In-Depth Analysis of Crash Contributing Factors and Potential ADAS Interventions Among At-Risk Drivers Using the SHRP 2 Naturalistic Driving Study

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ABSTRACT

Objective: Motor vehicle crashes remain a significant problem. Advanced driver assistance systems (ADAS) have the potential to reduce crash incidence and severity, but their optimization requires a comprehensive understanding of driver-specific errors and environmental hazards in real-world crash scenarios. Therefore, the objectives of this study were to quantify contributing factors using the Strategic Highway Research Program 2 (SHRP 2) Naturalistic Driving Study (NDS), identify potential ADAS interventions, and make suggestions to optimize ADAS for real-world crash scenarios.

Methods: A subset of the SHRP 2 NDS consisting of at-fault crashes (n=369) among teens (16-19 yrs), young adults (20-24 yrs), adults (35-54 yrs) and older adults (70+ yrs) were reviewed to identify contributing factors and potential ADAS interventions. Contributing factors were classified according to National Motor Vehicle Crash Causation Survey pre-crash assessment variable elements. A single critical factor was selected among the contributing factors for each crash. Case reviews with a multidisciplinary panel of industry experts were conducted to develop suggestions for ADAS optimization. Critical factors were compared across at-risk driving groups, gender, and incident type using chi-square statistics and multinomial logistic regression.

Results: Driver error was the critical factor in 97% of crashes. Recognition error (56%), including internal distraction and inadequate surveillance, was the most common driver error sub-type. Teens and young adults exhibited greater decision errors compared to older adults ($p<0.01$). Older adults exhibited greater performance errors ($p<0.05$) compared to teens and young adults. Automatic emergency braking (AEB) had the greatest potential to mitigate crashes (48%), followed by vehicle-to-vehicle communication (38%) and driver monitoring (24%). ADAS suggestions for optimization included (1) implementing adaptive forward collision warning, AEB, high-speed warning, and curve-speed warning to account for road surface conditions (2) ensuring detection of non-standard road objects, (3) vehicle-to-vehicle communication alerting drivers to cross-traffic, (4) vehicle-to-infrastructure communication alerting drivers to the presence of pedestrians in crosswalks, and (5) optimizing lane keeping assist for end-departures and pedal confusion.

Conclusions: These data provide stakeholders with a comprehensive understanding of critical factors among at-risk drivers as well as suggestions for ADAS improvements based on naturalistic data. Such data can be used to optimize ADAS for driver-specific errors and help develop more robust vehicle test procedures.

INTRODUCTION

Motor vehicle crashes continue to be a significant source of mortality and morbidity in the United States and worldwide. Globally, road traffic injuries remain a leading cause of death, particularly for low to middle-income countries and are the leading cause of death for children and young adults (5-29 yrs) (WHO 2018). In the United States, despite a reduction in vehicle miles traveled stemming from the COVID-19 stay-at-home measures, motor vehicle fatality rates rose nearly 5% since 2019; the greatest increase was observed during the summer of 2020 when states began to revoke stay-at-home measures and reopen (NCSA 2020b). Postulated reasons for this increase include increased risky driving behavior, lower seat belt use, drug/alcohol use, waiver of the on-road exam for newly licensed drivers, and relaxed restrictions for commercial drivers (Valentic 2020; Shepardson 2021; OBSR 2021).

Regardless of the reasons for the increased crash rate over the past year, advanced driver assistance systems (ADAS) have the potential to mitigate these crashes, reducing overall crash severity, injuries, and deaths. Injury reduction models have suggested that ADAS have the potential to reduce crashes and injuries by up to 57% (Kusano et al. 2010; Rosen et al. 2010; Searson et al. 2014; Kusano et al. 2014; Edwards et al. 2014, 2015). However, in order to optimize these systems for real-world crash scenarios, a comprehensive understanding of the factors contributing to crashes and potential for ADAS to mitigate these scenarios must be understood.

The Strategic Highway Research Program 2 (SHRP 2) Naturalistic Driving Study (NDS) provides extensive data on real-world crashes, offering a unique opportunity to identify factors contributing to crashes that are not present in archival databases. Our previous SHRP 2 research has focused on quantifying naturalistic crash and near crash rates, vehicle dynamics, and evasive maneuvers among at-risk driving groups – specifically, young and older drivers (Seacrist et al. 2016, 2018; 2020a; 2020b). However, a more in-depth understanding of the behavioral and environmental factors most relevant to the causation of crashes is needed to optimize ADAS for the unique needs of these at-risk drivers.

Recently, Khattak et al. (2021), classified driver errors and violations among crashes, near crashes, and baseline events using the SHRP2 NDS, with the goal of correlating driver errors across different roadway localities. This study classified driver errors and violations based on the *Driver Behavior* variable in the SHRP 2 NDS. Their findings highlighted the continued contribution of driver errors to crashes as well as differences in driver error type across roadway locality. While this study provides valuable information on driving errors and violations based on naturalistic data from a city and regional planning perspective, this study did not explore how contributing factors varied across driver demographics or crash mode. Among at-risk drivers, *driver-specific factors* – such as inexperience and skill deficits among young drivers (McKnight & McKnight, 2003; White and Caird, 2010; Curry et al., 2011; McDonald, 2013, McDonald et al. 2014; Montgomery et al. 2014; Loeb et al. 2015; McGehee et al., 2016) and declining health and motor skills among older drivers (Braitman et al. 2007; Callaghan et al. 2017; Conlon et al. 2017; Owsley et al. 1998; Oxley et al. 2005) – as well as *incident type* may have a greater influence on causation factors than roadway locality. This study aimed to fulfill this gap by providing a comprehensive review of factors contributing to *at-fault* naturalistic crashes among at-risk drivers. Additionally, this study aimed to provide traffic safety stakeholders with data on the potential efficacy of currently available ADAS at mitigating real-world crash scenarios as well as provide suggestions for ADAS optimization.

METHODS

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

SHRP 2 Dataset

Briefly, the SHRP 2 NDS collected comprehensive data from all trips, crashes, near crashes, and balanced-baseline samples among more than 3,000 drivers from 2010 – 2013 (Hankey et al. 2016). A subset of the SHRP 2 NDS data set was obtained via a data use license with the Virginia Tech Transportation Institute (VTTI). Scene videos, event narratives, secondary tasks, incident type, evasive maneuvers, and times series data pre- and post-event were obtained for all crash events (n=1,317) previously identified by VTTI for four age groups: teens (16–19 yrs), young adults (20–24 yrs), adults (35–54 yrs), and older adults (70+ yrs). All participants were independent drivers; no learner stage (supervised) drivers were included in the SHRP 2 NDS. Time series data ranged from 20 s prior to 10 s post event and were collected at 10 Hz. Crash events were previously identified by VTTI based on vehicle dynamics, automated crash notification, data collection site reports, analyst review, and/or participant self-report; crash events were verified by video review (Hankey et al. 2016). Crashes were further sub-divided into four severity levels: *most severe*, *police reportable*, *minor*, and *low-risk tire strike* (Hankey et al. 2016).

Data Reduction

In this study, a *crash* was defined as an event where the instrumented vehicle contacted another vehicle, cyclist, pedestrian, animal, or object, or departed the roadway with significant severity, where the instrumented vehicle was *at-fault*. *At-fault* was defined as an event where the driver of the instrumented vehicle committed an obvious error that led to the crash (e.g., illegal vehicle maneuvers and distracted driving). *Non-fault* was defined as an event where another driver, pedestrian, or cyclist committed an obvious error or the sudden appearance of an animal/object resulted in a crash (e.g., illegal vehicle maneuvers and the sudden appearance of a deer).

Crashes were filtered based on SHRP 2 variables of *Crash Severity*, *Event Severity*, and *Fault*. Crashes were previously verified to meet the aforementioned definitions of *crash* and *at-fault* based on scene video and event narrative review (Seacrist et al. 2016; 2018; 2020a). Crashes classified as *low-risk tire strikes* (e.g., curb bumps), crashes with small animals (e.g., bird, squirrel) and minor road objects (e.g., traffic cones), and *non-fault* (e.g., rear-end struck) crashes were ignored. The post-filtered dataset consisted of 369 at-fault crashes.

Crashes were previously classified into eight incident types – (1) rear-end (n=95), (2) road departures (n=202), (3) intersection (n=32), (4) side-swipe (n=6), (5) head-on (n=1), (6) animal (n=1), (7) pedestrian/cyclist (n=4), and (8) other (n=28) based on scene video and event narrative review (Seacrist et al. 2016; 2018; 2020a).

Contributing and Critical Factors

Contributing factors were classified according to the National Motor Vehicle Crash Causation Survey (NMVCCS) Field Coding Manual *Critical Reason for Critical Pre-Crash Event* (PRECRASH.CRITICAL_REASON) variable element attributes (NHTSA 2008). A detailed layout of this taxonomy is shown in Table A1. All factors contributing to each at-fault crash were tallied by two independent coders (one behavioral scientist and one traffic safety engineer). Agreement of all contributing factors in a single crash occurred in 24% (n=90) of crashes; the median number of inconsistent contributing factors between the two coders was one factor.

A single *critical factor* was selected for each crash from among the contributing factors by each coder. The *critical factor* was defined as the most influential reason for the crash, without which the crash may have been avoided; this critical factor is often, though not necessarily, the last failure in the causal chain (NHTSA 2008). Critical factor agreement occurred in 73% (n=270) of crashes. Among the remaining 27% of crashes where critical factors differed between coders, it was noted that the critical factor selected by one coder was identified as a contributing factor by the second coder 81% (n=78) of the time. Complete agreement (all contributing factors + critical factor) between coders occurred in 22% (n=80) of crashes.

As noted in the NMVCCS Field Coding Manual, the *critical factor* is based on the preponderance of evidence and can be subjective in nature, requiring additional verification. Therefore, discrepancies in both contributing factors and the critical factor were extensively vetted in weekly crash reviews with the larger study team. Upon completion of the vetting process, the study team was in unanimous (100%) agreement with the final list of contributing and critical factors.

Potential ADAS Interventions

ADAS considered for this study were compiled from a combination of MyCarDoesWhat.org (National Safety Council n.d.; website created by The National Safety Council and the University of Iowa), the Consumer Reports Nomenclature Initiative (Barry 2020), and manufacturer-specific ADAS suggested during expert panel case reviews. A comprehensive list of ADAS considered in this study are listed below:

- Active Park Assist
- Adaptive Cruise Control (ACC)
- Adaptive Head Lights
- Automatic Emergency Braking (AEB)
    - Cyclist Detection (CD)
    - Pedestrian Detection (PD)
- Back-Up Warning (BUW)
- Brake Control Systems (BCS)
    - Anti-lock Braking System (ABS)

  - Electronic Stability Control (ESC)
  - Traction Control (TCS)
- Blind Spot Warning (BSW)
- Brake Assist (BA)
- Curve Speed Warning (CSW)
- Driver Alcohol Detection System for Safety (DADSS)
- Driver Monitoring (DM)
- Following Distance Warning System
- Forward Collision Warning (FCW)
- High Speed Warning (HSW)
- Hill Descent Assist
- Intersection Assist (IA)
- Intelligent Clearance Sonar (ICS)
- Intelligent Speed Adaptation
- Lane Departure Warning (LDW)
- Lane Keeping Assist (LKA)
- Obstacle Detection
- Parking Sensors
- Rear Cross Traffic Alert (RCTA)
- Temperature Warning
- Tire Pressure Monitoring System
- Vehicle-to-Vehicle (V2V)
- Vehicle-to-Infrastructure (V2I)

To characterize the potential for ADAS to mitigate these crash scenarios, all ADAS that would be capable of intervening in each crash scenario were tallied by two independent coders. Agreement of all potential ADAS interventions in a single crash occurred in 17% (n=64) of crashes; the median number of inconsistent ADAS between the two coders was one ADAS. The median percent agreement of potential ADAS interventions in a single crash was 67%. Discrepancies were reconciled by the study team during the aforementioned vetting process. Upon completion of the vetting process, the study team was in unanimous (100%) agreement with the final list of potential ADAS interventions.

Expert Panel Case Reviews

To gain detailed insight into the more complex crash scenarios, case reviews with a multidisciplinary team of industry experts and traffic safety researchers were conducted for crashes classified as *most severe* (n=64), consisting of the following incident types: rear-end (n=28), road departure (n=18), intersection (n=14) and pedestrian/cyclist (n=4). Industry members with expertise in ADAS, active safety, crashworthiness, crash reconstruction, human factors, passive safety, product evaluation, and vehicle design were recruited from member companies of the Center for Child Injury Prevention Studies (CChIPS). Eleven case reviews consisting of 5-6 crashes per review were conducted. Contributing factors, critical factors, and potential ADAS interventions determined by the study team were vetted with the expert panel.

Recommendations on how to optimize current ADAS to mitigate these more complex crash scenarios were developed by both the expert panel and research team.

Statistical Analysis

Crash error categorization rates were compared across three factors: age group, gender, and incident type. Animal, head-on, intersection, pedestrian/cyclist, side-swipe, and other crashes were combined into an expanded "Other" incident type category. Differences in error distribution across critical factors were evaluated with Chi-square tests with significance level 0.05. Pairwise comparisons of error rates between factor parameters were performed with proportion tests. Significance was determined using Benjamini and Hochberg's method of controlling the false discovery rate (Benjamini & Hochberg 1995) with significance level 0.05. Overall impact of critical factors and their odds ratios were evaluated by multinomial logistic regression both individually and in an adjusted model controlling for all factors. Associations across factors were determined by Chi-square tests with significance level 0.05. All analyses were performed in SAS 9.4.

RESULTS

Crash Contributing Factors

Overall, driver error was a contributing factor in 97% of all at-fault SHRP 2 crashes. Vehicle factors contributed to 1% of SHRP 2 crashes. Environmental factors were a contributing factor in 33% of SHRP 2 crashes. The mean (± SD) number of contributing factors per crash was 2.1 ± 1.0, up to a maximum of five contributing factors for a single crash scenario. The proportion of crashes per the total number of contributing factors was: 35% had one contributing factor, 36% had two factors, and 18% had three factors, 9% had four factors, and 2% had five factors. Among *most-severe* crashes, driver error was a contributing factor in 100% of crashes and environmental factors contributed to 44% of crashes; no vehicle factors were found to contribute to *most severe* crashes. The mean number of factors per *most severe* crash was 2.4 ± 0.9.

Crash Critical Factors

Critical factors among at-fault SHRP 2 crashes as well as critical factors from NMVCCS (Singh 2018) are shown in Figure 1. Among critical recognition errors, internal distraction (e.g. cell phone use, passenger interaction, tending to objects in vehicle) (43%) was the most common followed by inadequate surveillance (34%), external distraction (18%), and inattention (5%). Among critical decision errors, too fast for conditions (e.g. traveling at an unsafe speed for traffic or snowy conditions) (41%), aggressive driving behavior (15%), and too fast for curve/turn (e.g. traveling at an unsafe speed to negotiate a curve) (13%) were the most common. Poor directional control (92%) represented most critical performance errors. Critical factors by age group, gender, and incident type are listed in Table A3.

Critical factors by age group

Critical factors across age group are shown in Figure 2. Recognition error was the most common critical error for all age groups. A significant interaction effect was observed between age group and incident type (DF = 6, $\chi2 = 20.6$, $p < 0.01$). The proportion of driver error significantly differed across age group (DF=9, $\chi2=39.6$, $p < 0.01$). The proportion of crashes due to decision error was significantly greater among teens ($p < 0.01$) and young adults ($p < 0.01$) compared to older adults. Contrarily, the proportion of crashes due to performance error was significantly greater among older adults compared to teens ($p < 0.01$) and young adults ($p < 0.01$). No significant differences were observed in the proportion of crashes due to recognition error ($p > 0.33$) or non-performance error ($p > 0.12$) across age group. The multinomial regression model indicated a significant effect of age group on driver error (DF=9, $\chi2=30.3$, $p < 0.01$). Older adults were significantly more likely than teens to exhibit a recognition error (OR=5.7; 95% CI: 2.3-14.0) and performance error (OR=11.0; 95% CI: 3.5-34.7) compared to a decision error.

Critical factors by gender

Critical factors across gender are shown in Figure 3. The proportion of driver error did not differ by gender (DF = 3, $\chi2 = 2.6$, $p = 0.45$). No interaction was observed between gender and age group (DF = 3, $\chi2 = 4.4$, $p = 0.22$) nor between gender and incident type (DF = 2, $\chi2 = 1.9$, $p = 0.39$). The multinomial regression model indicated a no effect of gender on driver error (DF=3, $\chi2=2.6$, $p = 0.43$).

Critical factors by incident type

Critical factors across incident types are shown in Figure 4. The proportion of driver error significantly differed by incident type (DF = 6, $\chi2 = 39.3$, $p < 0.01$). A significant interaction effect was observed between age group and incident type (DF = 6, $\chi2 = 20.6$, $p < 0.01$). The proportion of rear-end crashes due to recognition error was significantly greater than road departure ($p < 0.01$) and other ($p < 0.01$) crashes. The proportion of road departure crashes due to decision error was significantly greater than rear-end crashes ($p < 0.01$). The proportion of rear-end crashes due to performance error was significantly less than road departure ($p < 0.01$) and "other" crashes ($p = 0.01$). No significant difference was observed in the proportion of road departure and "other" crashes due to recognition error after Benjamini-Hochberg correction ($p < 0.05$). No significant differences were observed in the proportion of crashes due to non-performance errors ($p > 0.20$). The multinomial regression model indicated a significant effect of incident type on driver error (DF=6, $\chi2=33.4$, $p < 0.01$). The multinomial regression model indicated a significant effect of age group on driver error (DF=9, $\chi2=30.3$, $p < 0.01$). Rear-end crashes were significantly more likely than road departures to exhibit a recognition error (OR=10.2; 95% CI: 4.1-25.5) compared to a decision error.

Potential ADAS Interventions

Potential ADAS interventions for all crashes as well as crashes labeled as *most severe* are shown in Figures 5 and 6 as well as Tables A3 and A4, respectively. The proportion of potential ADAS interventions by age group is shown in Figure A1. ADAS with a potential intervention rate of < 5% among all crashes were combined into an "other" category. The mean (± SD) number of

ADAS that could potentially intervene per crash was 3.4 ± 1.6, up to a maximum of 8 ADAS. Among all crashes (Figure 5), AEB (48%) exhibited the greatest potential to mitigate crashes, followed by V2V technology (38%) and driver monitoring (24%). Similar findings were observed among *most severe* crashes (Figure 6) with AEB (64%), V2V technology (56%), FCW (45%), and driver monitoring (34%) having the greatest potential to mitigate crashes. Among *most severe* crashes, AEB and driver monitoring were applicable to all four incident types.

ADAS Suggestions for Optimization

Specific suggestions for ADAS improvements garnered from the expert panel case reviews were:

- AEB – adapt to road surface conditions; detect non-standard road objects (e.g. trailers, partial road obstructions, snowbanks)
- CSW – adapt warning threshold for road surface conditions
- CD – detect cyclist cross traffic at intersections
- DM – identify inattentive drivers (looking but not comprehending)
- FCW – adapt warning threshold for road surface conditions
- HSW – alert drivers to unsafe speed during congested traffic; adapt warning threshold for road surface conditions
- ISA – detect and mitigate aggressive driving
- IA – alert drivers to pedestrians/cyclists traveling opposite to the flow of traffic on one-way roads
- LDW – alert the driver to end-departures
- LKA – detect and mitigate end departures; compensate for "pedal confusion" leading to end-departures
- V2I – alert driver to the presence of pedestrians in crosswalks, presence of traffic congestion in tunnels, and icy conditions on bridges
- V2V – alert the queue of vehicles to cross-traffic at intersections; alert surrounding traffic to an illegal or unexpected maneuver conducted by the driver

DISCUSSION

To our knowledge, this is the first study to compare both crash causation factors and potential ADAS interventions among at-risk drivers with a specific focus on *at-fault* crashes. Similar to NMVCCS, which quantified factors contributing to crashes using police-reported crashes and scene investigations (Singh 2018), as well as the SHRP 2 NDS at-large (Khattak et al. 2021), driver error was the *critical* factor in over 90% of crashes among at-risk drivers (teens, young adults, older adults).

The most common driver error across all age groups was recognition error (Figure 2), suggesting that recognition is a consistent problem regardless of driver age. Decision errors decreased with increasing age group, whereas performance errors increased, particularly among older adults. These findings are consistent with prior research showing that inexperience among teens, leading to decision errors, (McKnight & McKnight, 2003; White and Caird, 2010; Curry et al., 2011; McDonald, 2013, McDonald et al. 2014; Montgomery et al. 2014; Loeb et al. 2015; McGehee et al., 2016) and declining motor skills among older adults, leading to performance errors

(Braitman et al. 2007; Callaghan et al. 2017; Conlon et al. 2017; Owsley et al. 1998; Oxley et al. 2005) are significant contributors to crashes within these age groups.

Recognition error represented a greater proportion of driver error compared to NMVCCS (Figure 1). One possible explanation is the inherent advantage of naturalistic data collection at identifying distracted driving behavior prior to a crash compared to traditional methods based on police-reports, scene investigations, and driver surveys. However, another likely reason for the observed increase in recognition error is the increased use of handheld devices during driving. From 2009 to 2018, the use of handheld devices during driving increased substantially, particularly among younger drivers (NCSA 2019; Kidd et al. 2019). Among the crashes included in this study, cell phone use occurred in 31% of crashes where internal distraction was the critical factor. Among all trips in SHRP 2, drivers in the SHRP 2 NDS averaged more than one text/call per hour of driving (Atwood et al. 2018) with rates nearly 3 times higher among teens. With in-vehicle infotainment (IVI) systems being readily deployed in new vehicles, the proportion of crashes due to recognition error, in particular internal distraction, may continue to increase.

Interestingly, no differences were observed in critical factors across gender. While previous research has identified differences in crash risk (Massie et al. 1995; IIHS 2019), injury risk (Kahane 2013; Santamariña-Rubio et al. 2014), crash severity (Li et al. 1998), and crash responsibility (Williams & Shabanova 2003) across gender, our findings suggest that the underlying reason for those gender-based differences is *not* due to differences in the driver error type.

Not surprisingly, driver error varied across incident type (Figure 3). Rear-end crashes were primarily the result of recognition error, mainly distraction and inadequate surveillance. The consistency of these recognition error sub-types across rear-end crashes suggests this crash mode can be mitigated by a narrower set of ADAS, specifically FCW, AEB, and DM (Figures 5 & 6). Road departures, on the other hand, were due to a much more diverse set of driver errors. While recognition error (44%) continued to be a factor in road departures, both decision errors (25%) – such as traveling too fast for conditions – and performance errors (20%) – such as overcompensation and "pedal confusion" – together contributed to a similar proportion. While LDW and LKA can likely address some of the less severe road departures including those due to distraction, a more comprehensive set of ADAS features is likely needed to both alert and compensate for driver error leading to road departures.

Though driver error was the critical error in nearly all SHRP 2 crashes, this does not necessitate that the responsibility for the crash rests solely with the driver. Nor should it be inferred that eliminating human error by transitioning to automated driving systems would prevent nearly all crashes. While automated driving systems have the potential to reduce crashes caused by human error, it is important to highlight that one-third of all crashes and nearly half (44%) of *most severe* crashes had additional *non-driver* contributing factors. These additional factors included view obstructions, poor signage, complex roadway design, lighting changes, and glare. Qualitatively, these crashes occurred in more complex driving scenarios such as merges, constructions zones, and tunnels. Such scenarios can prove challenging even for more experienced drivers and may also present challenges for automated driving systems. These more complex naturalistic driving scenarios could serve as test cases for optimizing and evaluating automated driving systems.

Regarding ADAS, AEB had the greatest potential to mitigate SHRP 2 at-fault crashes, being applicable to nearly half (48%) of all crashes and two-thirds (64%) of *most-severe* crashes. These data support the effort initiated by NHTSA and IIHS to have OEMs voluntarily standardize AEB on new light-duty vehicles by 2022-2023; 10 OEMs recently met this pledge ahead of schedule (IIHS 2020). The findings of this study suggest that these standardization efforts should have a significant impact on real-world crash reduction. Along with AEB, other ADAS associated with braking (BA, BCS, FCW), vehicle communications (V2V), and distraction (DM) were the most universally applicable, being relevant to all four crash categories. These findings correspond to other research showing that driver distraction is a significant cause of crashes (NCSA 2020a; NAS 2021). Of interest was the high potential impact of both V2V and V2I technology. These findings can be used by OEMs and traffic safety stakeholders to advocate for the inclusion of these emerging technologies in new model years.

ADAS related to speed (CSW, HSW, BCS) tended to heavily favor younger drivers (Figure A1), suggesting traffic safety stakeholders should prioritize these systems for vehicles purchased by younger drivers. ADAS such as BUW, BSW, and V2I tended to favor older drivers, corresponding to the need to augment older driver scanning and hazard perception due to declining physical health. Additionally, we observed that pedal confusion – pressing the accelerator when intending to press the brake –primarily occurred in older adults. Therefore, LKA and LDA – once optimized for end departures – could be prioritized among vehicle models purchased by older adults. While males may be more likely than females to be involved a crash (Massie et al. 1995; IIHS 2019) – warranting that traffic safety stakeholders prioritize implementing ADAS in vehicle models more typically purchased by males – the results of this study do not suggest that specific ADAS are more warranted for either gender.

While nearly all animal-related crashes were considered *non-fault* due to the sudden appearance of the animal, a single animal-related crash was included as *at-fault*. This particular crash involved a deer visibly crossing the roadway while the driver was distracted. Potential ADAS interventions including DM to address distraction and BA to augment the driver’s late reaction. While rare, such crashes could warrant the optimization of FCW and AEB systems for the detection of large animals, particularly for vehicle models more commonly sold in rural areas.

The current study utilized a combination of inter-rater coding, study team case reviews, and expert panel case reviews. Given the number of contributing factors and potential ADAS interventions considered for each crash as well as the plethora of data available in SHRP 2 for each event, we anticipated low initial inter-coder agreement and the need for an extensive vetting process. However, despite this complexity, complete agreement among contributing factors was achieved for nearly a quarter of the crashes. The disagreement between coders was typically limited to only one or two contributing factors. Critical factor agreement was very good; even among the crashes where critical factors were different, in most crashes the disagreement was simply regarding which contributing factor was the *critical* factor. Rarely was there a complete discordance between the critical factors selected between coders. Similarly, initial ADAS intervention agreement was low, but the difference was again typically only 1-2 ADAS features.

That being said, for more complex crashes, we emphasize the utility of using a study team and expert panel vetting process. Such processes have been used previously in crash scene investigation research (Durbin et al. 2001; Arbogast et al. 2007). The expert panel collaboration as part of this project proved invaluable in determining the final list of factors and potential ADAS crash.

Several limitations warrant discussion. First, compared to analyses based on police-reports and insurance claims, which include more severe crashes, the SHRP 2 NDS included less severe crashes, with very few injurious crashes and no fatal crashes. While the overall distribution of critical factors and driver error sub-types were similar to the NVMCCS (Figure 1), suggesting that these factors are comparable to those in more severe crash databases, it is possible that the specific critical errors may differ between these naturalistic crashes and more severe injurious or fatal crashes. Additionally, it is important to note that Figures 5 & 6 represent the *potential* for ADAS to mitigate crashes. For ADAS to truly mitigate these crashes, these systems must correctly identify and appropriately respond to potential hazards. This is particularly important for warning-based ADAS (SAE Level 0), such as FCW and LDW, which require the driver to appropriately respond to the alert for it to ultimately be effective. However, limitations of current automated systems may also result in reduced real-world effectiveness compared to Figures 5 & 6. Previous research assessing the effectiveness of currently available AEB systems at mitigating rear-end SHRP 2 crashes showed that, while AEB was very effective at preventing crashes, there were particular crash scenarios – specifically those with weather conditions or high speeds – where current AEB was ineffective (Seacrist et al. 2020b). Consequently, Figures 5 & 6 should be taken as ADAS mitigation targets rather than on-road effectiveness of currently available ADAS systems. Finally, it is not explicitly known that the vehicles in SHRP 2 did not have ADAS features. Among the crashes included in this analysis, only 1% (n=5) involved vehicles labeled as an "advanced technology vehicle." This SHRP 2 variable indicates that the vehicle had some form of advanced technology, though not necessarily ADAS. However, even among these five crashes, ADAS intervention was ***not*** mentioned in any of the event narratives. Overall, this suggests that ADAS influence in these crashes was minimal, if not non-existent.

Nevertheless, this study utilizes the largest naturalistic driving study to-date to provide traffic safety stakeholders with a comprehensive understanding of contributing factors among at-risk drivers, the potential for ADAS to mitigate specific incident types, as well as suggestions for ADAS improvements based on naturalistic crash scenarios. Such data can be used to optimize ADAS for driver-specific errors and help develop more robust vehicle test procedures. Furthermore, these data can be used to identify the types of human error as well as environmental factors that automated driving systems will need to predict and contend with in various crash scenarios.

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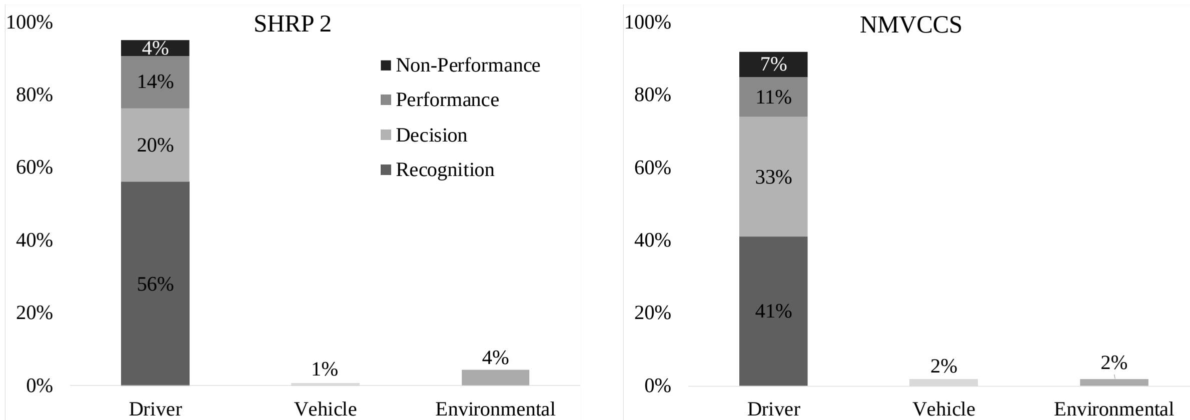

Figure 1. Critical factors among *at-fault* SHRP 2 crashes (left) and crashes from NMVCCS (right) (Singh et al. 2008).

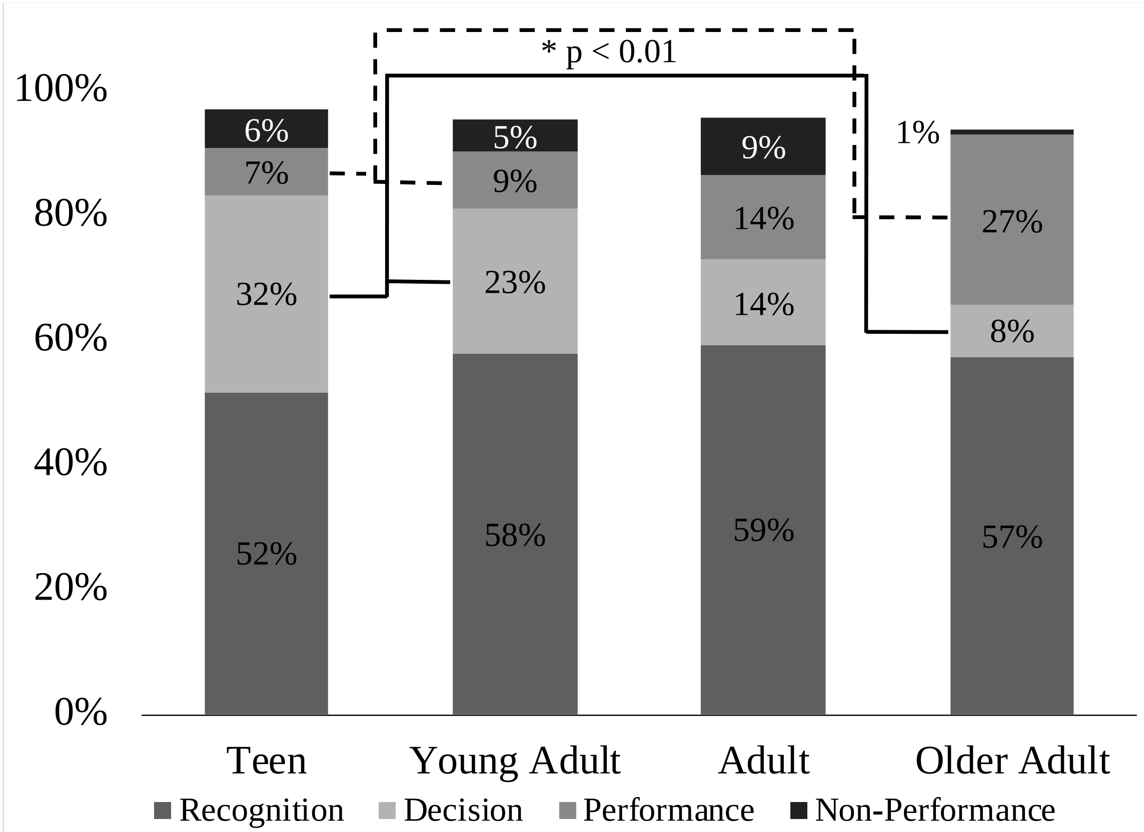

Figure 2. Critical factors across driver age group.

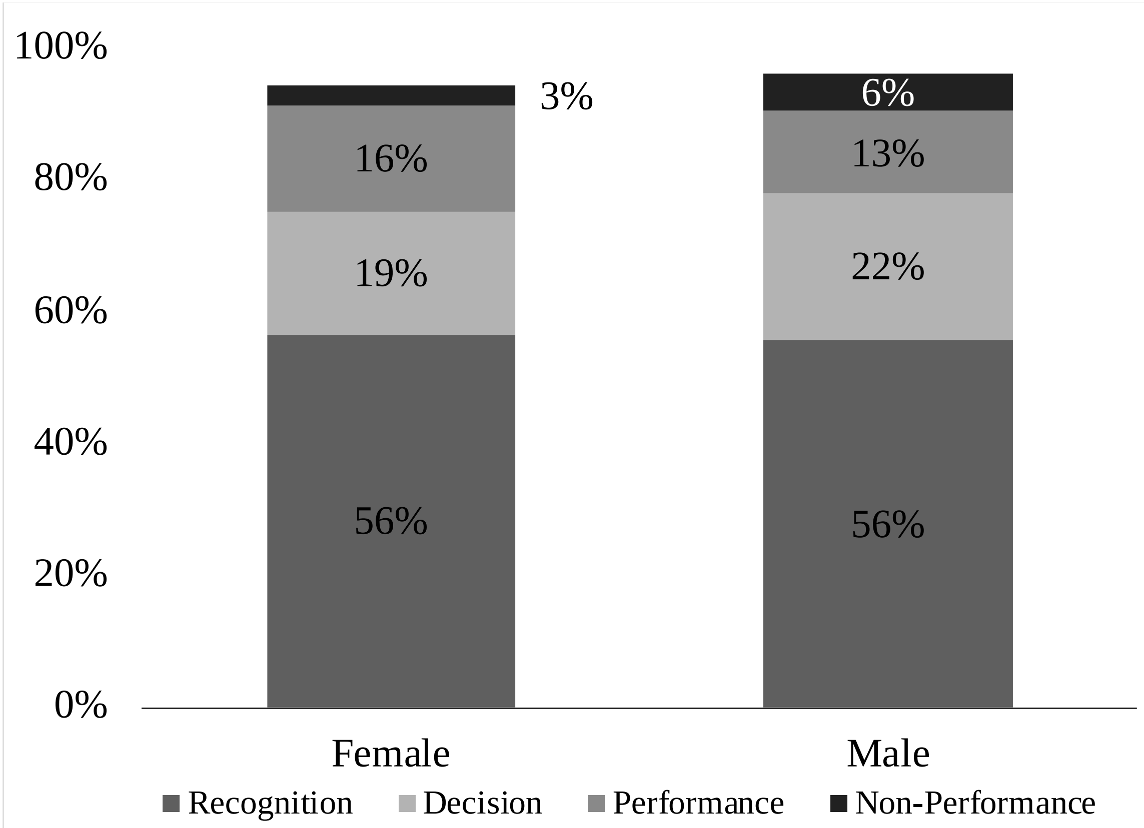

Figure 3. Critical factors by gender.

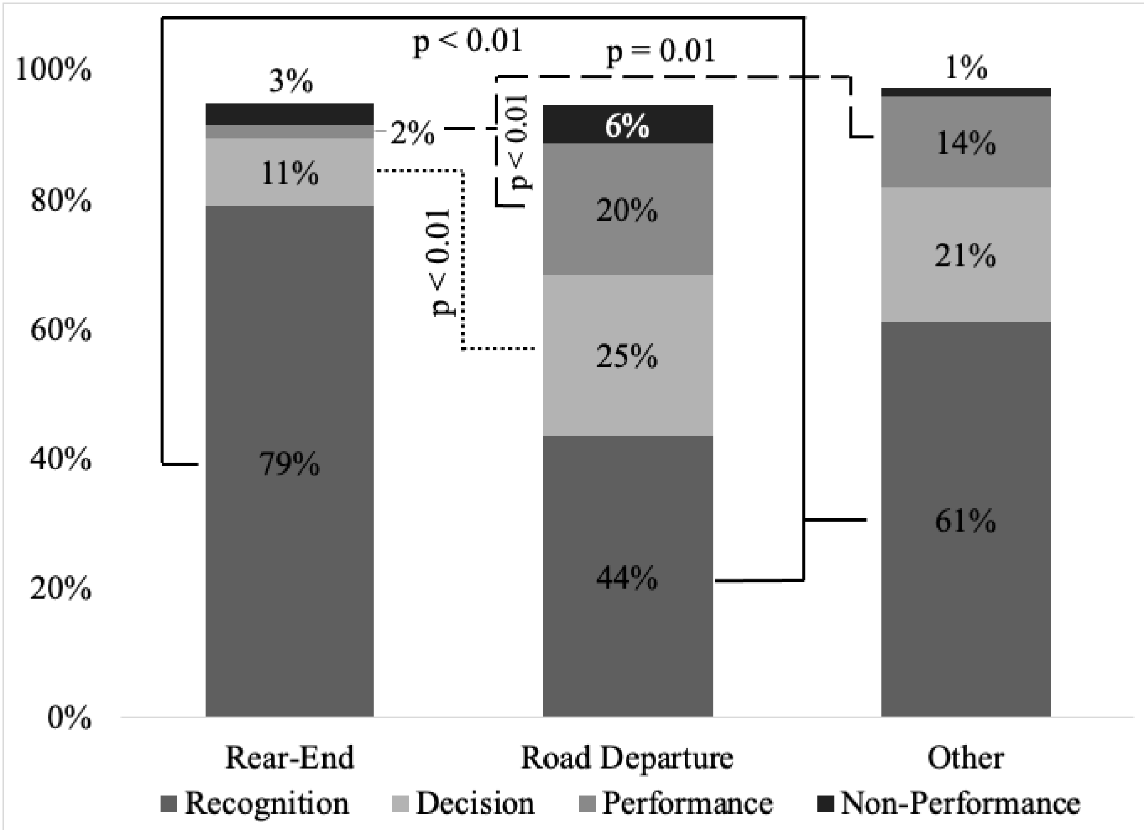

Figure 4. Critical factors by incident type.

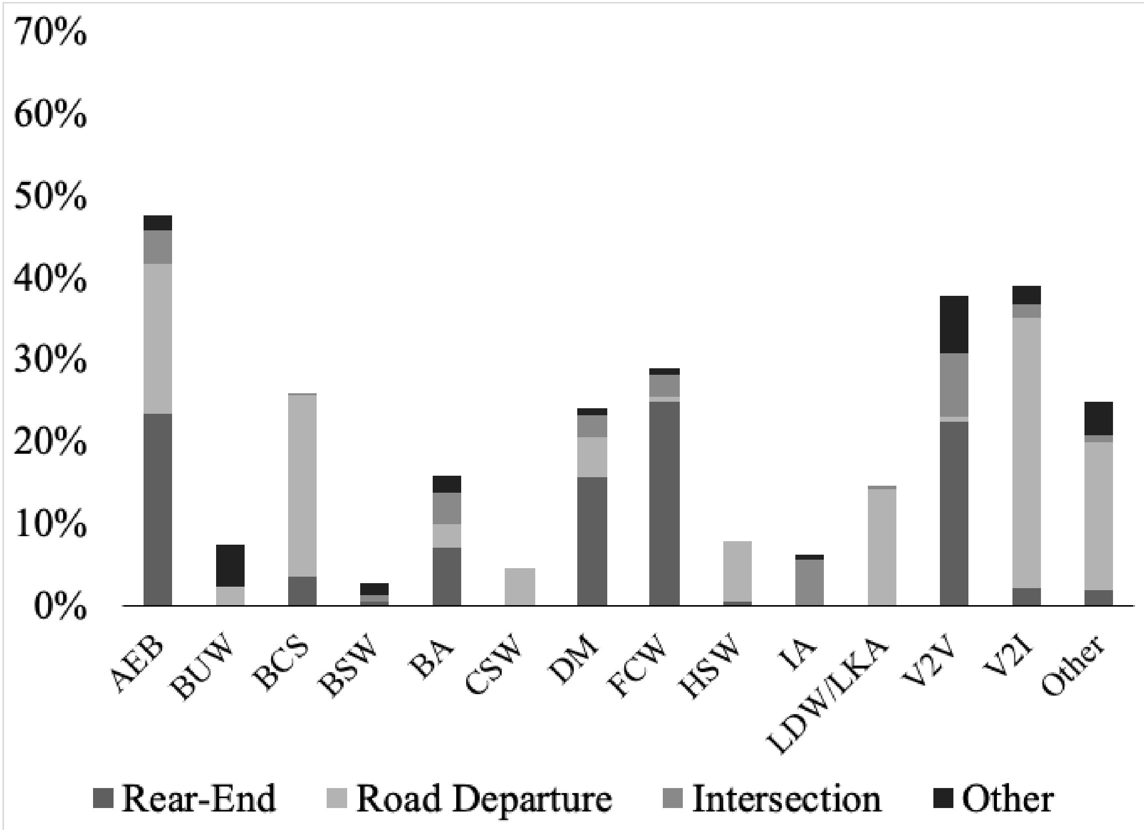

Figure 5. Potential ADAS interventions for *at-fault* SHRP 2 crashes.

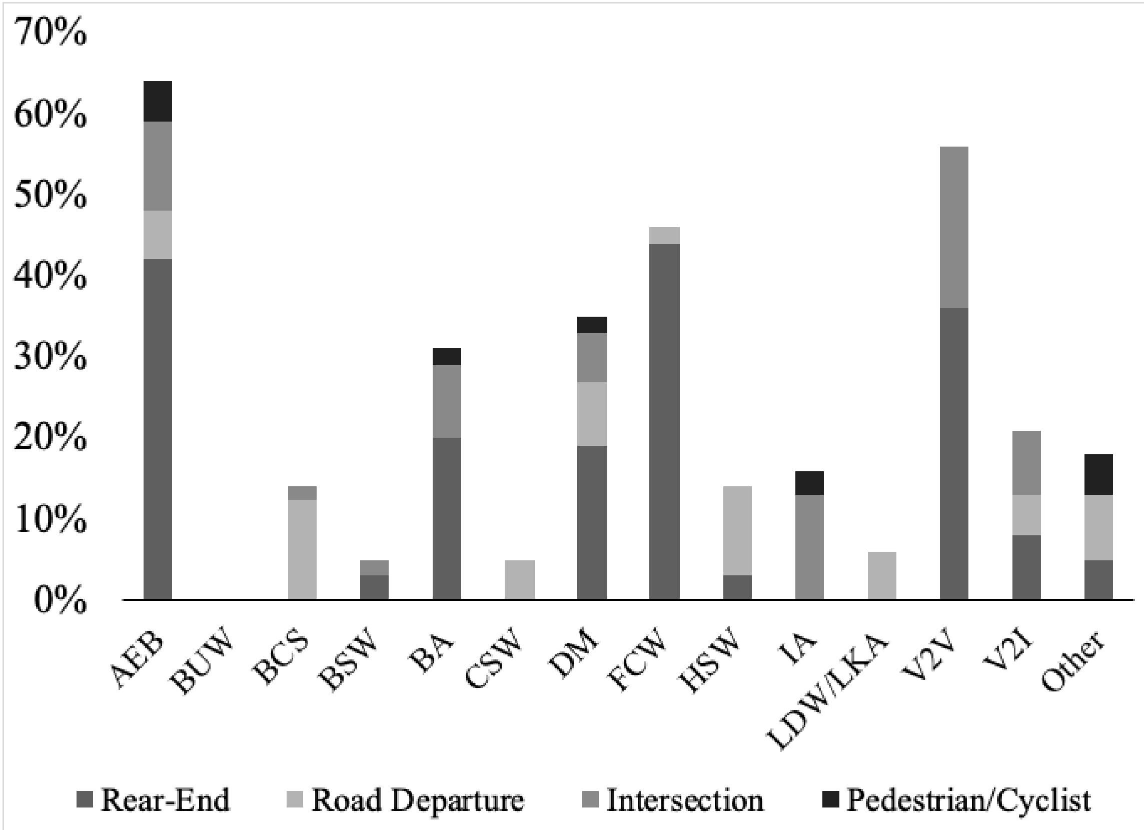

Figure 6. Potential ADAS interventions for *most severe* SHRP 2 crashes.

APPENDIX

Table A1. Contributing Factor Taxonomy

General Factor	Sub-Factor	Specific Factor
Driver	Recognition	Inadequate surveillance
		Inattention
		External distraction
		Internal distraction
		Other
	Decision	Too fast for conditions
		Too fast to respond to unexpected actions of others
		Too fast for curve/turn
		False assumption of other's action
		Illegal maneuver
		Inadequate evasive action
		Incorrect evasive action
		Misjudgment of gap or other's speed
		Following too closely
		Aggressive driving behavior
		Turned with obstructed view
		Other
	Performance	Overcompensation
		Poor directional control
		Panic/freezing
		Other
	Non-Performance	Sleep, actually asleep
		Heart Attack or Other Physical Ailment
		Other
Vehicle	-	Brakes
		Engine, steering, suspension, transmission
		Tires
		Other
Environmental	Roadway	Slick roads (ice, debris, etc.)
		View obstructions
		Signs/signals
		Road design
		Other
	Atmospheric	Fog/rain/snow
		Glare
		Other

*NMVCSS also includes an *Unknown* element. This element was not needed in this analysis since sufficient data was present to identify the contributing/critical factor(s) for all crashes.
**Detailed definitions for each factor can be found in the NMVCCS Field Coding Manual (NHTSA 2008).

Table A3. Critical Factors Across Age, Gender, and Incident Type

Cohort	Driver				Vehicle	Environmental	
	Recognition	Decision	Performance	Non-Performance		Roadway	Atmospheric
Age Group							
Teen	52%	32%	7%	6%	1%	2%	0%
Young Adult	58%	23%	9%	5%	0%	4%	1%
Adult	59%	14%	14%	9%	0%	5%	0%
Older Adult	57%	8%	27%	1%	1%	3%	3%
Gender							
Female	56%	19%	16%	3%	0%	4%	2%
Male	56%	22%	13%	6%	1%	3%	0%
Incident Type							
Rear-End	79%	11%	2%	3%	2%	3%	0%
Road Departure	44%	25%	20%	6%	0%	4%	1%
Other	61%	21%	14%	1%	0%	1%	1%

Table A4. Potential ADAS Interventions Across Incident Type (All Crashes)

ADAS	Rear-End	Road Departure	Intersection	Other	Total
AEB	24%	18%	4%	2%	48%
BCS	4%	22%	0%	0%	26%
BSW	1%	0%	1%	1%	3%
BA	7%	3%	4%	2%	16%
CSW	0%	5%	0%	0%	5%
DM	16%	5%	3%	1%	24%
FCW	25%	1%	3%	1%	29%
HSW	1%	7%	0%	0%	8%
IA	0%	0%	6%	1%	6%
LDW/LKA	0%	14%	0%	0%	15%
V2V	22%	1%	8%	7%	38%
V2I	2%	33%	2%	2%	39%
Other	2%	21%	1%	8%	32%

Table A5. Potential ADAS Interventions Across Incident Type (Most Severe)

ADAS	Rear-End	Road Departure	Intersection	Pedestrian/Cyclist	Total
AEB	42%	6%	11%	5%	64%
BCS	0%	13%	2%	0%	14%
BSW	3%	0%	2%	0%	5%
BA	20%	0%	9%	2%	31%
CSW	0%	5%	0%	0%	5%
DM	19%	8%	6%	2%	35%
FCW	44%	2%	0%	0%	46%
HSW	3%	11%	0%	0%	14%
IA	0%	0%	13%	3%	16%
LDW/LKA	0%	6%	0%	0%	6%
V2V	36%	0%	20%	0%	56%
V2I	8%	5%	8%	0%	21%
Other	5%	8%	0%	5%	18%

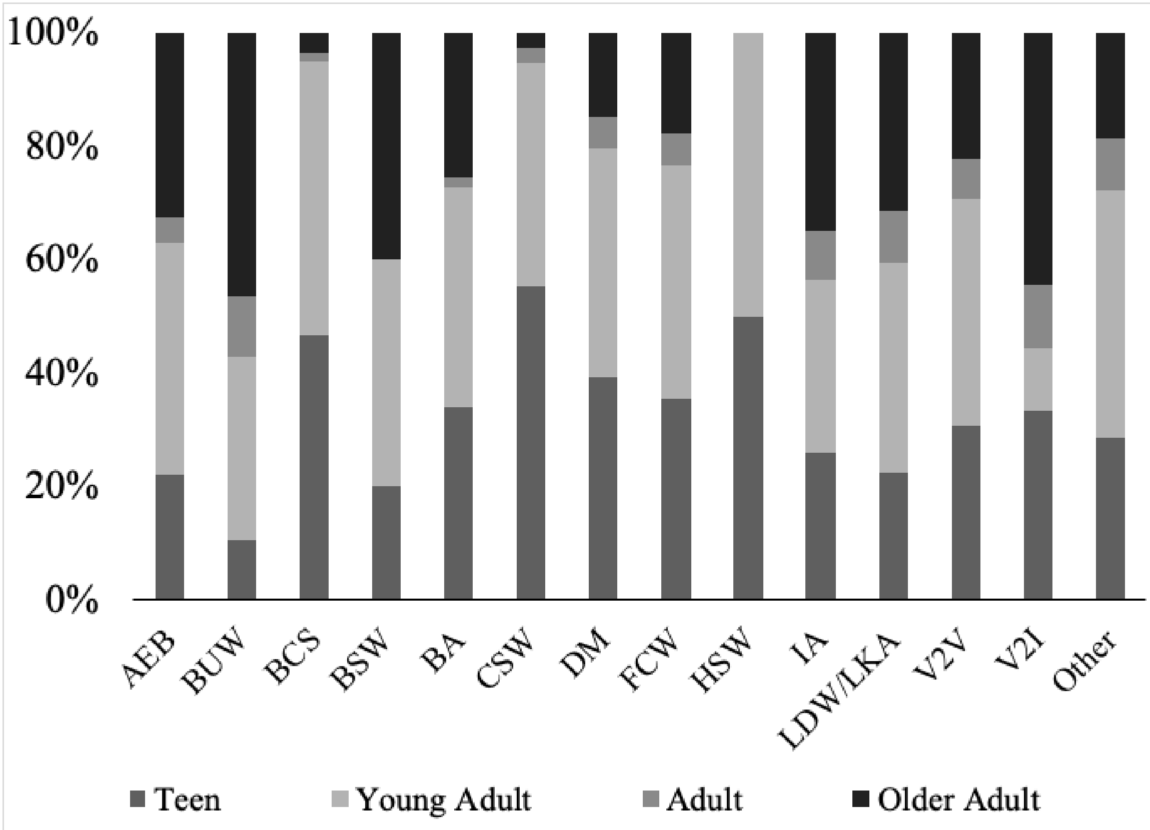

Figure A1. Proportion of potential ADAS interventions by age group.

Table A2. Contributing Factors Across Age, Gender, and Incident Type

Cohort	Driver				Vehicle	Environmental	
	Recognition	Decision	Performance	Non-Performance		Roadway	Atmospheric
Age Group							
Teen	68%	53%	12%	6%	3%	34%	13%
Young Adult	72%	38%	23%	9%	1%	30%	7%
Adult	68%	27%	18%	14%	0%	23%	18%
Older Adult	68%	21%	38%	1%	1%	18%	14%
Gender							
Female	71%	33%	26%	6%	1%	25%	11%
Male	68%	39%	22%	7%	2%	28%	11%
Incident Type							
Rear-End	84%	31%	5%	6%	2%	21%	5%
Road Departure	59%	34%	35%	8%	1%	35%	13%
Other	79%	49%	21%	1%	1%	11%	14%