Safety Science 128 (2020) 104746

Contents lists available at ScienceDirect

Safety Science

journal homepage: www.elsevier.com/locate/safety

Efficacy of automatic emergency braking among risky drivers using counterfactual simulations from the SHRP 2 naturalistic driving study

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ARTICLE INFO

Keywords:
Risky drivers
AEB
ADAS
Counterfactual simulations
SHRP 2
Naturalistic driving

ABSTRACT

Motor vehicle crashes remain a significant problem in the US and worldwide. Automatic emergency braking (AEB) is designed to mitigate the most common crash mode: rear-end striking crashes. However, assessing the efficacy of AEB in real-world crash scenarios is challenging given that avoided crashes are rarely documented except during naturalistic driving studies. In the absence of such data, AEB can be evaluated in real-world crash scenarios by retrospectively adding AEB to naturalistic crashes using counterfactual simulations. AEB was retrospectively applied to rear-end striking crashes (n = 40) from the SHRP 2 database among teen (16–19 yrs), young adult (20–24 yrs), adult (35–54 yrs), and older (70+ yrs) drivers. Real-world AEB deceleration profiles from IIHS AEB tests were paired with SHRP 2 vehicles based on vehicle make and class. AEB onset for SHRP 2 crashes was based on a brake threat number (BTN) algorithm. AEB curves were adjusted to match the speed of the vehicle at AEB onset. AEB deceleration curves were scaled based on road surface conditions. Driver reaction was accounted for by beginning the deceleration curve at the current driver-initiated braking level. Overall, AEB was found to be very effective, preventing 83% (n = 33) of rear-end striking crashes. However, AEB was less effective for crashes that occurred at higher speeds and during inclement weather conditions. These data provide a counterfactual evaluation of AEB that can be used by OEMs to prioritize AEB optimization for higher speed crashes and sub-optimal road conditions.

1. Introduction

Motor vehicle crashes continue to be a significant problem in the United States and worldwide. While the National Center for Statistics and Analysis found a decrease in the number and rate of fatal crashes in 2018 as well as for the first quarter of 2019 (NCSA, 2019) – bringing the US out of a multi-year increase in fatal crashes – motor vehicle crashes remain a leading cause of death for those 65 years and younger as well as the second leading cause of unintentional injury-related deaths (Webb, 2018). Globally, road traffic fatalities remain a leading cause of death, particularly among low to middle-income countries (WHO, 2015).

Advanced driver assistance systems (ADAS), such as forward collision warning and lane keeping assist, have the potential to mitigate these crashes, reducing overall crash severity, injuries, and deaths. Previous injury reduction models have suggested that ADAS can prevent up to 57% of crashes and resulting injuries (Rosen et al., 2010; Edwards et al., 2014, 2015; Kusano et al., 2014; Searson et al., 2014; Fildes et al., 2015; Cicchino, 2017). Automatic emergency braking (AEB) is designed to mitigate the most common crash mode: rear-end striking crashes. However, assessing the efficacy of AEB in real-world crash scenarios is challenging given that avoided crashes are rarely documented except during naturalistic driving studies. Several studies have attempted to illustrate the effectiveness of AEB using counterfactual simulations (Kusano and Gabler, 2010; Kusano and Gabler, 2012; Kim et al., 2015; Bärgman et al., 2017). While these studies provide useful information on the potential efficacy of AEB, they do have limitations including (1) being based on archival data such as police reports and insurance claims which lack real-world vehicle dynamics data, (2) using idealized AEB deceleration profiles including step or ramp pulses and have assumed constant jerk, (3) have assumed a static lead vehicle, and (4) have not accounted for road conditions. Naturalistic driving studies offer a

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https://doi.org/10.1016/j.ssci.2020.104746
Received 1 December 2019; Received in revised form 19 February 2020; Accepted 28 March 2020
Available online 25 April 2020
0925-7535/

unique opportunity to provide real-world data on these variables, which can serve as inputs for more realistic counterfactual simulations.

The Strategic Highway Research Program 2 (SHRP 2) Naturalistic Driving Study (NDS) offers a unique opportunity to evaluate the potential efficacy of AEB on real-world crash scenarios. These data include vehicle dynamic data such as radar distance to the lead vehicle, host vehicle velocity, and host vehicle acceleration (Hankey et al., 2016), which can be used to provide inputs to counterfactual simulations. Additionally, the Insurance Institute for Highway Safety conducts test-track-based AEB evaluations of currently available vehicles and provides year/make/model specific information on deceleration profiles and activation times through IIHS TechData (IIHS, 2013). Therefore, this study aimed to conduct AEB counterfactual simulations utilizing measured host and lead vehicle dynamics data and vehicle-specific AEB deceleration profiles as well as accounting for driver reaction and road conditions. A secondary goal of this study was to compare the efficacy of AEB among risky driving groups, specifically *young* and *older* drivers that exhibit increased crash risk.

2. Method and materials

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

2.1. SHRP 2 dataset

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, incident type, and times series data pre- and post-event including vehicle velocity, acceleration, and radar data were obtained for all crashes (n = 1317) previously identified by VTTI for four age groups: teens (16–19 yrs), young adults (20–24 yrs), adults (35–54 yrs), and older adults (70+ yrs). Time series data ranged from 20 s prior to 10 s post event and were collected at 10 Hz.

2.2. Data reduction

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

2.3. AEB counterfactual simulations

2.3.1. SHRP 2-IIHS vehicle pairing

The SHRP 2 database includes the year, make, and classification (*car, SUV/crossover, pickup/truck, van*) for each vehicle involved in the NDS. To generate AEB deceleration profiles, measured deceleration curves for 20 kph and 40 kph AEB tests (IIHS, 2013) conducted by the Insurance Institute for Highway Safety (IIHS) were downloaded from IIHS TechData (https://techdata.iihs.org) and used as inputs for the counterfactual simulations. IIHS AEB tests were paired with each SHRP 2 rear-end striking crash by selecting the most recent IIHS AEB test of the same vehicle make and classification. Pairing with the most recent IIHS AEB test ensured that the most up-to-date AEB system for each make and model was represented in the counterfactual simulation.

If a particular make or classification was not tested by IIHS or the SHRP 2 subject vehicle was no longer in production, a classification-paired vehicle from the parent OEM was selected. Exemplar SHRP 2-to-IIHS vehicle pairing is shown in Table 1.

During the SHRP 2-IIHS vehicle pairing, there were five instances in IIHS TechData (corresponding to nine SHRP 2 rear-end striking crashes) where two vehicles of the same year, make, and class could be paired to the SHRP 2 vehicle make/class. Consistent with our aforementioned pairing criteria, the most recent IIHS AEB test was selected. The alternative IIHS pairings for these nine SHRP2 crashes are listed in Table A2. To assess the sensitivity of these pairing selections, counterfactual simulations were also conducted using the alternate IIHS vehicle pairings.

Table 1
Exemplar SHRP 2-IIHS Vehicle Pairing.

SHRP 2 Vehicle Information			IIHS AEB Test Information			
Year	*Make*	*Class*	*Year*	*Make*	*Model*	*Test #*
2000	Jeep	SUV	2019	Jeep	Renegade	1921
2002	Honda	CAR	2019	Honda	Insight	1822
2002	Mercury*	CAR	2017	Ford	Fusion	1619

*Mercury was manufactured by Ford, but no longer in production. Thus the latest Ford vehicle IIHS AEB test of the same *class* was selected.

2.3.2. AEB activation

A brake threat number (BTN) algorithm (Brännström et al., 2008) was used to determine the onset of AEB for each rear-end striking crash. This algorithm has previously been used for AEB counterfactual simulations (Bärgman et al. 2017). To increase the accuracy of the BTN algorithm, the BTN activation curve was scaled to match the AEB onset times measured during the IIHS AEB tests. Goodness of fit of the BTN activation curve was assessed using a minimum root mean square error (RMSE) criteria. An exemplar scaling of the BTN curve to the measured IIHS data is shown in Fig. 1.

2.3.3. AEB deceleration pulse optimization

IIHS AEB tests are conducted at 20 kph and 40 kph (IIHS, 2013). If the vehicle velocity at the time of AEB onset was ≤ 30 kph, the 20 kph IIHS AEB tests were used for the counterfactual simulation. If the vehicle velocity at AEB onset was > 30 kph, the 40 kph IIHS AEB tests were used. Repeated AEB trials at the selected velocity were then averaged to generate a vehicle-specific AEB deceleration pulse for use in the counterfactual simulation.

To account for changes in the AEB deceleration profile due to road surface conditions, the deceleration magnitude was scaled by a road surface friction factor (Gustafsson, 1997): dry = 1.0, wet = 0.7, snowy = 0.3, icy = 0.1. An exemplar scaling of an AEB deceleration pulse based on the road surface friction factor is shown in Fig. 2. Scaling of the road surface factor based on Gustafsson (1997) has previously been used to simulate changes in road friction during AEB driving simulator research (Koglbaur et al., 2018).

To account for any driver-initiated braking at the time of AEB onset, the AEB deceleration curve initiated at the driver's current braking magnitude (Fig. 3). The portion of the AEB deceleration curve below the driver-initiated braking magnitude was excluded.

To ensure that the paired AEB deceleration pulse was proportional to

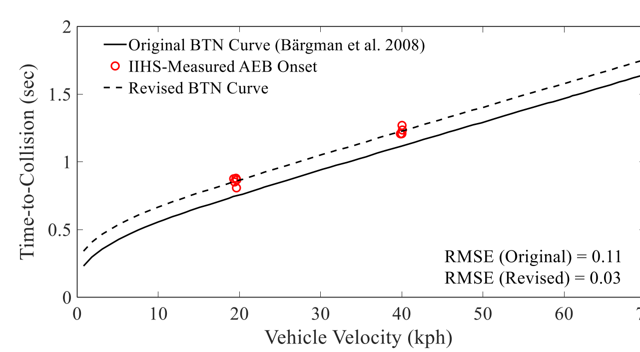

Fig. 1. Exemplar BTN Activation Curve.

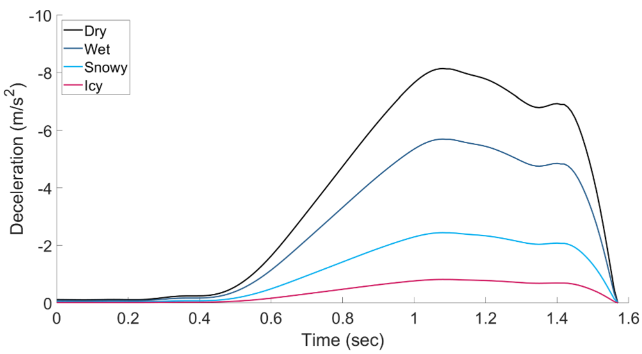

Fig. 2. Exemplar Road Surface Friction Factor Scaling.

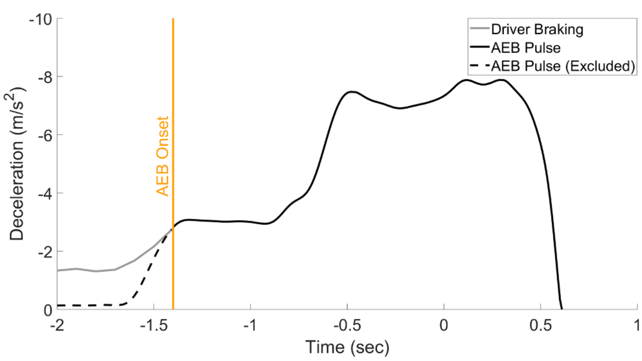

Fig. 3. Exemplar compensation for driver braking prior to AEB activation.

the subject vehicle's velocity at the time of AEB onset, the pulse was either truncated or extrapolated to match the deceleration required to bring the velocity of the vehicle to exactly 0 kph. A qualitative review of the AEB deceleration pulses used in this study revealed that the primary difference between the 20 kph and 40 kph IIHS AEB tests was the presence of an extended middle or "steady-state" portion of the deceleration pulse. Therefore, if the AEB deceleration pulse was insufficient to bring the vehicle velocity to 0 kph, the pulse was extrapolated by extending the steady-state portion of the AEB deceleration using a shape-preserving piecewise cubic Hermite interpolating polynomial (pchip) fit. Contrarily, if the AEB deceleration pulse provided more deceleration than was necessary to bring the vehicle velocity to 0 kph, the steady-state portion was truncated using a pchip fit, until the steady-state portion of the pulse was eliminated. If further reduction of the 20 kph deceleration pulse was required after the steady-state portion of the pulse was eliminated, the AEB deceleration pulse was scaled down proportionally in both magnitude and duration. Exemplar AEB pulse truncation and extrapolation for various onset velocities is shown in Fig. 4.

Initial jerk was computed as the mean instantaneous jerk from the time of AEB onset to the onset of the steady-state portion of the pulse.

2.3.4. Counterfactual simulations

Counterfactual simulations were conducted in MATLAB 2019a (Mathworks, Inc). To simulate changes in vehicle dynamics due to AEB activation, the following equations were used:

$$V_{aeb}(t) = \int_{t_{aeb}}^{t_{crash}} A_{aeb}(t) + V_{SV}(t_{AEB}), \text{ where } t_{aeb} \le t \le t_{crash} \tag{1}$$

$$X_{aeb}(t) = \int_{t_{aeb}}^{t_{crash}} (V_{SV}(t) - V_{aeb}(t)) + X_{LV}(t), \text{ where } t_{aeb} \le t \tag{2}$$

t_{aeb} = time of AEB activation
t_{crash} = time of original SHRP 2 crash
A_{aeb} = subject vehicle acceleration with AEB
V_{SV} = velocity of subject vehicle
V_{aeb} = velocity with AEB activation
X_{LV} = relative distance to lead vehicle
X_{aeb} = relative distance to lead vehicle with AEB activation

If the addition of the AEB deceleration caused the simulation to extend beyond the time of the original SHRP 2 crash (t_{crash}), the lead vehicle velocity was assumed to remain constant and the equations below were used:

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

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

t = end time of simulation, when either $V_{aeb} = 0$ or $X_{aeb} = 0$

If V_{aeb} reached zero prior to $X_{aeb} = 0$, it was concluded that AEB prevented the crash. If X_{aeb} reached zero with $V_{aeb} > 0$, the crash was considered to have still occurred. The reduction in crash velocity (ΔV) was calculated as the difference between $V_{aeb}(t_{aeb})$ and $V_{aeb}(t_{crash})$ for simulations where the crash still occurred. Exemplar counterfactual simulations for a prevented and non-prevented crash are shown in Fig. 5.

2.4. Statistical analysis

Statistical analysis was conducted in MATLAB 2019a (Mathworks, Inc.). A Kolmogorov-Smirnov test of normality was conducted on AEB onset velocity and initial jerk among simulations with *dry* road conditions. The data were not normally distributed; therefore, a Wilcoxon rank sum test was used to compare these metrics between *dry* prevented and *dry* non-prevented simulations.

3. Results

A total of 99 rear-end striking crashes among 95 drivers were identified from the four age groups. Among these rear-end striking crashes, 30 events had no radar data. An additional 29 events were removed due to unreliable radar data. The final dataset for counterfactual simulations consisted of 40 rear-end striking crashes. A comprehensive compilation of SHRP 2 descriptive variables and counterfactual simulation results are listed in the Appendix (Table A1).

According to SHRP2 Crash Severity 1 classifications, 23% (n = 9) were *Most Severe*, 28% (n = 15) were *Police-reportable*, and 40% were *Minor*. Among these crashes, 31 occurred in *dry* conditions, seven in *wet* conditions, and one in *snowy* conditions. Evasive maneuvers executed by the driver prior to each rear-end striking crash included *braking* (78%; n = 31), *braking & steering* (5%; n = 2), and *none* (17%; n = 7).

Overall, AEB prevented 83% (n = 33) of SHRP 2 rear-end striking crashes. AEB also reduced mean (± SE) impact velocity of non-prevented crashes (n = 7) by 41% ± 6%. Among crashes that were not prevented, 43% (n = 3) occurred during *wet* and *snowy* conditions. A detailed list of the counterfactual simulation results for each SHRP 2 crash is listed in Table A1.

The mean (± SE) initial jerk among *dry* prevented and non-prevented crashes was -13.3 ± 5.0 m/s^3 and -12.1 ± 4.1 m/s^3, respectively. No significant differences between *dry* prevented and *dry* non-prevented crashes were observed for initial jerk ($p = 0.91$). The mean (± SE) vehicle velocity at AEB onset among *dry* prevented and *dry* non-prevented crashes was 26.3 ± 5.2 kph and 56.4 ± 10.8 kph, respectively. Velocity at AEB onset was significantly lower ($p < 0.05$) for *dry* prevented crashes compared to *dry* non-prevented crashes.

Comparison of counterfactual simulation results across age group are listed in Table 2. A lower percentage of crashes were prevented for teen drivers, which exhibited a higher mean/median AEB onset velocity than the other age groups.

Results of the alternate IIHS AEB test pairings are listed in Table A2. Selection of the alternate IIHS AEB tests had no effect on the counterfactual simulation results. All nine SHRP 2 crashes were prevented when paired with either possible IIHS AEB test.

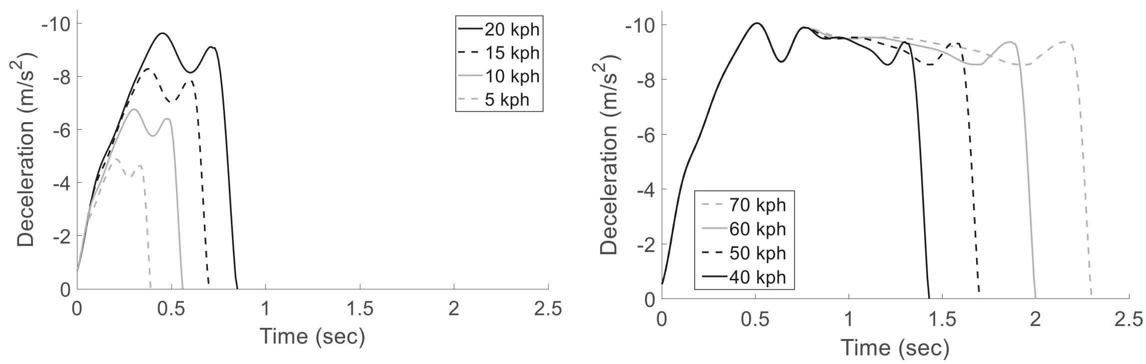

Fig. 4. Exemplar AEB pulse truncation (left) and extrapolation right).

4. Discussion

In the absence of large-scale naturalistic studies involving vehicles equipped with AEB, counterfactual simulations using the SHRP 2 NDS provide a viable means of evaluating the efficacy of AEB in real-world crash scenarios. The current study utilized real-world vehicle dynamics data, road conditions, and driver reactions from SHRP 2 rear-end striking crashes as well as vehicle-specific measured AEB pulses as inputs for AEB counterfactual simulations. Overall, AEB was found to be very effective, preventing 83% of this subset of SHRP 2 rear-end striking crashes. This percentage is greater than previously reported, which ranged from 38% to 70% (Jermakian, 2011; Fildes et al., 2015; Cicchino, 2017). One potential explanation for this increase is the inherent advantage of naturalistic driving studies at capturing *lower severity* crashes, not just police-reported, insurance claims, or fatal crashes, which were the focus of previous studies. Prior research has indicated that nearly 30% of crashes, particularly non-injurious crashes, are unreported (M. Davis & Co, 2015). These lower severity crashes are exactly what current AEB systems are designed to prevent. Among the SHRP 2 crashes included in these simulations, 40% (n = 16) were classified as *Minor*; 88% (n = 14) of these *Minor* crashes were prevented by AEB. The addition of these lower severity crashes may have yielded a higher efficacy rate than archival databases. Additionally, our IIHS pairing may have contributed to the increased AEB rate, as these latest model year pulses be more effective at preventing crashes than the previous model years used by other studies. Other potential factors that could have influenced these results include our AEB pulse scaling methodology and small sample size. Ideally, each vehicle would be tested at the approach velocity measured in SHRP 2. In the absence of these data, IIHS AEB pulses were extrapolated or truncated to match the AEB onset velocity. While these pulses are more comprehensive than the constant jerk assumption used by previous counterfactual simulations, they do represent extrapolated data and may not be representative of real-world AEB performance, particularly at speeds substantially greater than 40 kph. Additionally, though based on naturalistic data, the crashes included in these counterfactual simulations may not be representative of all rear-end striking scenarios. These factors should be taken into consideration when generalizing these results to the entire vehicle fleet.

Among non-prevented crashes, AEB still reduced crash velocity by more than 41% on average. This represents a significant reduction in impact severity and has important implications for the potential reduction of injury severity, coinciding with previous research suggesting that AEB is capable of reducing occupant injuries by up to 57% (Kusano et al., 2010).

A smaller percentage of crashes that occurred during poor weather conditions (56%) were prevented compared to *dry* conditions (87%). To our knowledge, no AEB system currently on the market adapts its activation algorithm based on changes in road surface conditions. These data suggest that OEMs should consider implementing adaptive AEB, capable of modifying its activation algorithm – typically based on a combination of time-to-collision and vehicle velocity – for changes in road surface conditions. Adaptive AEB has previously been shown to be more effective at preventing crashes during simulated drives (Han et al., 2014) as well as foster increased trust in AEB among drivers (Koglbauer et al., 2018).

The remaining four non-prevented crashes all occurred during *dry* weather conditions. One potential explanation for why these crashes were not prevented may be due to velocity at the time of AEB onset. Among non-prevented crashes where weather was *not* a contributing factor, it was noted that mean vehicle velocity at AEB onset was greater among these *dry* non-prevented crashes (56 kph) compared to *dry* prevented crashes (26 kph). These data suggest that AEB systems can potentially be optimized for higher speed crash scenarios.

When comparing AEB effectiveness across risky driving groups (Table 2), it was noted that a lower percentage of crashes were prevented among teen drivers, whose crashes tended to occur with higher AEB onset speeds than the other three age groups. Of note, the current study assumed AEB activated at all speeds. However, this is not the case with all manufacturers. While OEMs are releasing high-speed AEB systems, most low to moderate speed systems have a peak AEB activation speed of approximately 58 kph (36 mph). Consequently, the current study represents the potential

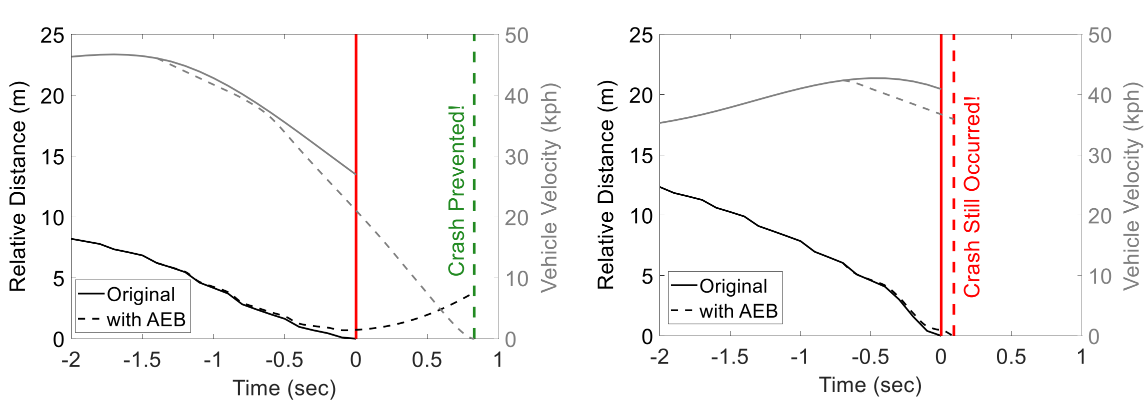

Fig. 5. Exemplar prevented crash (left) and non-prevented crash (right).

Table 2
Simulation Results Across Age Group.

Group	Age (yrs)	Simulated Crashes (#)	Crashes Prevented		AEB Onset Velocity (kph)	
			#	%	Mean ± SE	Median
Teen	16–19	14	11	77%	41 ± 8	42
Young Adult	20–24	16	14	88%	28 ± 6	19
Adult	35–54	3	3	100%	9 ± 3	11
Older Adult	70–98	7	5	71%	23 ± 6	20

of high-speed AEB to prevent rear-end striking crashes. Applying this 58 kph limit to our AEB counterfactual simulations results in three crashes, for an overall AEB efficacy of 73%. While still very effective, these data do illustrate the need for higher speed AEB to help prevent all crashes. Interestingly, all three of these higher speed crashes occurred among young drivers, as illustrated in Fig. 6. This suggests that limiting AEB activation to low/moderate speeds will have reduced efficacy among younger drivers, who are already at elevated crash risk. A lower proportion of older driver crashes was also observed, however this can be attributed to the small sample size of older driver crashes (n = 7). Among these two non-prevented crashes, one occurred during *snowy* conditions and the second exhibited a unique AEB pulse with a lower relative initial jerk (-8.4 m/s^3), suggesting that weather and vehicle factors were primarily responsible, as opposed to an inherent difference among older driver rear-end crashes.

For one SHRP 2 counterfactual simulation (Event #23668565), the AEB actually performed worse than the driver's braking reaction to the crash. Examination of this specific event revealed that the driver executed an extremely hard braking maneuver that exhibited a higher initial jerk (-21 m/s^3) than the AEB system (-15.7 m/s^3). Due to this higher jerk, the driver reached peak deceleration and maintained that deceleration for a longer duration than the AEB system. This difference in manual compared to automatic braking has been observed previously. Recent test track research (Graci et al., 2019) comparing the effect of manual and automatic braking on occupant response revealed that manual braking achieved greater peak deceleration and initial jerk compared to the AEB system.

While these counterfactual simulations suggest that AEB can be very effective at mitigating rear-end striking crashes across all age groups, it is important to also consider the unintended consequences of AEB systems increasing the likelihood of a subsequent rear-end struck crash. Previous research using police-reported crash data have shown that vehicles equipped with both FCW and AEB are 20% more likely to be involved in rear-end struck crashes (Cicchino, 2017). This increased likelihood of a rear-end struck crash coupled with the fact that higher jerk braking pulses are more likely to displace the occupants from initial position (Graci et al., 2019) could lead to increased prevalence of rear-end struck injuries, such as whiplash injuries. When optimizing AEB parameters, OEMs should not only consider the potential reduction in vehicle velocity, but also its effects on occupant kinematics and subsequent rear-end struck crashes that may occur.

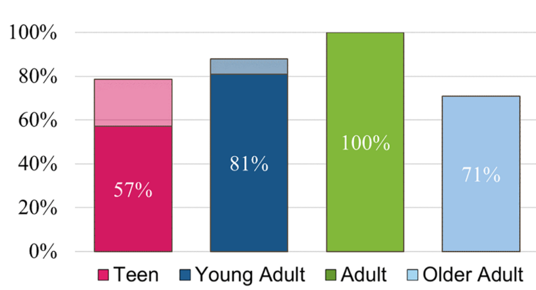

Fig. 6. Counterfactual simulation results across age group with 58 kph upper AEB limit. Transparent sections indicate crashes that were no longer prevented with 58 kph limit.

5. Limitations

Several limitations warrant discussion. First, AEB is typically coupled with forward collision warning (FCW). The current study assumed that FCW did not alter the driver's reaction to the crash. Theoretically, FCW could cause a driver to brake sooner or more severely than his natural reaction. Consequently, these counterfactual simulations represent the "worst-case" scenario for AEB. Of note, drivers executed an evasive maneuver in 83% (n = 33) of the simulated rear-end striking crashes. Furthermore, among the seven crashes where the driver exhibited no evasive maneuver, AEB effectively prevented all seven of these crashes without any input from the driver. Hence, any additional braking by the driver due to the presence of FCW would not influence the outcome of the simulation; the crashes would still be prevented. Consequently, the influence of FCW's ability to alter drivers' reactions on these results is likely limited.

Additionally, these counterfactual simulations did not take into account the influence of drivers' steering maneuvers. Theoretically, evasive steering would augment the efficacy of AEB at preventing crashes by providing another crash avoidance mechanism than just braking. Drivers executed a steering maneuver (in conjunction with braking) in only 5% (n = 2) of the 40 rear-end striking crashes; both of which were prevented by AEB. Therefore, the effect of driver steering on these results should also be limited. Furthermore, radar data were only available for a subset (40%) of rear-end striking crashes. This possibly introduced selection bias because this subset may not be representative of all rear-end striking crashes in SHRP 2. Similarly, this study focused on the riskiest driving groups with a baseline comparison group of experienced adult drivers. Additional rear-end striking crashes were present among 25–34 (n = 15) and 55–69 (n = 11) year olds, but these crashes were not included in this analysis. Therefore, these results may not be generalizable to the excluded age groups.

6. Conclusion and recommendations

To our knowledge, this study represents the first counterfactual simulations of AEB to utilize a combination of measured vehicle dynamics, driver reaction, and road conditions from naturalistic data as well as measured AEB deceleration pulses. Our findings suggest that AEB is very effective at preventing rear-end striking crashes. However, AEB is less effective for crashes occurring in poor weather conditions or crashes that occur at higher speeds. Future AEB systems should be optimized to account for poor weather conditions and higher speed crashes.

Acknowledgements

The authors acknowledge the National Science Foundation (NSF) Center for Child Injury Prevention Studies (CChIPS) IU/CRC at the Children's Hospital of Philadelphia (CHOP) and the Ohio State University (OSU) for sponsoring this study and its Industry Advisory Board (IAB) members for their support, valuable input, and advice. This material is also based upon work supported by the National Science Foundation under Grant Number EEC-1460927. The views presented here are solely those of the authors and not necessarily the views of CHOP, CIRP, OSU, the NSF, or the IAB members.

Appendix A

See Tables A1 and Table A2.

Table A1
Counterfactual Simulation Inputs and Results.

SHRP2 Event ID	Age Group	SHRP2 Vehicle			Weather Conditions	Lighting Conditions	Evasive Maneuver	Crash Velocity (kph)	AEB Crash Velocity (kph)
		Year	Make	Class					
5,592,471	Teen	1998	Ford	Car	Dry	Daylight	Braked	31	15
5,592,867	Teen	2001	Toyota	SUV/Crossover	Dry	Dawn	Braked	67	32
10,556,972	Teen	2006	Ford	Car	Dry	Darkness (lit)	Braked	47	0
10,556,978	Teen	2002	Kia	Car	Dry	Daylight	Braked	11	0
10,814,077	Teen	2004	Toyota	Car	Wet	Darkness (lit)	Braked	44	0
17,726,433	Teen	2006	Honda	SUV/Crossover	Dry	Daylight	Braked	32	0
23,668,565	Teen	1999	Toyota	Car	Dry	Daylight	Braked	23	52
29,730,845	Teen	2002	Mercury	Car	Wet	Daylight	Braked	6	0
33,575,051	Teen	2003	BMW	Car	Dry	Darkness (lit)	None	5	0
60,633,157	Teen	2002	Nissan	Car	Dry	Daylight	Braked & Steered	38	0
61,427,019	Teen	2007	Toyota	Car	Dry	Daylight	Braked	4	0
116,168,855	Teen	2000	Jeep	SUV/Crossover	Dry	Daylight	Braked	37	0
132,704,674	Teen	1994	Mitsubishi	Car	Dry	Daylight	Braked	50	0
151,337,488	Teen	1998	Honda	Car	Dry	Daylight	Braked	10	0
7,303,270	Young Adult	2002	Honda	Car	Dry	Daylight	None	3	0
10,528,254	Young Adult	2006	Ford	Car	Wet	Daylight	Braked	21	24
10,858,068	Young Adult	2003	Chevrolet	Car	Dry	Daylight	Braked	58	0
16,992,778	Young Adult	2009	Hyundai	Car	Dry	Daylight	Braked	5	0
16,992,779	Young Adult	2001	Hyundai	Car	Dry	Daylight	Braked	15	0
17,726,065	Young Adult	1999	Toyota	Car	Dry	Daylight	Braked	32	0
29,714,734	Young Adult	2003	Ford	Car	Dry	Daylight	Braked	10	0
61,211,855	Young Adult	2007	Honda	Car	Dry	Daylight	Braked	31	0
61,427,000	Young Adult	2007	Ford	Car	Dry	Daylight	Braked	3	0
116,591,910	Young Adult	1999	Toyota	Car	Dry	Daylight	Braked	9	0
128,888,430	Young Adult	2005	Ford	SUV/Crossover	Dry	Daylight	Braked & Steered	13	0
128,888,508	Young Adult	2004	Honda	SUV/Crossover	Wet	Daylight	Braked	20	0
135,427,628	Young Adult	2008	Chevrolet	Car	Wet	Daylight	Braked	11	0
142,053,492	Young Adult	1997	Jeep	SUV/Crossover	Dry	Daylight	Braked	10	0
151,337,351	Young Adult	2009	Chevrolet	Car	Wet	Daylight	Braked	7	11
151,568,381	Young Adult	2004	Hyundai	Car	Dry	Daylight	Braked	27	0
35,257,227	Adult	2007	Nissan	Car	Dry	Daylight	None	9	0
116,163,026	Adult	2009	Toyota	Car	Wet	Daylight	None	6	0
132,364,436	Adult	2009	Ford	Car	Dry	Daylight	None	4	0
8,093,681	Older Adult	2004	Honda	Car	Dry	Daylight	None	5	0
10,556,976	Older Adult	2005	Nissan	Car	Dry	Daylight	Braked	9	0
10,560,148	Older Adult	2010	Ford	Car	Dry	Daylight	Braked	18	0
17,724,527	Older Adult	2011	Buick	Car	Dry	Daylight	Braked	41	36
22,485,021	Older Adult	2000	Toyota	Car	Wet	Daylight	Braked	28	0
116,168,870	Older Adult	2001	Oldsmobile	Car	Snowy	Daylight	Braked	14	14
116,592,027	Older Adult	2002	Nissan	Car	Dry	Daylight	None	3	0

Table A2
Alternate IIHS-SHRP 2 Vehicle Pairing Results.

SHRP2 Event ID	Age Group	SHRP2 Vehicle			IIHS Paired Vehicle			Alternate Choice		Crash Still Prevented?
		Year	Make	Class	Year	Model	Test ID	Model	Test ID	
10,556,976	Older Adult	2005	Nissan	Car	2019	Maxima	1908	Altima	1837	Yes
10,858,068	Young Adult	2003	Chevrolet	Car	2017	Bolt	1705	Volt	1629	Yes
33,575,051	Teen	2003	BMW	Car	2019	3 series	1911	X5	1907	Yes
35,257,227	Adult	2007	Nissan	Car	2019	Maxima	1908	Altima	1837	Yes
60,633,157	Teen	2002	Nissan	Car	2019	Maxima	1908	Altima	1837	Yes
116,168,855	Teen	2000	Jeep	SUV/Crossover	2019	Renegade	1921	Cherokee	1820	Yes
116,592,027	Older Adult	2002	Nissan	Car	2019	Maxima	1908	Altima	1837	Yes
128,888,430	Young Adult	2005	Ford	SUV/Crossover	2020	Escape	1929	Explorer	1927	Yes
142,053,492	Young Adult	1997	Jeep	SUV/Crossover	2019	Renegade	1921	Cherokee	1820	Yes

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