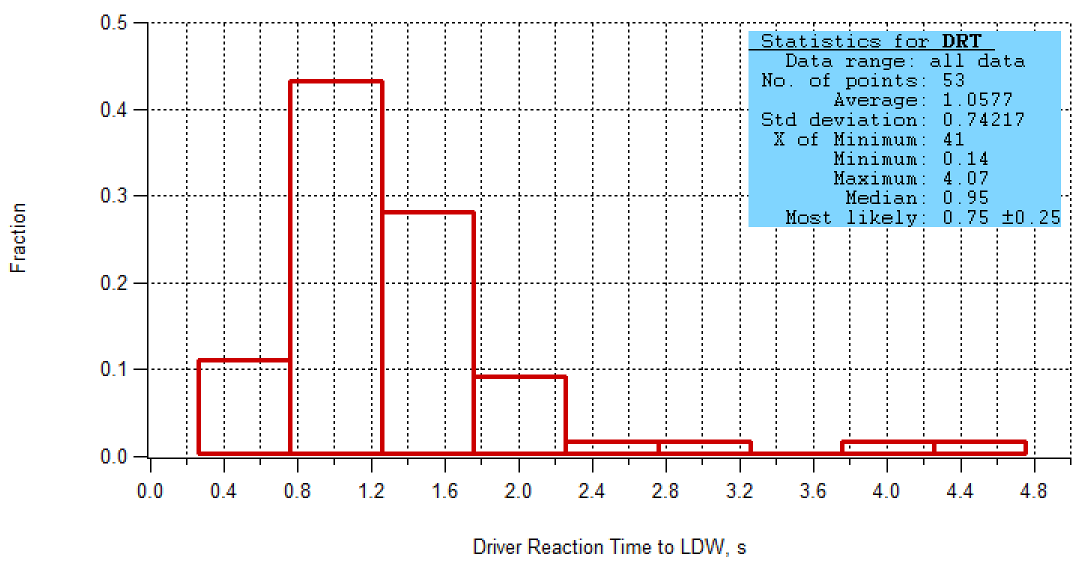


Figure C-7 LKA Distribution of Driver Reaction Time to LDWs from IVBSS

The simulation with technology also employed a driver response model in response to the FCW. This consists of a driver deceleration (the same model used in the baseline simulations), which follows a time delay that represents a driver's reaction time in responding to an alert. The response to the FCW alert variable is a combination of data from the literature and observations of drivers responding to FCW alerts in cases that suggest that immediate braking was required by the driver from IVBSS FOT. The outcome of these simulations determined whether a crash occurred and if it did occur, an estimate of the relative speed at impact is generated.

The delay between when an FCW was issued and braking by the host driver was modeled using the distribution shown in Figure C-8. The data for this distribution was derived from 236 FCW and braking events from IVBSS FOT. All required the release of the accelerator pedal within 1s after the FCW time and reaction time is defined as time between FCW and initiation of braking.

An interesting artifact of modeling longitudinal conflict using this methodology is the fact that no simulations have to be re-run to estimate the benefits of different FCW triggering algorithms or distributions of Driver Brake Reaction time. Since the reference simulation set includes all possible FCW triggering thresholds and all possible values of driver reaction times, a change in these rules simply points to a different distribution of impact speeds from the set of all possible outcomes.

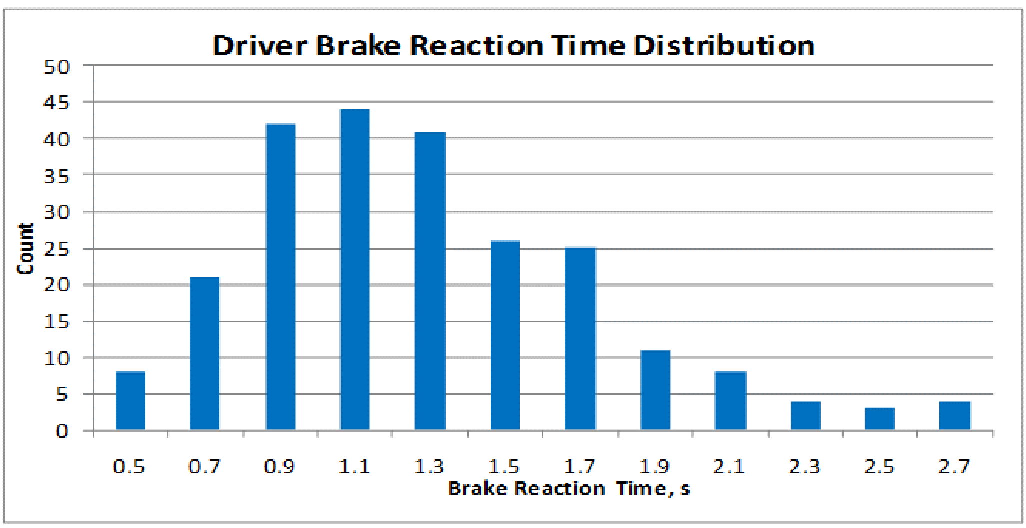


Figure C-8 AEB Driver Brake Reaction Time Distribution from IVBSS

Countermeasure Activation Algorithms

For both AEB and LKA, the countermeasure technology automatically activates when certain conditions are satisfied. For LKA this condition was simple and activation is initiated simultaneously with the lane departure in the simulation model. Conceptually, in a lane departure event this is when the distance between the vehicle wheel and the lane boundary marker goes to zero.

For AEB the trigger was the same for the Slowing, Slower, and Cut-in lead vehicle scenarios and less conservative for Stopped. The two AEB algorithms are given below in Table C-2.

Table C-2 AEB Activation Algorithms

Lead Vehicle Scenario	Triggering Algorithm
Slowing, Slower, and Cut-in	TTC <= 1.5 s and DecelAvoid < -4.0 m/s2 and Range-rate < -2.2 m/s
Stopped	TTC <= 1.0 s

Countermeasure Models

The countermeasure model for LKA is modeled as a lateral acceleration input as a function of time. Three different models were considered and are shown in Figure C-9. Countermeasure 2 shown in the figure was derived from empirical data collected from an actual vehicle tested on public roads with an independent measure of lane position and lateral acceleration. Countermeasure 1 and 3 are derived from 2. Countermeasure 1 is simply 75% of 2. Countermeasure 3 was derived to have a peak acceleration close to the peak found for the Driver Response 1 model given in Figure C-9. It represents an aggressive LKA correction similar to the type of correction found in the video review of actual drivers responding to lane departures while distracted.

For all three, countermeasure activation is initiated simultaneously with the lane departure in the simulation model. In simulations involving both a driver response and a countermeasure model, the model that delivered highest level of corrective lateral acceleration was used in the simulation.

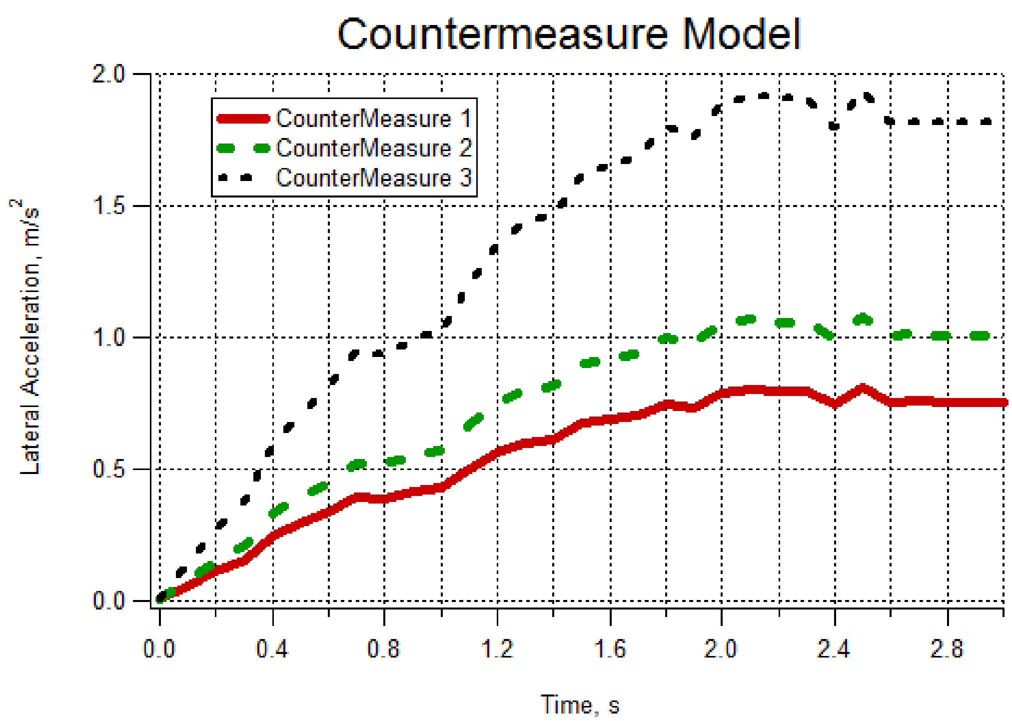


Figure C-9 Countermeasure Models (LKA) for the Simulation of Lateral Assist System Effects

The countermeasure model for AEB is modeled as a longitudinal acceleration input as a function of time. Three different models were considered and are shown in Figure C-10. The rules for triggering each level are given in Table C-2. Each of these algorithms was used independently and then with FCW. In the simulations with AEB alone, it was assumed that the driver is incapacitated and therefore could not respond to the FCW. In the simulations with FCW, the additional benefit of AEB was measured.

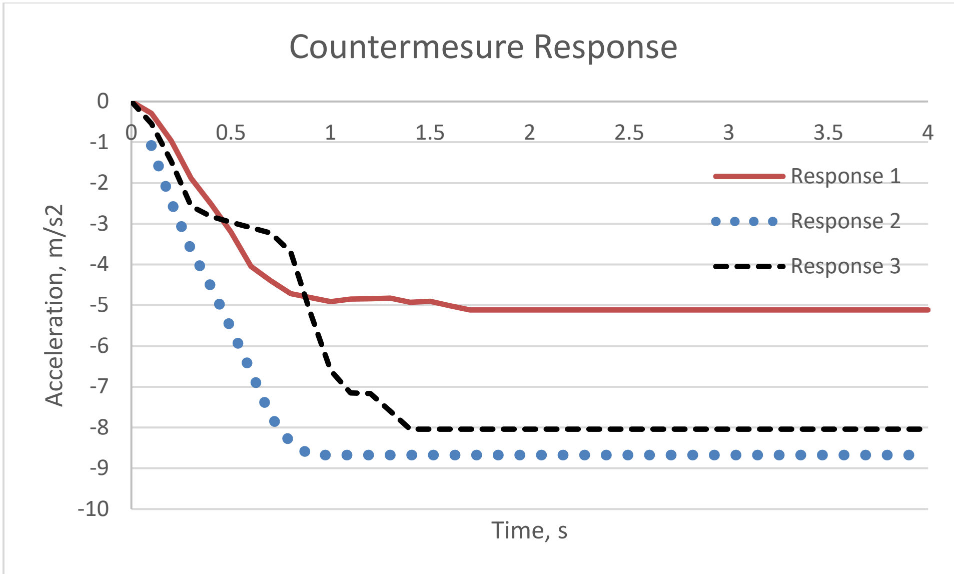


Figure C-10 Countermeasure Models (AEB) for the Simulation of the Automatic Control Effects

LKA Simulation Results

A total of six combinations (2 Driver Response Models x 3 Countermeasure Models) were simulated for a total of over 870,000 runs when initial conditions and driver delay time are taken into account.

The results of the simulation are time-series measures of longitudinal and lateral distance, lateral distance of the road (given a radius value), longitudinal and lateral speed estimates, lateral acceleration, and distance from the lane all as a function of time (10 Hz simulation).

To illustrate the calculation of vehicle trajectories given a set of initial conditions and a driver response model consider Figure C-11. The initial conditions for this example are forward speed of 57 mph (25.5 m/s), a lateral speed of 1.6 mph (0.7 m/s) and a road radius of 8000 meters (assumed to be constant). Driver response model 1 from Figure C-6 is used in this illustration. The time resolution of each simulation is 0.1 s. For each set of initial conditions the simulation is repeated 61 times, increasing the driver input delay time from 0 to 6.0 s in increments of 0.1 s. For this example, the figure shows the trajectories for four driver delay times: 0.0, 1.0, 2.0, and 2.1 s.

The y-axis of Figure C-11 shows the lateral distance of each trajectory and the road edge as a function of distance traveled (time is easily derived given a constant forward speed assumption) along the x-axis. In the first simulation, the driver delay time is 0.0 s meaning the driver input response starts simultaneously with the simulation. In this case, the vehicle travels longitudinally 30.54 m and has a maximum deviation from the lane edge of 0.3 m. For the 1.0 s delay time, the vehicle travels 71 m with a maximum lateral deviation of 1.1 m. For the 2.0 s delay time, the vehicle travels 107 m with a maximum lateral deviation of 2.0 m. Finally, the trajectory for a 2.1 s delay is shown to illustrate the resolution of the simulation delay time step.

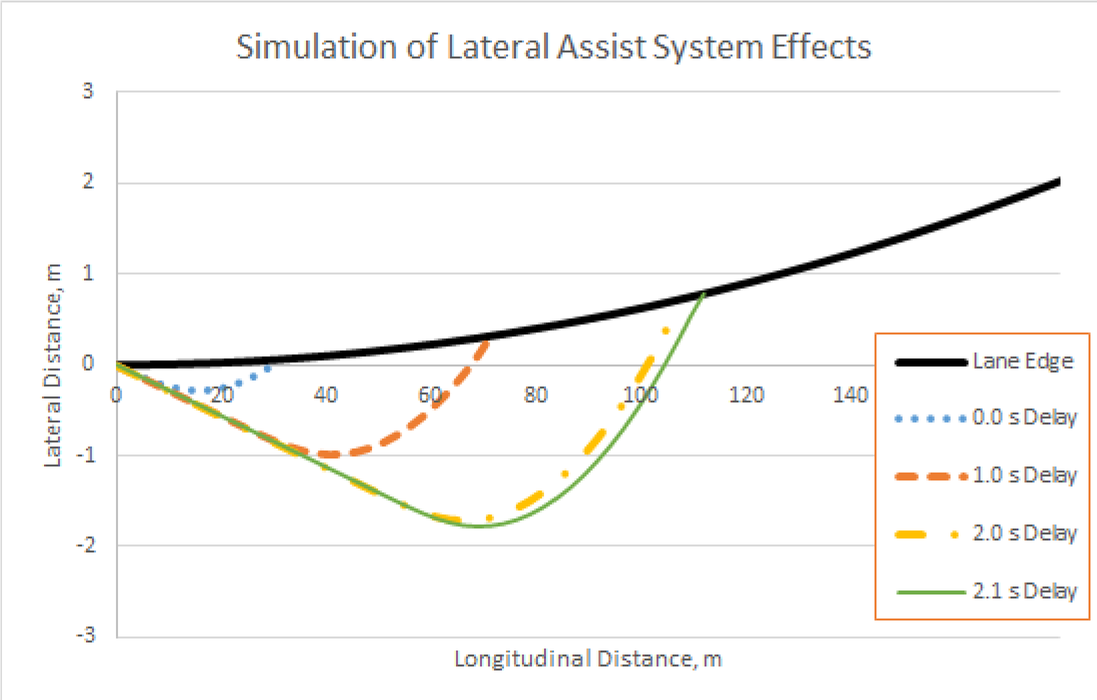


Figure C-11 Example of Vehicle Trajectories for Four Driver Delay Response Times.

The time series results were then reduced into the following summary metrics:

- Average lateral speed moving away from the lane boundary (moving out of lane)
- Average lateral speed moving toward the lane boundary (moving toward the lane)
- Distance and time the departure was between 0 and 1 meter
- Distance and time the departure was between 1 and 2 meters
- Distance and time the departure was between 2 and 3 meters
- Distance and time the departure was more than 3 meters
- The maximum lateral distance from the lane boundary
- The time when the LDW was issued

These metrics were calculated for all baseline simulations for both driver response models (no countermeasure model used) and the combination of driver response and countermeasure models. The summary metrics were then used as input into the statistical modeling detailed in the section below.

AEB Simulation Results

For the AEB simulation effort a representative deceleration profile for each of these cases will be used. Given a host driver braking profile, a set of IC and the associated lead vehicle deceleration profile the reference simulation requirements are met with the exception of the host vehicle braking delay time. Since the amount of time that the host driver delays before braking is unknown, all possible delay times are simulated. Using an interval of 0.1 s, the simulation is run repeatedly starting with a delay of 0.0 s and increasing delay time until the start of the host braking is coincident with a rear-end crash with the lead vehicle. An illustration of this approach is shown in Figure C-12

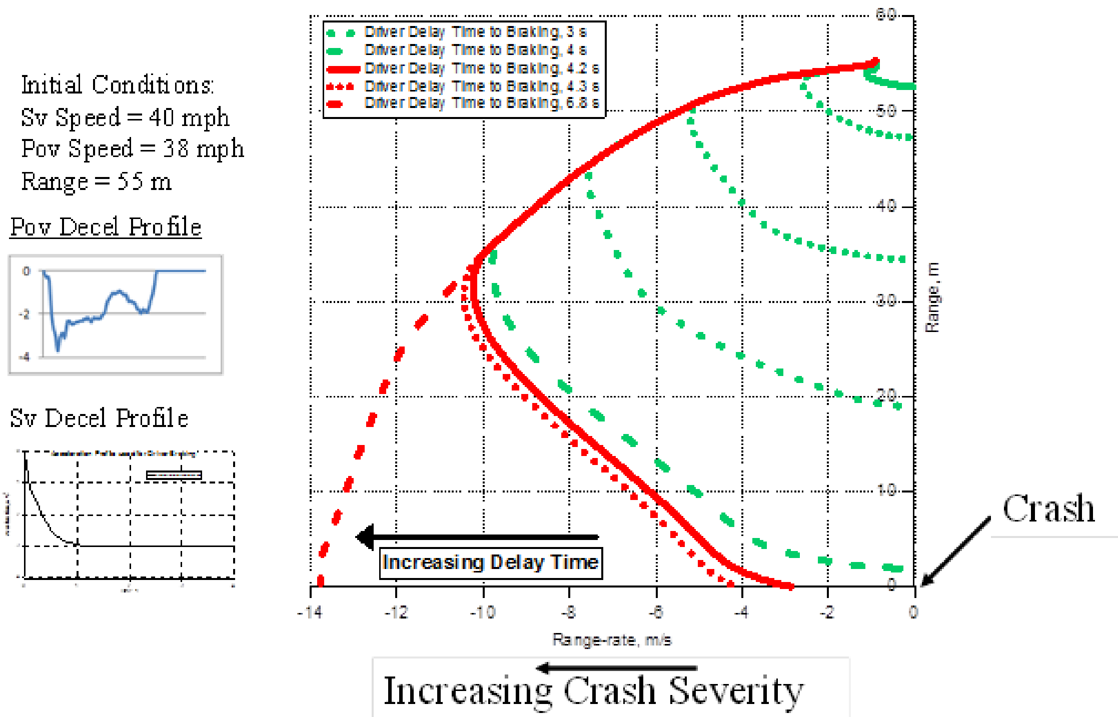


Figure C-12 AEB Illustration of the simulation approach to produce the impact speed distribution

The figure shows Range (distance between vehicles) along the y-axis as a function of Range-Rate (relative speed between the host and lead vehicles—a negative value is closing) along the x-axis. When Range is zero the rear-end crash occurs. The severity of the crash is measured by increasing values of closing speed (a negative value of Range-Rate). The traces show the relationship between Range and Range-Rate for different host driver delay time to braking. (Note: not all simulations are shown in the figure.) Simulations that resulted in no rear-end crash, and their corresponding delay times, are identified by having a positive value of Range when the closing speed between the two vehicles reaches zero. The initial conditions, lead vehicle (POV) deceleration profile, and host vehicle (SV) braking profile are shown to the left of the plot. In this illustration, a driver delay to braking time between 0 and 4.0 s did not result in a rear-end crash. However, a delay time of 4.2 s did with an impact speed of -2.8 m/s. Each subsequent increase in delay time results in an increase in the impact speed until the maximum delay time of 6.8 s is reached. This delay time to braking is coincident with the rear-end crash and represents the highest impact speed due to no braking by the host vehicle driver. It is the worst case scenario for this set of conditions. There is no single best cast scenario since many different delay time to braking values (0 to 4.1 s or 42 simulations) resulted in no rear-end crash.

Time-series measures for each simulation that resulted in a crash with the lead vehicle were saved to a master database. From these data queries are written that to build a reference set of conditions and the speed at impact for each crash. The analysis elements of this reference set of crashes includes:

- A RunId that uniquely identifies the results with a set of IC and lead vehicle deceleration profile time-series.
- The host-vehicle driver delay-time that indicates many seconds the driver waited before applying the brakes
- The simulation time of the impact.
- The speed of the host and lead vehicle at impact.
- The acceleration of the host and lead vehicle at impact.

Both warning and automatic control technology rely on conflict measures to determine the urgency of the situation. Common conflict measures include:

- Time-to-Collision (TTC): For a given set of conditions, TTC is the number of seconds until impact. Commonly, TTC is defined at –Range/Range-rate.
- Deceleration-to-Avoid (DA): For a given set of conditions, DA is the amount of deceleration the host vehicle requires to avoid an impact. The algorithm to derive DA depends on the relative speed and acceleration between the host and lead vehicle.
- Range-rate: the rate of closing speed between the lead and host vehicle must be above a minimum threshold in some conflict algorithms. At the other extreme, closing range-rate values are ignored if too big which typically indicate an on-coming vehicle.
- Speed: Thresholds on speed, minimum and maximum speed, are often included in algorithms for passive and active rear-end crash mitigation systems.

Appendix D Task 4 Surveys and Driver Information

12.1.1 Initial Survey

UNIVERSITY OF MICHIGAN

Default Question Block

Participant ID

What year were you born?

What is your gender?

Male

Female

Approximately how many miles a week do you typically drive?

Less than 25 miles

Between 25-100 miles

Between 100 and 250 miles

Between 250 and 1000 miles

More than 1000 miles

What percent of the miles you drive are on freeways or highways?

Less than 25%

25-50%

50-75%

More than 75%

Rate the degree to which you are interested in different types of vehicle technologies

	No opinion	Not at all	Very little	Somewhat	Highly	Very highly
Forward lighting (headlamps)	O	O	O	O	O	O
Integration with smart phones	O	O	O	O	O	O
Occupant protection	O	O	O	O	O	O
Blind spot detection	O	O	O	O	O	O
Lane departure/lane keeping	O	O	O	O	O	O
Adaptive cruise control	O	O	O	O	O	O

12.1.2 ACC Survey

UNIVERSITY OF MICHIGAN

Default Question Block

Driver ID

Run ID (Week)

Based on your knowledge and experience with the vehicle speed control system, provide a rating of your level of agreement with the following statements.

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree	Not applicable
The speed control improves the safety of my driving.	O	O	O	O	O	O
The lights/symbols on the speed control display are easy to understand.	O	O	O	O	O	O
The sounds made by the system are easy to understand.	O	O	O	O	O	O
Using the system relieves me of stress when driving.	O	O	O	O	O	O
I tend to change lanes less frequently when using the system.	O	O	O	O	O	O

	Strongly agree	Somewhat agree	Neither agree nor disagree	Somewhat disagree	Strongly disagree	Not applicable
I tend to follow the vehicle ahead more closely when using the system.	O	O	O	O	O	O
I tend to set the system to a shorter following gap (closer following distance) in heavy traffic than in light traffic.	O	O	O	O	O	O
The system sometimes locks onto a vehicle other than the one immediately in front of me.	O	O	O	O	O	O
More cars cut me off or pull in front of me when I am using the system.	O	O	O	O	O	O
The system detects all sizes of vehicles ahead of me.	O	O	O	O	O	O
The system can help boost my braking in an emergency.	O	O	O	O	O	O

Based on your knowledge and experience with the vehicle speed control system, please rate how well the speed control system is suited to the following traffic conditions.

	Extremely appropriate	Somewhat appropriate	Neither appropriate nor inappropriate	Somewhat appropriate	Extremely inappropriate
On a freeway at night.	O	O	O	O	O
On city streets.	O	O	O	O	O
Following a vehicle on a freeway in stop-and-go traffic.	O	O	O	O	O
When you encounter a stopped vehicle on the roadway.	O	O	O	O	O

	Extremely appropriate	Somewhat appropriate	Neither appropriate nor inappropriate	Somewhat appropriate	Extremely inappropriate
On curvy roadways.	O	O	O	O	O
On high-speed rural roadways.	O	O	O	O	O
Along roadways with bicycles and pedestrians present.	O	O	O	O	O
In snowy conditions.	O	O	O	O	O
In rainy conditions.	O	O	O	O	O
On freeway off ramps.	O	O	O	O	O
In heavy traffic that is flowing.	O	O	O	O	O

Based on your knowledge and experience with the vehicle speed control system, how often would you say this has happened?

	Very often	Often	Occasionally	Rarely	Never
The system slowed down unexpectedly when there was no vehicle ahead of you.	O	O	O	O	O
The system would brake abruptly or brake hard causing the vehicle behind you to get uncomfortably close.	O	O	O	O	O
The system accelerated unexpectedly	O	O	O	O	O
You forgot to turn off the system.	O	O	O	O	O
The system turned itself off unexpectedly.	O	O	O	O	O
The system would not turn on when you tried to activate it.	O	O	O	O	O

Based on your knowledge and experience with the vehicle speed control system, rate how well you think you understand each adaptive cruise control function.

	Extremely Well	Very Well	Moderately well	Slightly well	Not well at all
How to activate the system.	O	O	O	O	O
How to set the travel speed of the vehicle with the system.	O	O	O	O	O
How to set the forward distance settings of the system	O	O	O	O	O
The conditions when the system will cancel itself.	O	O	O	O	O

Based on your knowledge and experience with the vehicle speed control system, have you ever been confused about:

	Extremely confused	Very confused	Moderately confused	Slightly confused	Not at all confused
What speed the system is set to?	O	O	O	O	O
What following distance the system is set to?	O	O	O	O	O
Why the system stopped working?	O	O	O	O	O

12.1.3 LKA Survey

UNIVERSITY OF MICHIGAN

Default Question Block

Driver ID

Run ID (Week)

Based on your knowledge and experience with the lane keeping assistant, provide a rating of your level of agreement with the following statements:

	Strongly Agree (1)	Somewhat Agree (2)	Neither Agree Nor Disagree (3)	Somewhat Disagree (4)	Strongly Disagree (5)	Not Applicable (6)
Lane keeping assist improves the safety of my driving.	○	○	○	○	○	○
The lights/symbols on the lane keeping assist display are easy to understand.	○	○	○	○	○	○
The sounds made by the lane keeping assist system are easy to understand.	○	○	○	○	○	○
Use of lane keeping assist relieves me of stress when driving.	○	○	○	○	○	○
I tend to do less passing when lane keeping assist is available.	○	○	○	○	○	○

	Strongly Agree (1)	Somewhat Agree (2)	Neither Agree Nor Disagree (3)	Somewhat Disagree (4)	Strongly Disagree (5)	Not Applicable (6)
I prefer to to use lane keeping assist when no other traffic is present on the roadway.	O	O	O	O	O	O
I pay less attention to lane boundaries when lane keeping assist is active.	O	O	O	O	O	O
I tend to wait for lane keeping assist to intervene before I adjust my steering.	O	O	O	O	O	O
I don't always understand when lane keeping assist stops working.	O	O	O	O	O	O
Lane keeping assist helps me during passing maneuvers.	O	O	O	O	O	O

Based on your knowledge and experience with the lane keeping assistant, please rate how well the lane keeping assist can deal with the following traffic situations.

	Extremely appropriate	Somewhat appropriate	Neither appropriate nor inappropriate	Somewhat inappropriate	Extremely inappropriate
Freeway travel at night	O	O	O	O	O
City streets	O	O	O	O	O
Multi-lane freeway in daylight	O	O	O	O	O
Construction zones	O	O	O	O	O
Congested roadways	O	O	O	O	O
Very curvy roadways	O	O	O	O	O
High-speed rural roadways	O	O	O	O	O
Roadways with bicycles and pedestrians present	O	O	O	O	O

	Extremely appropriate	Somewhat appropriate	Neither appropriate nor inappropriate	Somewhat inappropriate	Extremely inappropriate
Snow covered roadways	O	O	O	O	O
Rainy conditions	O	O	O	O	O
On freeway ramps	O	O	O	O	O
Heavy, free-flowing traffic	O	O	O	O	O
Responding to objects in the center of the roadway	O	O	O	O	O
Responding to potholes	O	O	O	O	O
Deer or other animals in the roadway	O	O	O	O	O

Based on your knowledge and experience with the lane keeping assistant, how often would you say this has happened with the lane keeping assist system.

	Very often	Often	Occasionally	Rarely	Never
The system failed to keep you in your lane	O	O	O	O	O
The system failed to warn you of a lane departure	O	O	O	O	O
The system unexpectedly intervened	O	O	O	O	O
The system warned/controlled the vehicle unnecessarily	O	O	O	O	O
The system turned off unexpectedly	O	O	O	O	O
The system refused to activate unexpectedly	O	O	O	O	O

Based on your knowledge and experience with the lane keeping assistant, in using the lane keeping assist system, have you ever been confused about:

	Definitely yes	Probably yes	Might or might now	Probably not	Definitely not
Whether the system is turned on	O	O	O	O	O
At what point the system would begin to warn/correct your lane position	O	O	O	O	O
Why the system stopped working	O	O	O	O	O

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12.1.4 Supplemental Story

ACC Description/Story:

To help you remember some things about Adaptive Cruise Control (ACC), we made up a story we would like you to think about when using it.

Think of the ACC as a service managed by a specialized car-elf named Ziggy. Ziggy will try to keep your car at a desired speed, except he can also see a car ahead of you and make sure you don't get too close by braking or backing off the accelerator.

Ziggy jumps into action when you turn on the ACC, if he thinks conditions are right. He's rather strict about this, so be sure you know what his rules are.

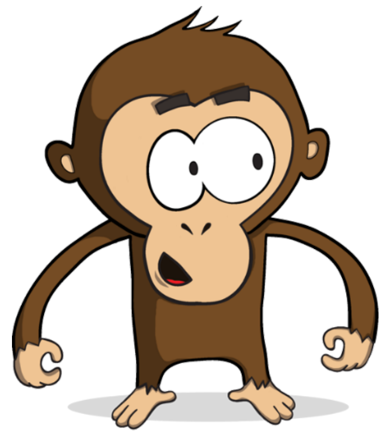
You need to tell Ziggy what speed to go by pressing the SET button when you are at the speed you like. You can also choose different distances that Ziggy can keep back from a car in front of you.

Ziggy is also wary of contradicting your intentions. If he sees you start to brake, Ziggy will assume you want to handle things and get out of the way until you 'ask' for his help by pressing the RESume button. If you accelerate, Ziggy will not apply the brakes. Ziggy will step back whenever he thinks the driver is taking over. He does not want to annoy his master.

You should be aware that Ziggy does not have very much power to slow the car down. He is small and kind of weak; he may not brake hard enough if you need to slow down a lot. In that case, you should take over braking from Ziggy.

Ziggy's eyesight is also limited. He sees large vehicles ahead, but can miss smaller objects like bicycles, motorcycles, pedestrians, and even animals in the road. Ziggy's vision is also peculiar—he sometimes can't see objects that are stopped, moving very slowly, or offset from the direction the car is pointing (like on a curved or hilly road). For example, he might not see a pile of bricks sitting in the middle of the roadway. Ziggy means well, but he may not always be helpful. You need to remember to watch Ziggy closely.

LKA Description Story (Both):



Think of Lane Keeping Assist as a function controlled by Mojo, a little helper monkey. Mojo's job is to help keep you vehicle between the two lane lanes if you start to go out of the lane and to alert you that you are crossing lane lines if this happens.

You first need to ask Mojo for help by turning on the LKA function in situations where Mojo is best able to help, otherwise Mojo won't be very helpful. He will stay asleep and dream about bananas. Mojo is best able to help on roads with lane markings, and when the vehicle is moving at a speed above 45 mph.

Also, Mojo only helps when he can clearly see the lane lines ahead of the vehicle through the front window. If he gets confused about the line markings, or if he can't see them clearly because the window is dirty, Mojo will give up and leave it to you. The lane lines in the display will turn solid when he sees them, otherwise they're dotted. This can happen in construction areas, in rain, snow, or fog, and when you follow close to another vehicle so you can't see the lines in the road.

Like Ziggy, Mojo will also back off if he thinks you are actively steering or changing lanes.

You should also know that Mojo is small and is only capable of making gentle steering actions to push your car back into your lane. He can't handle stiff crosswinds, banked roads, or very tight curves. Mojo is also kind of single-minded about his job and sees it as keeping your car between lane lines. He doesn't think steering around other objects is part of his job. Be sure you don't let Mojo steer you into a boulder in the middle of the road! He also would ignore bicyclists at the side of the road and might even resist you steering away from them to pass.

Also beware, that Mojo may get nervous if he thinks you're leaving the steering entirely to him. He may make some noises if you take your hands off the steering wheel for more than a short time.

Appendix E Analysis of Lane/Road Departure Crash Mechanisms

Further characterization of lane/road departure (L/RD) crashes. This appendix extends the discussion of Section 6.1.

Crash severity

As a group, L/RD crashes tended to be more severe in terms of fatalities and injuries than other LTV crash types, though one subset of L/RD crashes, same-direction sideswipes, was less severe. Table E-1 shows the distribution of LTV crashes by crash severity. Overall, the distribution of L/RDs was similar to that of other single-vehicle crashes (comparing the *all lane/road departure* row with the *other single-vehicle* row in the table), with about 0.6% resulting in a fatality, and 2.7% in a serious injury (defined as an incapacitating injury). However, lane/road departures that resulted in opposite direction crashes were significantly more severe than other crash types, with about 2% resulting in a fatal injury, and 4.4% to 6.5% resulting in a serious injury. Similarly, off-road crashes often result in rollovers or collisions with massive fixed objects, both of which can be very severe. In contrast, same-direction sideswipes were much less serious (0.1% resulting in a fatality, 0.5% serious injury), primarily because in such crashes the vehicles were going in the same direction and closing speeds were likely quite low.

Table E-1 Percent distribution of most severe injury in crash,
by L/RD crash type and other crash types

Crash type	Fatal	Serious injury	Other injury	No injury	Total
Drove off go straight	0.9%	4.6%	31.3%	63.2%	100.0%
Drove off neg. curve	1.1%	4.6%	31.3%	63.0%	100.0%
Other drove off	0.3%	2.2%	23.3%	74.2%	100.0%
Same direction	0.1%	0.5%	11.0%	88.4%	100.0%
Opp. dir., go straight	2.1%	6.5%	34.2%	57.2%	100.0%
Opp. dir. neg. curve	2.0%	4.4%	28.6%	65.0%	100.0%
Opp. dir. other	3.5%	6.7%	29.6%	60.1%	100.0%
All lane/road departure	*0.6%*	*2.7%*	*21.6%*	*75.0%*	*100.0%*
Other single-vehicle	0.6%	3.3%	24.4%	71.7%	100.0%
Other two-vehicle	0.1%	1.6%	25.5%	72.8%	100.0%
Other/unknown	0.5%	3.0%	36.4%	60.1%	100.0%
Total	0.2%	1.9%	25.9%	71.9%	100.0%

Driver age

Younger drivers and older drivers tended to be over-involved in L/RD crash types, compared with other crashes. L/RD crashes accounted for 8.4% of crash involvements for drivers up to age 17, and 7.2% for drivers 18 to 25, but L/RD crashes accounted for only 6.1% of the crashes of LTV drivers overall. Similarly, L/RD crashes were 6.7% of the involvements of LTV drivers 65 and over.

The specific types of L/RD crashes differed by driver age. Table E-2 shows the distribution of L/RD crash types for different age groups. Younger drivers (0-17 and 18-25) tended to be overinvolved in each of the drove off road crash types; older drivers were overinvolved in same-direction sideswipes. Younger drivers may have tended to be more distracted or disengaged from driving; on curves, they may have poorer driving skills and may have misjudged speeds and entered curves going too fast. On the other hand, older drivers' over-involvement in same-direction sideswipes may have been related to declines in the ability to physically turn and scan blind spots or to slower decision-making.

Table E-2 Distribution of L/RD crash type by driver age

	Driver age				
L/RD crash type	0-17	18-25	26-64	65+	Total
Drove off go straight	32.4%	34.9%	28.2%	22.1%	29.7%
Drove off neg. curve	12.7%	13.0%	9.7%	5.4%	10.4%
Other drove off	16.3%	7.9%	7.7%	6.7%	8.2%
Same direction	31.1%	36.1%	44.1%	58.3%	42.5%
Opp. dir., go straight	4.1%	4.8%	6.2%	5.1%	5.5%
Opp. dir. neg. curve	2.5%	2.8%	3.3%	2.0%	3.0%
Opp. dir. other	0.9%	0.5%	0.9%	0.3%	0.7%
All lane/road crashes	100.0%	100.0%	100.0%	100.0%	100.0%

Driver state

"Engagement", defined as driver distraction or fatigue, varied across the L/RD crash types. Table E-3 shows the percentage of coded fatigue and distraction for each of the types. Fatigue was most prevalent for road departures in which the vehicle simply went off the road, with about 15.6% (sum of "fatigued" and "both") where the vehicle went off while going straight, and 10.7% where the driver was negotiating a curve. The overall incidence of coded fatigue across all L/RD crash types was 6.5%. Distraction also was identified in a significant percentage of drove off road crashes. Where drivers went off the road while just going straight or negotiating a curve, they were effectively disengaged from the driving process in between 30% and 40% of the involvements. Many of the "other drove off road" crashes occurred at intersections while making a turn. The percentage of fatigue coded in these crashes was quite low, while the percentage of distracted cases was similar to the other crash types.

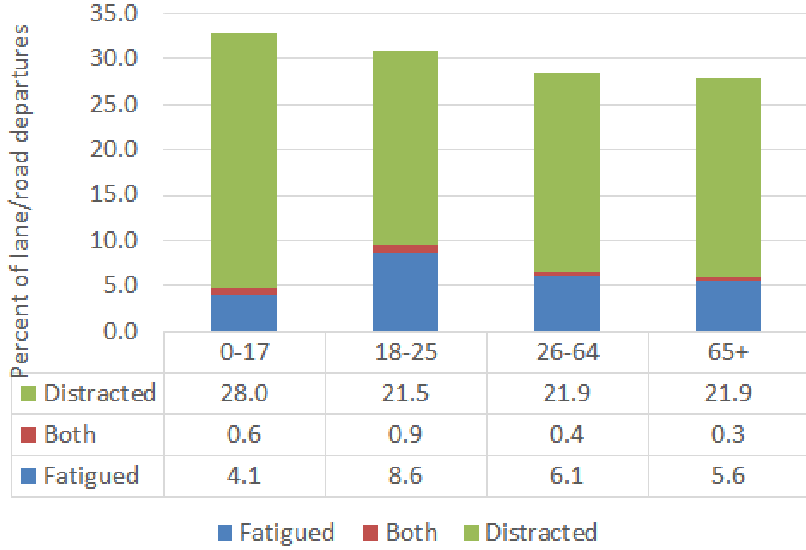
Table E-3 Distribution of driver "engagement" by L/RD crash types

L/RD crash type	Fatigued	Both	Distracted	Neither	Total
Drove off go straight	14.5%	1.1%	25.4%	59.1%	100.0%
Drove off neg. curve	10.7%	0.9%	18.9%	69.4%	100.0%
Other drove off	1.1%	0.5%	18.2%	80.2%	100.0%
Same direction	0.3%	0.0%	18.0%	81.6%	100.0%
Opp. dir., go straight	7.5%	0.9%	20.7%	71.0%	100.0%
Opp. dir. neg. curve	2.6%	0.0%	21.9%	75.5%	100.0%
Opp. dir. other	0.4%	0.0%	16.0%	83.5%	100.0%
All lane/road crashes	6.0%	0.5%	20.5%	73.0%	100.0%

Fatigue was identified in only 0.3% of same-direction sideswipes, though distraction was coded in 18.0%, within the range of the other L/RD types. The hypothesized mechanism in same-direction sideswipe crashes was hypothesized to be driver failure to detect the other vehicles, rather than drifting out of lane, and the results here are consistent with that hypothesis.

A lower percentage of drivers in opposite-direction crashes were coded as fatigued compared with drove off road crashes, but distraction percentages were comparable. It appears in some opposite-direction crashes (7.5% when going straight; 2.6% when negotiating a curve), fatigued drivers allowed their vehicles to cross the centerline into on-coming traffic. If there had been no traffic, those crashes may have resulted in one of the drove-off types (though going across at least one lane would allow additional recovery time for some drivers). Distraction was identified in about 20% of opposite-direction crashes. The primary mechanisms hypothesized for opposite-direction crashes were fatigue, distraction, and, for crashes in curves, excessive speed.

Coded distraction and fatigue in L/RD crashes varied by driver age (Figure E-1). Overall, distraction was much more common than fatigue, though it should be kept in mind that fatigue is generally difficult to identify post-crash and is widely believed to be underreported in crash data. But across all age groups in L/RD crashes, about 21.0% of drivers were coded as distracted and only 6.5% were coded as fatigued (Table E-3). Disaggregated by age group (Figure E-1), the youngest group of drivers (up to 17 years-old) tended to have higher rates of distraction; however, rates of distraction were comparable for the other age groups. Fatigue was most often noted for the 18-25 year-old group with 9.5% of L/RD crashes, while it was lowest (4.7%) for drivers up to 17. Older drivers (65+) had the lowest rates of coded fatigue (5.9%), though that was only slightly below the rate for drivers 26-64 (6.5%).



	0-17	18-25	26-64	65+
Distracted	28.0	21.5	21.9	21.9
Both	0.6	0.9	0.4	0.3
Fatigued	4.1	8.6	6.1	5.6

Figure E-1 Driver “engagement” by driver age, L/RD crashes

Driver age and vehicle model year

The over-involvement of young drivers in road departure crashes may be related to the age of the vehicles they were driving. More recent model years of passenger vehicles, particularly 2009 and later, are equipped with electronic stability control (ESC), which has been shown to reduce single-vehicle crashes substantially (Flannagan and Leslie 2012; Sivinski 2014). If younger drivers tended to drive older-model vehicles, that may account for some portion of their involvements. ESC could be considered as an intervention to reduce the lane/road departures.

To test that hypothesis, the distribution of L/RD crashes was compared for model years up to 2007 and 2009 and later, for each age group. Figure E-2 shows the proportions of L/RD crashes of all LTV crash involvements for each combination of driver age group and model year group. The overall length of each bar shows the percentage L/RD involvements of all crashes for the combination of driver age group and vehicle model year group. Within each driver age group (except for 65+ drivers), older vehicle model years had a higher proportion of L/RD crashes. The difference was most marked for the youngest driver age group, where 8.5% of their involvements in older-model vehicles were L/RD crashes, compared with 7.0% for younger drivers in model years 2009 and later. Similarly, within each driver age group, the percentage of drove-off-road L/RD types were greater in older model-year vehicles than for the more recent models. However, the same-direction sideswipe crash type is much less affected by model year, as would be expected because ESC should not affect that crash type. However, ESC may be an intervention that can address at least some L/RD crashes.

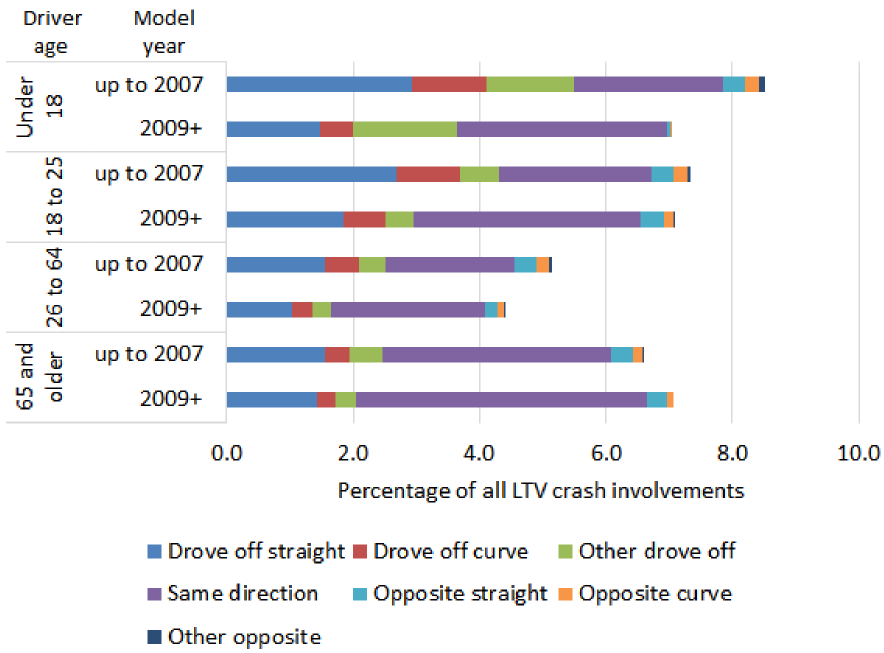


Figure E-2 L/RD type by driver age and vehicle model year

Appendix F Injury Probability Estimates for Road-Departure Crashes

Crash data from North Carolina were used to develop estimates of injury probabilities for run-off-road crashes. North Carolina data were used for this purpose because their crash reports, uniquely to our knowledge, captured the lateral distance between off-road objects struck and the road edge. The crash data also identified the type of objects struck and the posted speed limits of the roads from which the departures occurred. This information was used to develop estimates of injury probability by type of object struck and lateral distance from the road edge.

Run-off-road crashes were identified in the North Carolina crash file for 2010 (the most recent year available). The crashes met the criteria for single-vehicle ran-off road crashes used in this report. The crashes involved only light vehicles, the drivers were not impaired by alcohol or drugs, there was no loss of control prior to exiting the roadway, and the drivers were coded as just lane-keeping prior to road departure, with no maneuvering such as changing lanes or turning. In each case, the first harmful event in the crash was a collision with an object.

Objects were classified as “hard” or “soft”, based on a judgment of their physical characteristics. Hard objects included trees, utility poles, and bridge piers. Objects such as mailboxes, fence posts, and crash cushions were classified as soft. These classifications were generally validated by the probability of severe injury in the vehicles, controlling for road speed, but the basic classification was based on a subjective judgment. Posted speed limits were used to bin roads into three categories: speed limits up to 35mph, more than 35mph to 55mph, and over 55mph. These bins generally correspond to city streets; moderate speed 2-lane, 2-way highways; and high-speed highways, respectively. All the vehicles in the analysis ran off the road and struck an object as the first harmful event. Some of the vehicles also rolled over after hitting an object, which was recorded as rollover/no rollover.

A logistic regression model was fit to the data to verify that off-road distance to objects was related to the probability of injury to a vehicle occupant. The factors in the model were the distance to the object struck, the type of object (hard or soft), and the posted road speed limit. Distance to the object struck was categorized in the North Carolina crash data into three levels: 0 to 10 feet, 11 to 30 feet, and greater than 30 feet. The model also used the two-level object type classification (hard/soft) described above, and the three levels of posted speed limit, as a surrogate for travel speed. In addition, the model included a parameter for rollover, for vehicles that rolled over after striking an object. The outcome variable was the probability of an injury in the vehicle. Table F-1 shows the parameters in the model with the parameter coefficients and statistical significance. All parameters in the model were significant, including the interaction of object distance (obj_dist) and posted speed limit (spd_lmt).

Table F-1 Parameters and estimates,
logistic regression model of the probability of injury in run-off-road crashes

Parameter	Level		DF	Estimate	Standard error	Wald Chi-Square	Pr > ChiSq
Intercept			1	-1.2152	0.0783	241.1534	<.0001
Obj_dist	11 to 30		1	0.5302	0.1527	12.0575	0.0005
Obj_dist	>=31		1	1.08	0.2714	15.8349	<.0001
Obj_type	Hard		1	0.6937	0.0576	144.9662	<.0001
Spd_lmt	36-55		1	0.268	0.0863	9.6502	0.0019
Spd_lmt	>56		1	0.2845	0.1249	5.1919	0.0227
Roll	1		1	1.5251	0.0767	395.8572	<.0001
Obj_dist*Spd_lmt	11 to 30	36-55	1	-0.184	0.1688	1.1873	0.2759
Obj_dist*Spd_lmt	11 to 30	>56	1	-0.7832	0.2043	14.7048	0.0001
Obj_dist*Spd_lmt	>=31	36-55	1	-0.6482	0.303	4.5763	0.0324
Obj_dist*Spd_lmt	>=31	>56	1	-0.9915	0.338	8.6048	0.0034

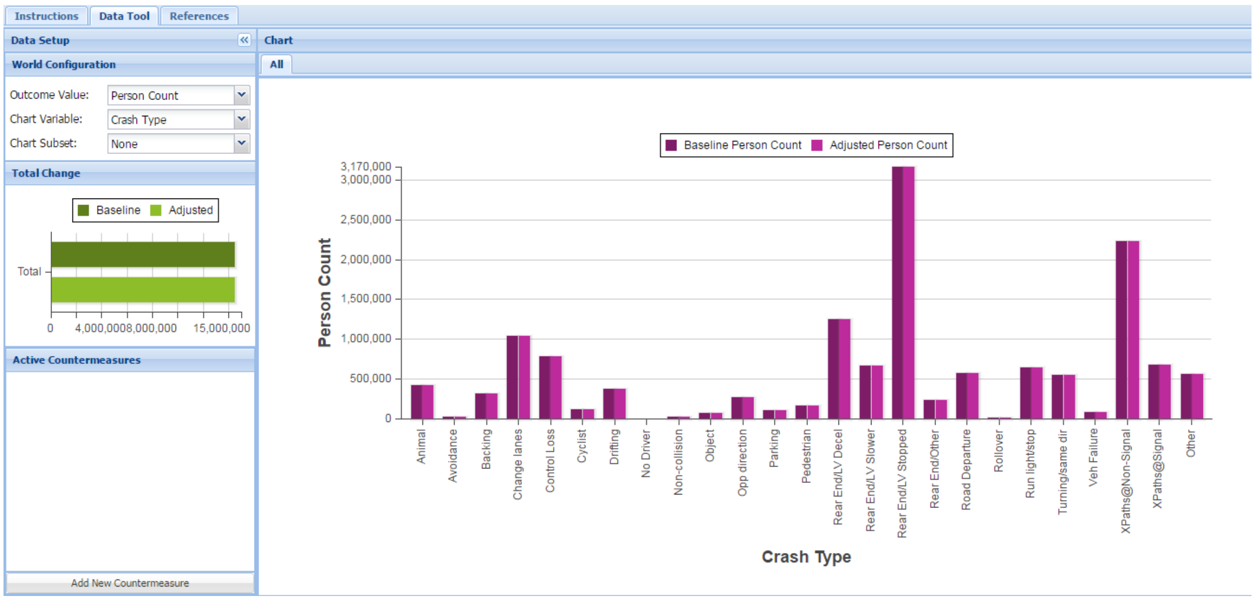
The model shows that the distance from the roadway to the object struck was associated with the probability of injury. Greater off-road distances were associated with higher probabilities of injury, even controlling for posted speed limit (as a surrogate for travel speed), the type of object struck, and rollover. Higher speeds were predictive of higher injury probability; hard objects predicted a greater probability of injury compared with soft objects. The parameter for rollover had the highest estimate, not surprisingly since rollover has long been known to be the most significant factor in off-road injury crashes. There was also a significant interaction between the obj_dist and spd_lmt parameters, such that crashes with more distant objects on higher speed roads were actually somewhat protective, as indicated by the negative sign of the coefficients for those combinations. High speed roads are designed to a high standard, and tend to have wide clear areas and protective features such as breakaway signs.

Having established that off-road distance and type of object struck were related to injury probability, a set of equations were fit to the data to predict injury probability for each of the speed bins in the simulation results. These equations were used to predict the decrease in injury probability if LDW or LKA had been active in the events.

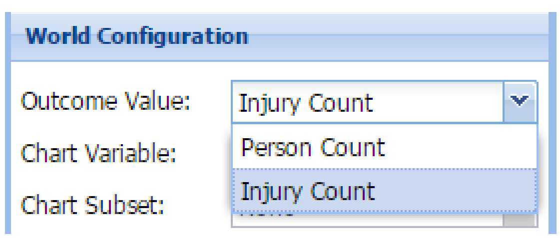
Appendix G UTMOST Tutorial

This appendix presents some tutorial information for using UTMOST online. The link to UTMOST is at utmost.umtri.umich.edu

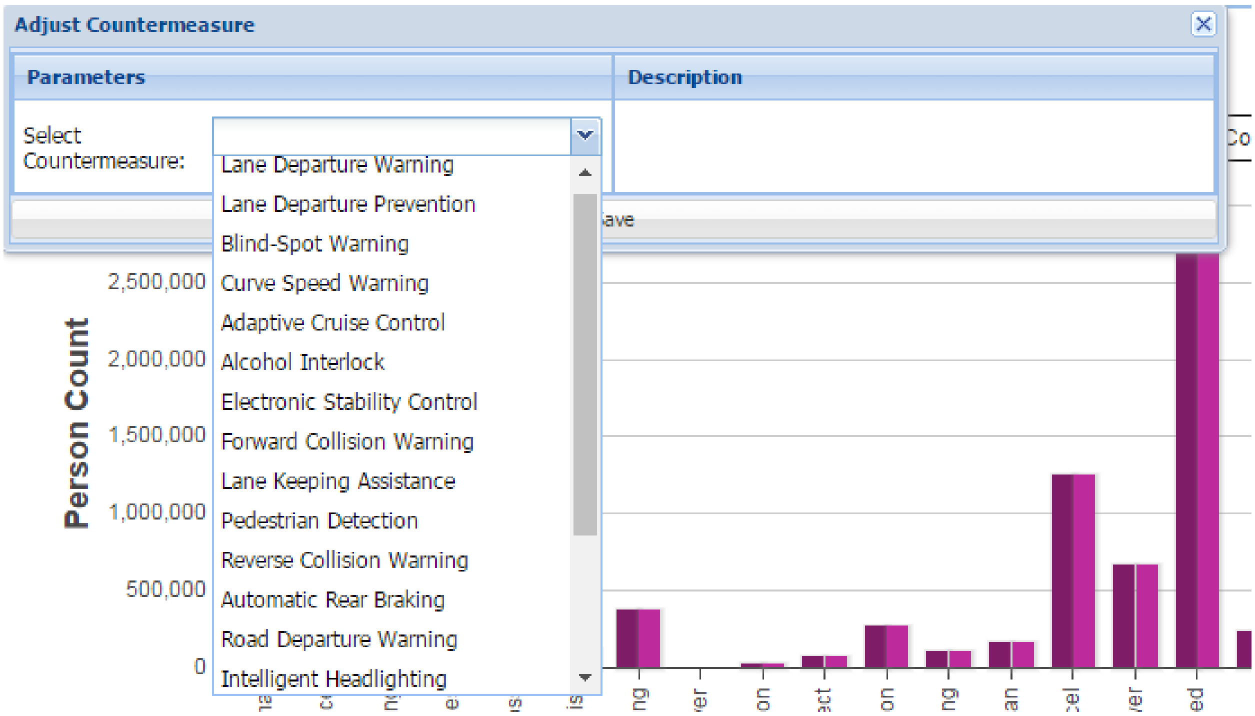
When you open UTMOST, you see the following default screen for the data tool:

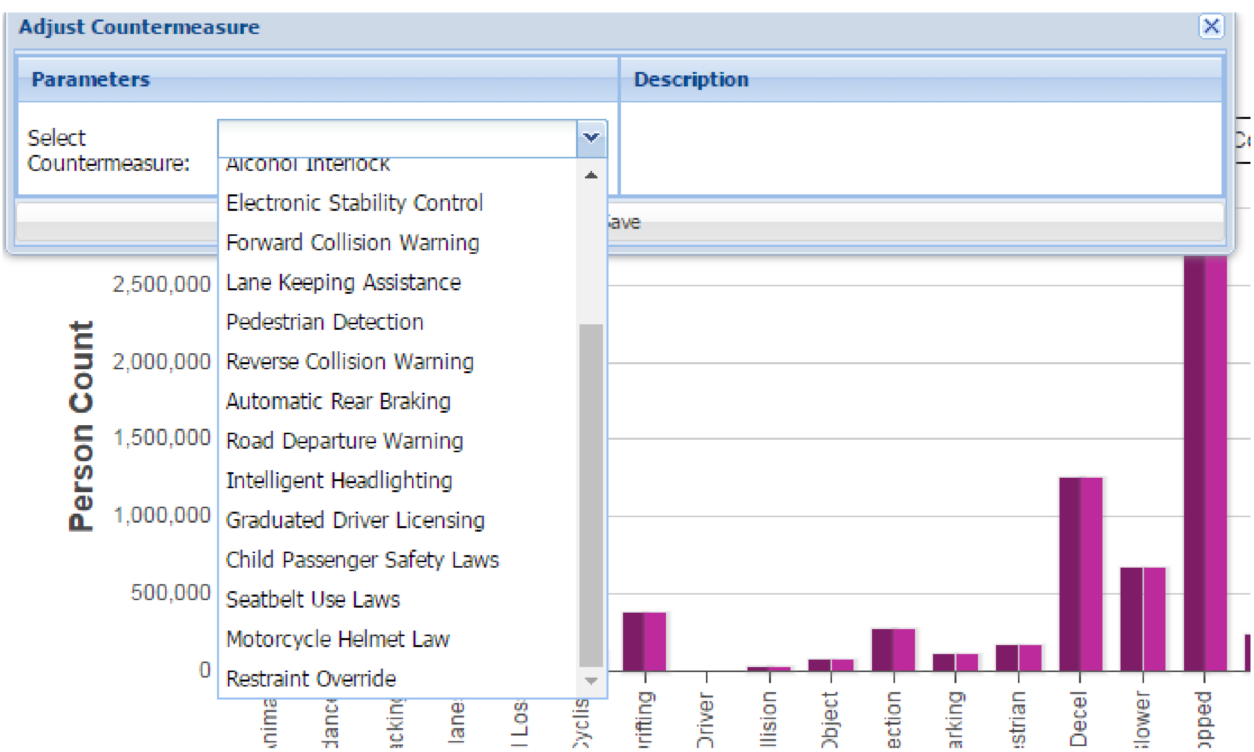


In the upper left box is the world configuration with three options. First choose the outcome variable as person count or injury count.

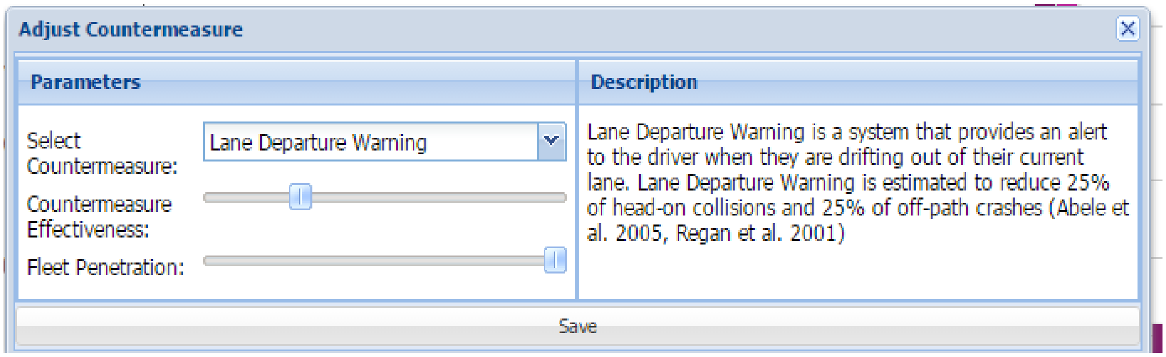


Next explore the effect of different countermeasures by choosing the “add new countermeasure” button on the bottom left. The dropdown menus below shows available choices, with active vehicle countermeasures listed first, followed by legislative and restraint countermeasures:

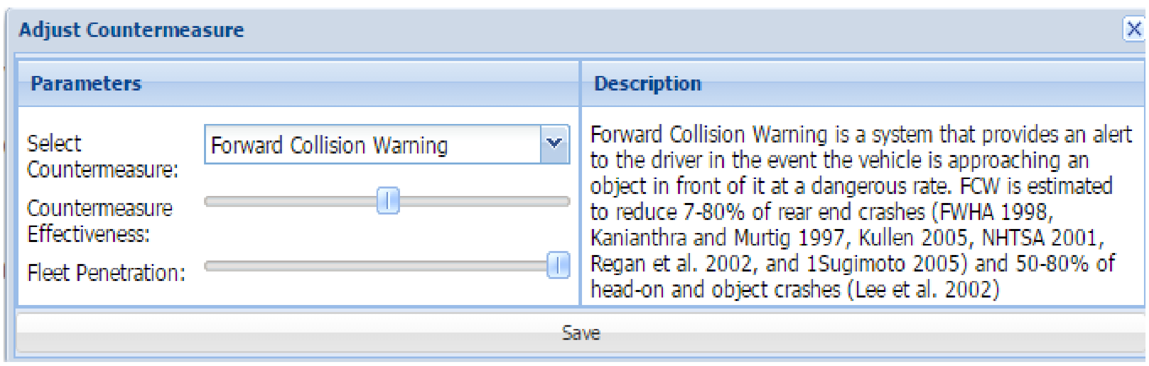




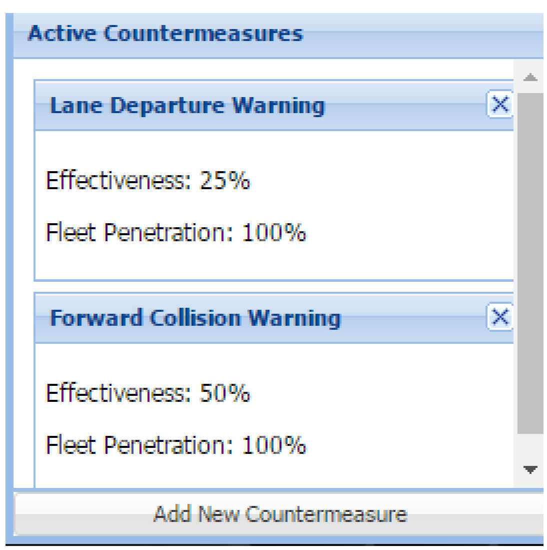
For the tutorial, we will first add lane departure warning. Options for adjusting this countermeasure and a brief description are shown below. We will leave LDW at its current effectiveness and 100% fleet penetration.



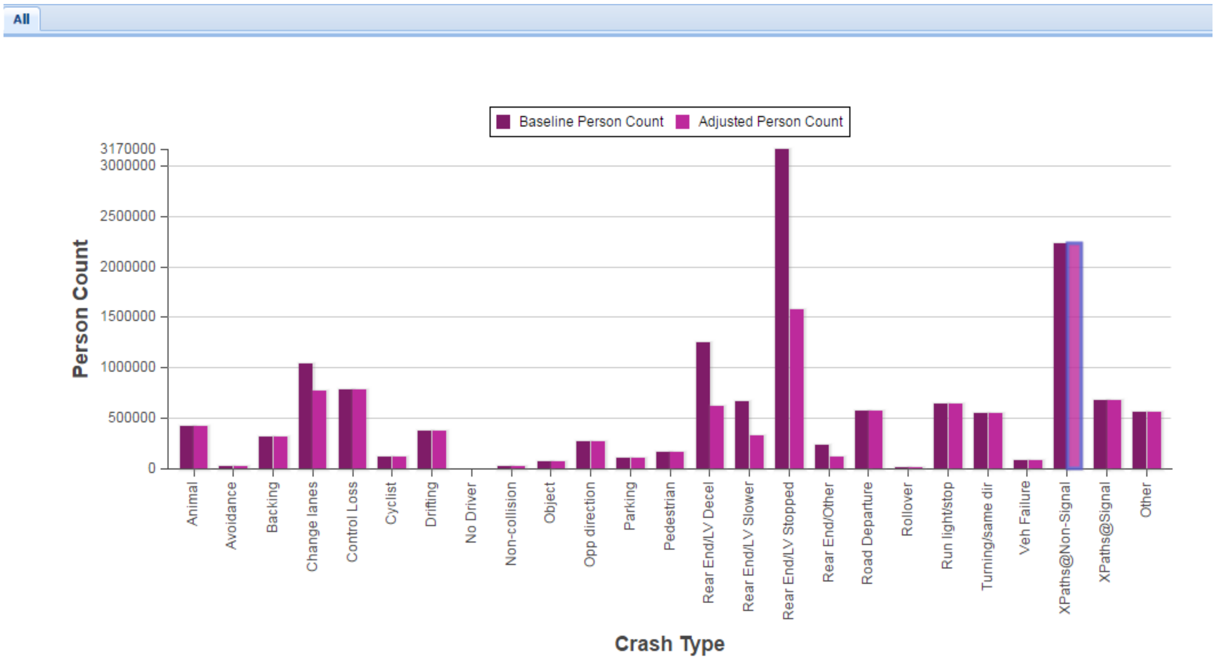
We will choose "add a new countermeasure" to look at multiple items at once. Information regarding forward collision warning is shown below.



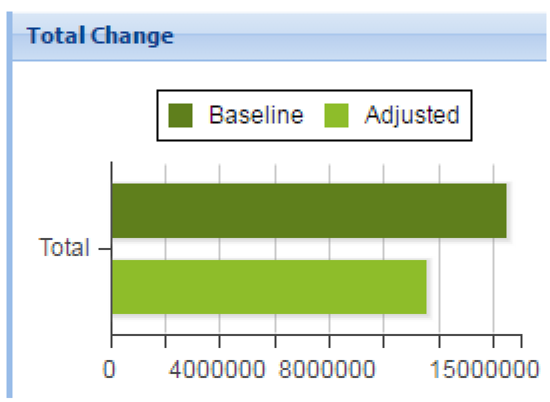
After you select countermeasures, the box on the lower left displays the options you choose as shown below.



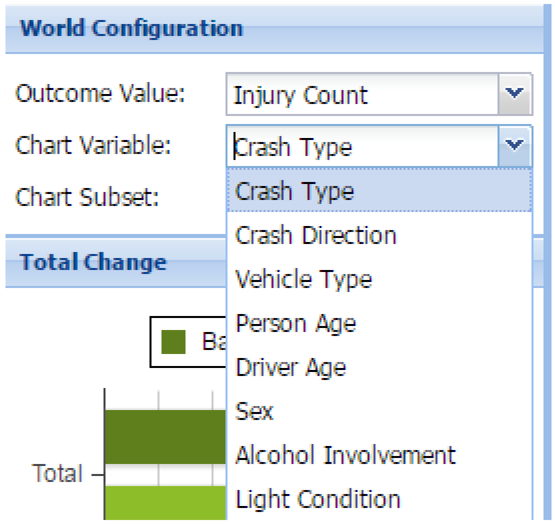
Once you add countermeasures, the effect is automatically displayed as the adjusted person count. The following graph shows the effect of these two measures on crash type. You can move your cursor over the bars to display the value.



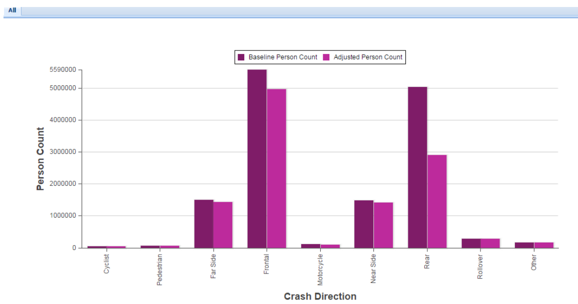
The middle box on the left shows the total baseline and adjusted person counts.

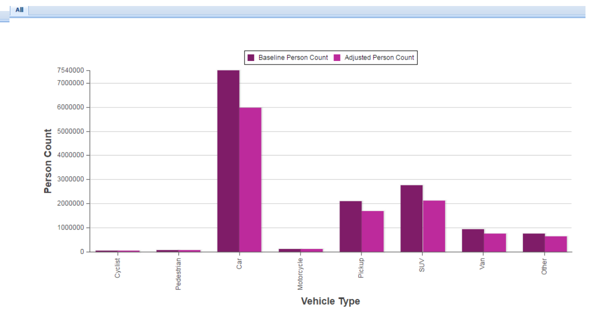


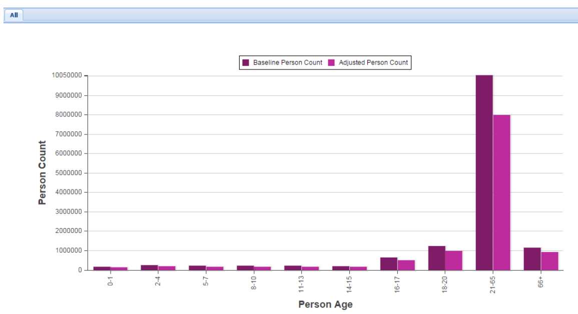
Next we go back to the World Configuration box on the upper left to see options for changing the x-axis variable shown below.

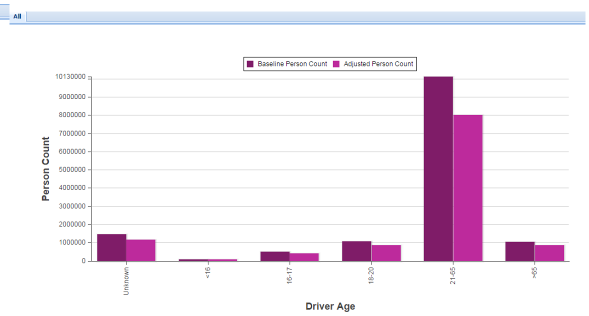

World Configuration
Outcome Value:
Injury Count
Chart Variable:
Crash Type
Chart Subset:
Crash Type
Crash Direction
Vehicle Type
Person Age
Driver Age
Sex
Alcohol Involvement
Light Condition
Total Change
Total

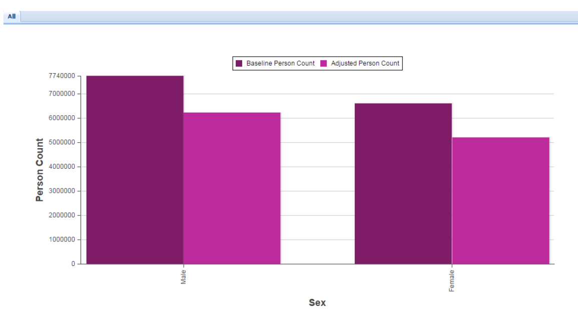
The plots below page show how the graphs change when different chart variables are selected for the x-axis.

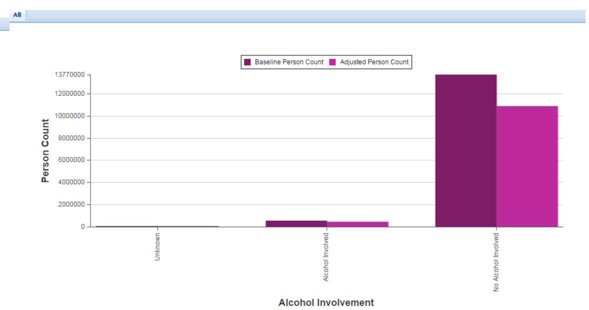


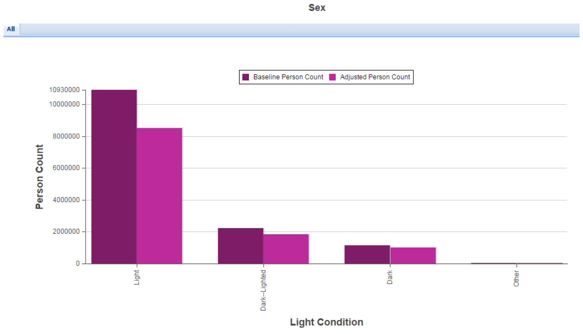




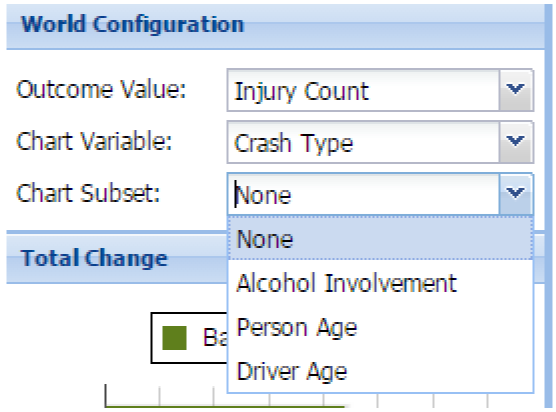




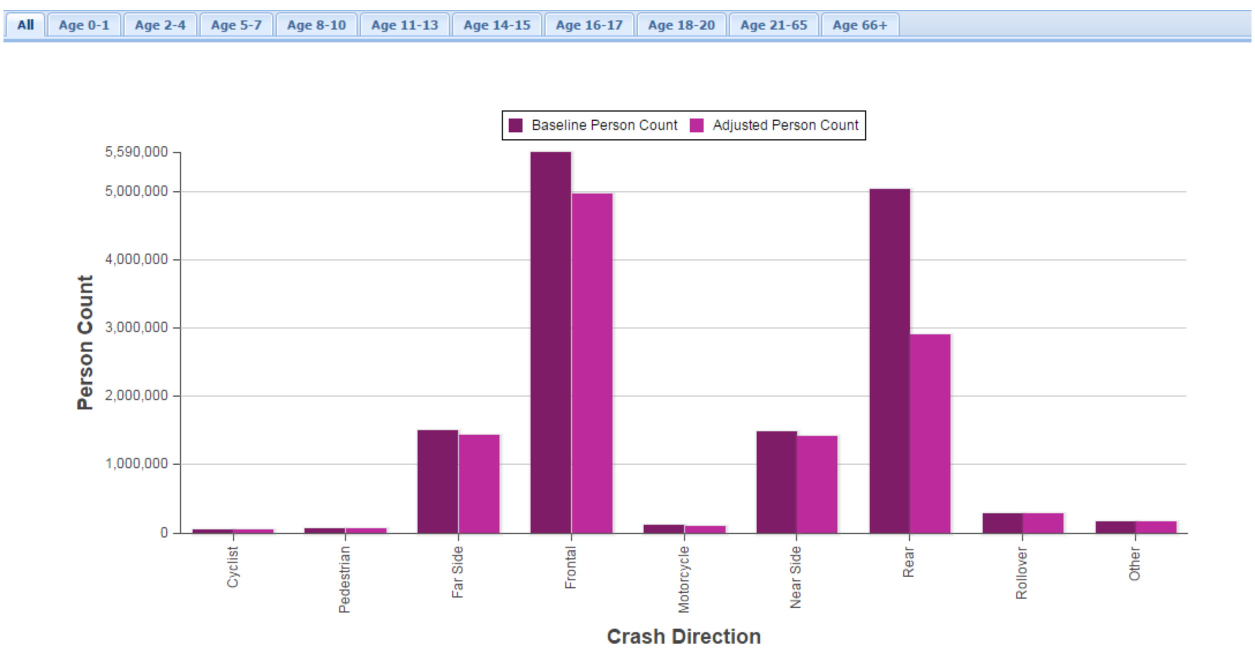




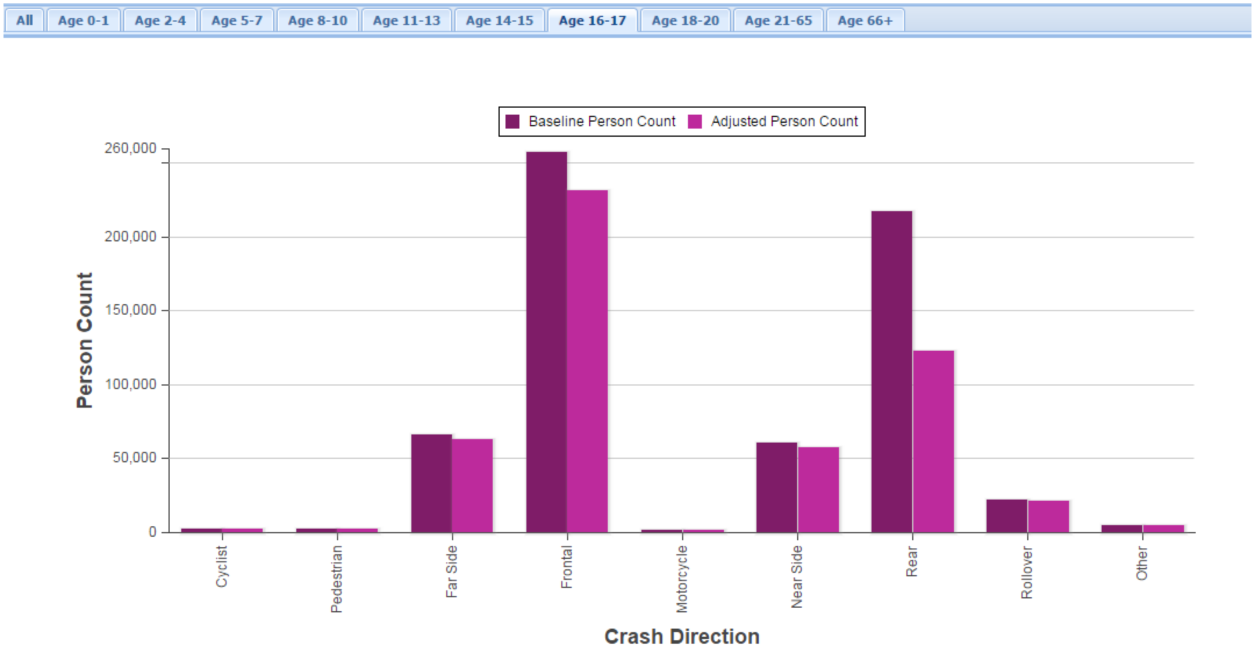
There are other options for focusing in on these plots. Under the world configuration box, there are several options under chart subset shown below.



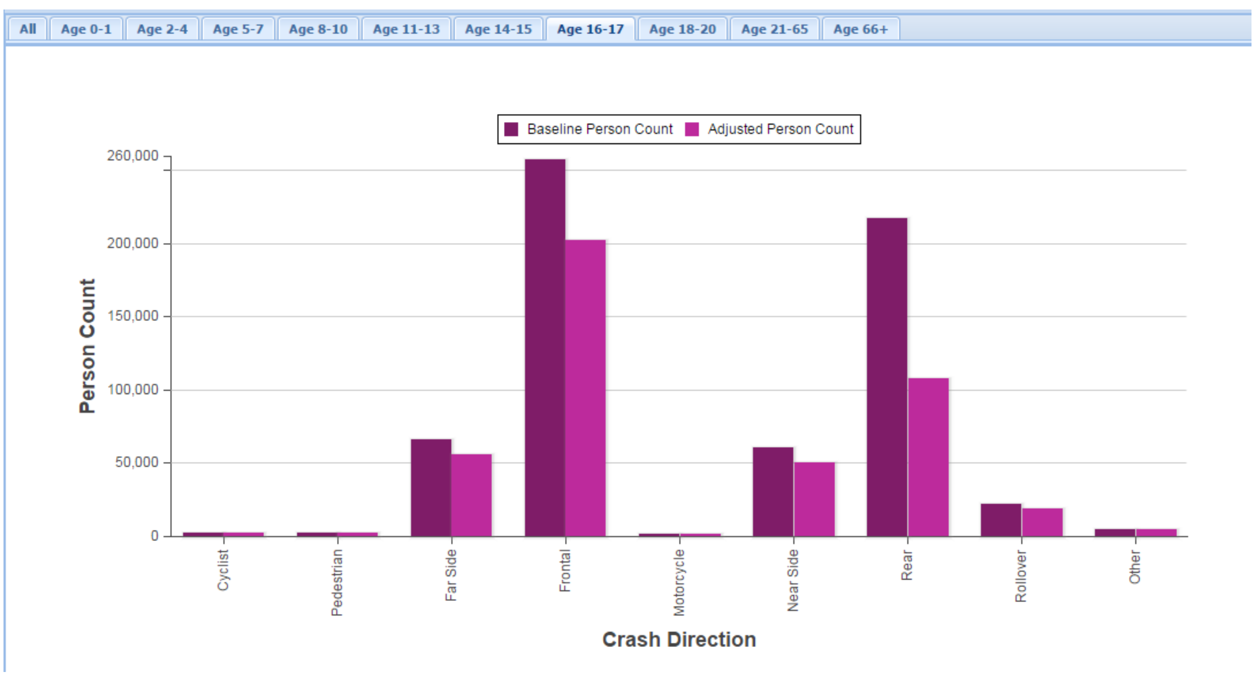
As an example, we can choose person age for the chart subset. As shown below, there are now tabs for different ages across the top.



To see the crash direction for teens aged 16-17, we choose that tab.



As you switch through different graphing options, you can also add new countermeasures. The plot below shows how 16-17 person count would change if all states had 9 strong GDL laws, in addition to the two active safety countermeasures in the previous graph.



Returning to the world configuration window, we reset the chart subset to “none” to display results for all persons and now choose “injury count” for the outcome value. The top chart shows results of adding FCW and LDW to all vehicles, while the bottom chart also includes having 100% of population covered by the strongest type of seatbelt law and child restraint laws corresponding to best practice.