TRB Annual Meeting

Examination of factors influencing the efficacy of automatic emergency braking

--Manuscript Draft--

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ABSTRACT

Automated vehicles are expected to significantly reduce traffic crashes and the resultant injuries and fatalities. However, it is unclear when fully automated vehicles will be market-ready, though it is important to note that lower levels of automation have already demonstrated some of this significant safety potential. This includes technologies such as automatic emergency braking (AEB), which is proposed to be a mandatory feature in all new vehicles by 2025. This study involves an evaluation of AEB test data from the Insurance Institute for Highway Safety (IIHS). These tests include various scenarios, including those were the test vehicle encounters a balloon car, as well as "dummy" pedestrians that are walking either parallel or perpendicular to the road. These tests are conducted at various speeds and lighting conditions. Further, the test vehicles range from model year 2013 to 2023, and include a diverse range of sensor configurations. A series of random-effects logistic regression models are estimated to evaluate the efficacy of these vehicles across these test scenarios. The results provide important insights as to the potential, as well as the limitations of these systems in their current form.

Keywords: *Autonomous emergency braking, pedestrian autonomous emergency braking, emergency braking response time, nighttime autonomous emergency braking, collision avoidance*

INTRODUCTION

Automatic emergency braking (AEB) is a safety system that activates a vehicle's brakes when a potential collision is imminent. As implied by the name, AEB is activated without the driver actually depressing the brake pedal. Its capabilities also allow for an automatic increase in braking force if the brakes have not been applied hard enough to avoid a collision. AEB systems rely on a series of sensors to detect vehicles, pedestrians, and other objects necessitating a stopping event. The system activates once the vehicle reaches a proximity wherein collision is expected if the vehicle maintains its speed and path. AEB is often used in combination with forward collision warning (FCW) systems, which use the same sensor technologies and are intended to alert the driver of an impending collision so they may take evasive action themselves, such as braking or steering.

These systems are anticipated to have the greatest potential impact in reducing rear-end collisions, which account for about 1.7 million crashes, 500,000 injuries, and 1,700 fatalities annually (*1*, *2*). In a collaborative study between the National Highway Traffic Safety Administration (NHTSA) and several automakers, the real-world effectiveness of FCW and AEB systems was investigated. The study estimated that vehicles equipped with these systems were approximately 50% less likely to be involved in a front-to-rear end crash with another vehicle. Additionally, these vehicles were found to be 53% less likely to result in an injury in the event of a crash. These findings highlight the significant potential of FCW and AEB technologies in enhancing vehicle safety and reducing the occurrence of accidents and injuries, reinforcing the results from similar research that has compared the frequency of rear-end crash involvement between vehicles equipped and not equipped with these technologies (*4*). Even when crashes do occur, lower collision speeds afforded by the systems make the crashes generally less hazardous for road users as the speed and momentum of impact are minimized (*5*).

Many automakers in North America now have AEB and FCW technology installed as either standard or optional safety features on their new series vehicles to reduce the frequency and severity of rear-end crashes. In 2015, ten automakers in North America voluntarily committed to making AEB (vehicle-to-vehicle) standard on nearly all of their light vehicles and trucks by 2022-2023(*6*). An additional ten automakers were added to this list in 2016. As of 2020, 10 automakers reported to have fulfilled this commitment well ahead of the 2020-2023 schedule, with several other auto manufacturers making significant strides toward meeting their commitment (*7*). This voluntary commitment by U.S. automakers is expected to result in 42,000 crash savings and 20,000 injury savings between 2015-2025. This estimate is based on IIHS research that shows that vehicles equipped with both AEB and FCW reduce rear-end crashes by 50% (*4*).

Early AEB systems were designed largely to avoid vehicle-to-vehicle collisions. However, pedestrians are 1.5 times more likely to be killed in a crash compared to vehicle occupants (*9*). As a result, many vehicle manufacturers have developed pedestrian automatic emergency braking (P-AEB) systems in their more recent vehicle series, applying similar technology to detect and avoid collisions with pedestrians. P-AEB systems are relatively newer and are generally available as standard or optional features in vehicles from model year 2019 or later (*10*).

In 2023, NHTSA announced a notice of proposed rulemaking requiring compliance for all light vehicles to include both AEB and P-AEB systems. When finalized, this rule is expected to save at least 360 lives and reduce injuries by about 24,000 annually (*8*).

Despite the increasing popularity of AEB and P-AEB systems in recent years, relatively few studies have assessed the effectiveness of these systems. A qualitative review of prior research showed that most of the published literature has focused on technical aspects of the systems, such as control simulation, detection algorithms, and the underlying camera, radar, and lidar technology(*11–24*). Additionally, other studies have examined collision warning and collision avoidance algorithms (*25–32*).

The purpose of this study is to investigate the effectiveness of AEB and P-AEB systems under various scenarios using data from tests conducted by the Insurance Institute for Highway Safety (IIHS). The research explores how the efficacy of these systems varies based upon the test scenario, test speed, lighting conditions, and model year of the vehicle. The results provide important insights as to progress that has occurred to date, as well as opportunity areas where further efforts are warranted.

LITERATURE REVIEW

Early research as to the effectiveness of AEB came in the form of a series of reports from the Highway Loss Data Institute (HLDI), which compared U.S. insurance claim rates between vehicles that were equipped with AEB and vehicles of the same model that were not equipped with AEB (*33–38*). Six different models were investigated in the study, which found that FCW alone was associated with a 7% - 22% reduction in property damage liability claims and a 4%-25% reduction in the rates of bodily injury claims. On the other hand, systems that included FCW and AEB were associated with 10-16% reductions in property damage liability claim rates and 14% - 32% reductions in bodily injury liability claim rates.

A subsequent study utilized Poisson regression models to examine the effects of FCW alone, low-speed AEB, and FCW with AEB on the crash involvement rate of insured vehicles while controlling for driver-related factors (e.g., age, gender, marital status, etc.) affecting crash risk. The study showed that FCW was associated with a 27% reduction in rear-end crashes. Low-speed AEB was associated with a 43% reduction in rear-end crashes, while a system comprising both AEB and FCW was associated with an approximately 50% reduction in rear-end crashes (*4*).

Another study used data from IIHS balloon car tests to examine the effectiveness of AEB and FCW (*39*). The study found differences in braking and collision avoidance performance between different vehicle manufacturers, with some vehicles performing noticeably better in collision avoidance. The research also observed noticeable differences when evaluating collision avoidance at different test speeds, with vehicles generally performing better at lower speeds. For example, some vehicles were able to successfully avoid a collision every time at a test speed of 12 mph; however, the collision avoidance rates for these same vehicles dropped from 63% to 87% at a test speed of 25 mph. The major determining factor between these vehicles was determined to be the AEB actuation time rather than the deceleration rate.

In early 2019, IIHS released its P-AEB performance specifications and ratings. Following this, a study was carried out in 2020 using the new specifications. The effectiveness of P-AEB systems in collision avoidance was assessed at test speeds of 12 mph, 25 mph, and 37 mph using data from IIHS tests. The study included vehicles from 11 manufacturer model years between 2018 and 2019. Comparisons were made between the FCW actuation distance to the pedestrian target, the brake application time of the P-AEB, and the collision avoidance rate for different manufacturers. As in the vehicle-to-vehicle tests, instances of impact tended to increase with the test speed. It was also observed that P-AEB exhibited phased braking with manufacturer-specific differences and did not apply their maximum theoretical breaking potential during phased braking. Some vehicles tested did not show any direct correlation between braking effort and test speed for each braking phase, exhibiting a relatively constant deceleration rate. In contrast, other vehicles showed an increase or decrease in deceleration rate at different test speeds(*40*).

The effectiveness of the target detection technology and AEB algorithm available to manufacturers undoubtedly play a role in the performance of these advanced driver-assistance systems (ADAS) during crash tests (*23*, *41*, *42*). However, this issue is somewhat difficult to address given the proprietary nature of these technologies (*43*, *44*). Detection is often hindered in poor weather conditions or nighttime conditions, such as adverse lighting conditions and high speeds (*45*).

OVERVIEW OF AEB AND P-AEB TESTS

The IIHS and HLDI conduct tests to evaluate the effectiveness of AEB and FCW systems in vehicles. The FCW test measures the system's ability to warn the driver of an imminent front-end collision, while the AEB/P-AEB tests assess the systems' ability to automatically apply the brakes to prevent or reduce the collision's severity. These tests result in ratings and valuable information to consumers and encourage manufacturers to enhance the safety of their vehicles.

The IIHS AEB testing protocol was developed in 2013 and is outlined in the *Autonomous Emergency Braking Test Protocol Version I*. This protocol involves simulations of potential vehicle-to-vehicle crashes at 12 and 25 mph using a stationary vehicle dummy target, or balloon car (*46*). In 2019, the *Pedestrian Autonomous Emergency Braking Test Protocol Version II* (*47*) was developed and updated in 2022 (*48*). The P-AEB testing protocol simulates vehicle-to-pedestrian crash scenarios with adult and child pedestrian dummies. Three testing scenarios evaluate the vehicle's ability to avoid or mitigate collisions with pedestrians. This includes separate tests for distinct targets, which include car-to-perpendicular nearside adult (CPNA), car-to-perpendicular nearside child (CPNC), and car-to-parallel adult (CPLA). The latter test is conducted under both daytime and nighttime conditions while the CPNA and CPNC tests are conducted under daylight only. Figure 1 illustrates the target placement for each test scenario.

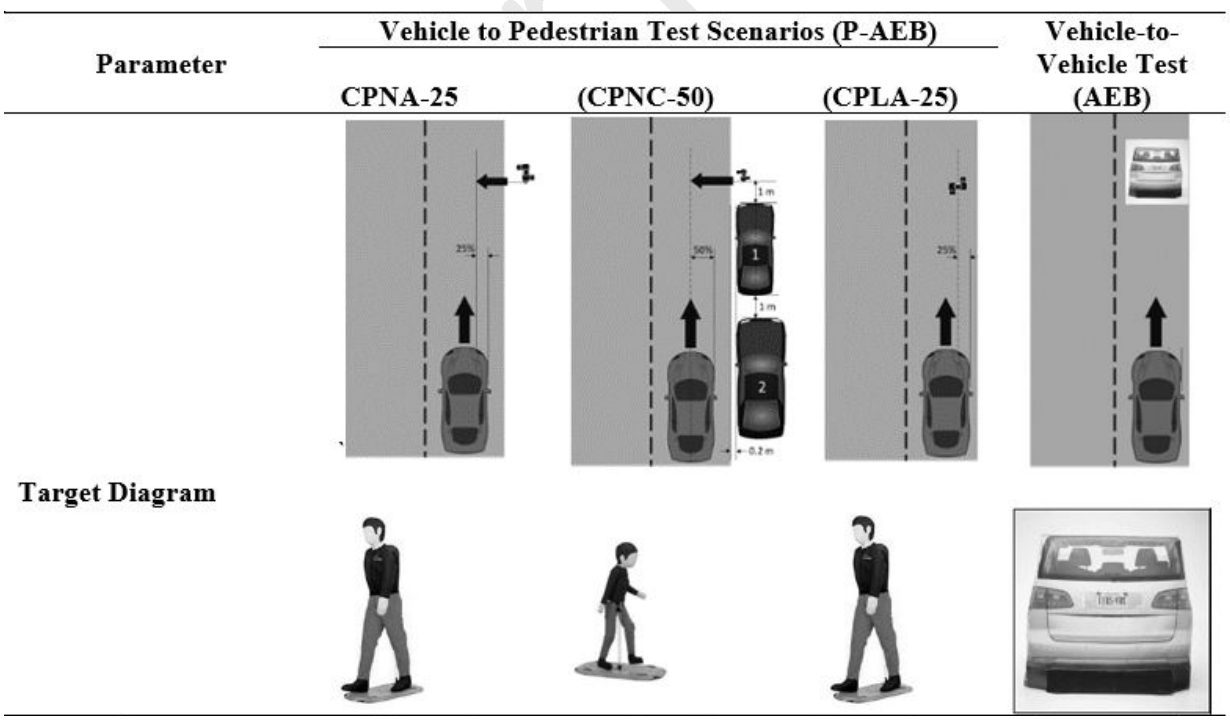

FIGURE 1 Target placement in each testing scenario (Adapted from IIHS, 2022).

All tests are performed on a closed course track to simulate field conditions. Five valid runs are conducted for each test vehicle. Table 1 presents a summary of the test scenarios used in this study. For both the AEB and P-AEB tests, vehicles travel straight as per the testing protocol, and their trajectory is tracked at 100 Hz using the Oxford RT2002 Inertial and GPS Navigation System. A camera records impact verification, forward collision warnings, accelerator pedal position, and steering wheel angle. The start of AEB or P-AEB system activation is determined when the vehicle decelerates to 0.5 m/s^2. FCW activation time is manually recorded based on the vehicle's visual, auditory, or tactile warning. All vehicles in this dataset are personal sedans, SUVs, and crossovers. Additional video documentation on the testing protocols is available from IIHS (*49*, *50*).

A total of 326 vehicles with model years ranging from 2013 to 2023 were evaluated in the AEB collision avoidance tests, while 222 vehicles with model years running from 2018 to 2023 were assessed during the P-AEB collision avoidance tests. Vehicle trajectory and summary data were downloaded from the IIHS FTP site in Microsoft Excel format. Each spreadsheet corresponds to a crash-tested vehicle and contains a summary sheet of all runs, testing scenarios, and raw time-series data for each run or testing scenario at 100Hz fidelity.

TABLE 1. Vehicle-to-vehicle test (AEB) and vehicle-to-pedestrian test scenarios (P-AEB) (Adapted from IIHS, 2013 and IIHS, 2022).

Parameter	Vehicle to Pedestrian Test Scenarios (P-AEB)			Vehicle-to-Vehicle Test (AEB)
	CPNA-25	CPNC-50	CPLA-25	
Test Vehicle Speed	12 & 25 mph	12 & 25 mph	25 & 37 mph	12 & 25 mph
Pedestrian Target Speed	4.5 ft/sec	4.5 ft/sec	0 mph	Not applicable
Target	Adult	Child	Adult	Stationary balloon car
Minimum Required Overlap with Vehicle	25%	50%	25%	N/A
Target Direction	Crossing (R-to-L)	Crossing (R-to-L)	Facing away	Facing away
Target Path (relative to vehicle test)	Perpendicular	Perpendicular	Parallel	Stationary
Lighting condition	Day	Day	Day & night	Day
Target Obstructed	No	Yes	No	No
Number of Valid Runs	1715	1715	1920	3260

DATA SUMMARY

For the purposes of this study, three datasets were developed. The first dataset was comprised of data from 3,260 test runs from the standard (i.e., vehicle-to-vehicle) AEB tests. The second dataset was developed based upon the scenarios where the child or adult pedestrian was crossing perpendicular to the test vehicle (i.e., CPNA and CPNC). The third and final dataset includes the remaining tests where the adult pedestrian is walking parallel to the travel way (i.e., CPLA).

Summary statistics that describe key parameters from these tests are detailed in Table 2 and Table 3. Within each of the three datasets, each observation represents one test run for one vehicle. The variables of interest include the model year of the vehicle, the test speed, and four variables that describe key aspects of the test outcome: (1) the time-to-collision, or TTC, at which the forward-collision warning (FCW) system was activated; (2) the TTC at which the automatic emergency braking (AEB) system was activated; (3) the maximum deceleration rate after the onset of braking; and (4) whether the test was successful and the collision was avoided.

Table 2 shows that across all of the AEB tests, the FCW activation occurred when the vehicle was 1.73 seconds from the target (assuming constant speed), and braking began 0.96 seconds before the target. Considering both test speeds, the success (i.e., collision avoidance) rate across the vehicle-to-vehicle tests was about 75%.

TABLE 2. Summary statistics for AEB vehicle-to-vehicle test data

Variable	Mean	Std. Dev.
Vehicle Model Year		
2013 (1 if yes; 0 if no)	0.04	0.20
2014 (1 if yes; 0 if no)	0.10	0.31
2015 (1 if yes; 0 if no)	0.09	0.29
2016 (1 if yes; 0 if no)	0.13	0.34
2017 (1 if yes; 0 if no)	0.16	0.36
2018 (1 if yes; 0 if no)	0.09	0.28
2019 (1 if yes; 0 if no)	0.12	0.32
2020 (1 if yes; 0 if no)	0.06	0.25
2021 (1 if yes; 0 if no)	0.10	0.30
2022 (1 if yes; 0 if no)	0.10	0.30
2023 (1 if yes; 0 if no)	0.01	0.11
Test Speed		
12 mph (1 if yes; 0 if no)	0.51	0.50
25 mph (1 if yes; 0 if no)	0.49	0.50
FCW activation time (s)	1.73	0.73
AEB activation time (s)	0.96	0.35
Maximum deceleration rate (ft/s^2)	27.63	6.74
Collision avoided (1 if yes; 0 if no)	0.75	0.43

Table 3 presents similar data for the P-AEB tests. These data are aggregated based upon whether the test involved a pedestrian crossing perpendicular to the vehicle (i.e., the CPNA and CPNC tests) or a pedestrian walking parallel to the travel way (CPLA). The perpendicular tests were conducted at test speeds of 12 mph and 25 mph during daytime conditions. In contrast, the longitudinal (i.e., parallel) test was conducted at test speeds of 25 mph and 37 mph during both daytime and nighttime conditions. In the CPLA dataset, data were only used for vehicles from model years 2021 through 2023 as these were the only model years for which nighttime tests were conducted.

TABLE 3. Summary Statistics for P-AEB Test Data

Variable	Perpendicular Tests (CPNA/CPNC)		Parallel Tests (CPLA)	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev**
Vehicle Model Year				
2018 (1 if yes; 0 if no)	0.02	0.13	n/a	n/a
2019 (1 if yes; 0 if no)	0.24	0.43	n/a	n/a
2020 (1 if yes; 0 if no)	0.20	0.40	n/a	n/a
2021 (1 if yes; 0 if no)	0.25	0.43	0.26	0.44
2022 (1 if yes; 0 if no)	0.22	0.41	0.48	0.50
2023 (1 if yes; 0 if no)	0.08	0.27	0.26	0.44
Test Scenario				
CPNA (1 if yes; 0 if no)	0.50	0.50	n/a	n/a
CPNC (1 if yes; 0 if no)	0.50	0.50	n/a	n/a
Vehicle Speed Test				
12 mph (1 if yes; 0 if no)	0.50	0.50	n/a	n/a
25 mph (1 if yes; 0 if no)	0.50	0.50	0.50	0.50
37 mph (1 if yes; 0 if no)	n/a	n/a	0.50	0.50
Lighting Conditions				
Daytime (1 if yes; 0 if no)	n/a	n/a	0.47	0.50
Nighttime (1 if yes; 0 if no)	n/a	n/a	0.53	0.50
FCW activation time (s) (daytime)	1.14	0.39	1.94	0.59
FCW activation time (s) (nighttime)	n/a	n/a	1.69	0.75
AEB activation time (s) (daytime)	0.83	0.38	1.36	0.73
AEB activation time (s) (nighttime)	n/a	n/a	1.45	1.11
Max Deceleration (ft/s^2) (daytime)	30.15	6.98	30.91	7.58
Max Deceleration (ft/s^2) (nighttime)	n/a	n/a	27.29	11.70
Collision avoided (daytime)	0.80	0.40	0.72	0.49
Collision avoided (nighttime)	n/a	n/a	0.50	0.49

Note: n/a = not applicable

For the perpendicular crossing tests, the FCW was displayed 1.14 seconds in advance of the perpendicular adult/child dummy target, and braking began when the vehicle was 0.83 seconds from the target. The average of the maximum deceleration rates across the CPNA/CPNC testing scenarios was 30.2 ft/s^2. For these P-AEB scenarios involving the perpendicular unobstructed adult dummy target (CPNA) and the perpendicular obstructed child dummy target (CPNC), the average success rate across tests was 80%.

Finally, for the longitudinal (i.e., parallel) adult dummy scenario (CPLA), the FCW warning was displayed about 0.25 s earlier in the daytime compared to the nighttime (1.94 s vs. 1.69 s). This suggests better sensor performance, or differences in algorithms under daytime conditions. However, the P-AEB systems were ultimately initiated around the same time during the daytime as the nighttime tests (1.36 s vs. 1.45 s). The deceleration rates also tended to be lower at nighttime on average (27.29 ft/s^2 vs. 30.91 ft/s^2), though the reason for this is less clear. The average success rate for the longitudinal (i.e., parallel) adult dummy scenario (CPLA) was 72% for the daytime test compared to 50% for the nighttime test.

STATISTICAL METHODS

To further investigate the efficacy of the AEB and P-AEB systems under various scenarios and conditions of interest, a series of regression models were estimated. The primary variable of interest in these analyses was whether the vehicle was able to successfully stop prior to striking the object. As this variable is dichotomous in nature, it is well suited to logistic regression. Within the context of this study, this model takes the form shown in Equation 1:

$$Y_i = logit(P_i) = ln\left(\frac{P_i}{1-P_i}\right) = \beta_o + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k, \tag{1}$$

where P_i is the probability of vehicle i successfully stopping prior to striking the target, X_1 to X_k are a series of predictor variables that are associated with test performance (e.g., scenario, test speed, vehicle model year, TTC at AEB activation), and β_1 to β_k are a series of parameters that are estimable using maximum likelihood techniques.

As each vehicle is tested multiple times, concerns arise with respect to positive correlation among tests of the same vehicle. Failure to account for this correlation may resulted in biased or inefficient parameter estimates. Consequently, a random effects modeling framework is adopted to account for correlation among observations from the same vehicle by allowing the constant term to vary as shown in Equation 2:

$$\beta_{0i} = \beta_0 + \omega_i, \tag{2}$$

where ω_i is a randomly distributed random effect for vehicle i. This allows the constant to vary across vehicles but retain the same value for all runs involving the same vehicle.

RESULTS AND DISCUSSION

The results from these logistic regression models are presented in Table 4 for the vehicle-to-vehicle (i.e., AEB) tests and in Table 5 for the vehicle-to-pedestrian (i.e., P-AEB) tests. When examining the model results, positive coefficients are reflective of variables that are associated with better performance, or a higher probability of successfully stopping. In contrast, negative coefficients suggest that vehicles performed more poorly (i.e., were less likely to stop) in these scenarios. In addition to the parameter estimates, standard errors are provided, along with the p-value and corresponding odds ratio, the latter of which represents the change in the odds of a test being successful as it relates to a one-unit increase in the associated predictor variable.

Starting with the AEB tests, these results show that vehicles were significantly less likely to stop at 25 mph as compared to 12 mph. These results support prior research by Rizzi et al. (*52*) and Omair et al. (*53*), both of which found AEB systems to be less effectiveness at lower speeds. As expected, the likelihood of successful collision avoidance was very sensitive to the AEB activation time. If the AEB system activates 0.1 s earlier, the odds of a successful test increase by about 67%. Similarly, an increase of 1 ft/s^2 in the deceleration rate of the test vehicle corresponded to a 35% reduction in the odds of a collision. The model year variables are particularly interesting as they show persistent improvements in test performance over time (with the exception of a small decrease in 2014 as compared to 2013). This is reflective of the dramatic improvements that have occurred in AEB systems over time. This includes advances in sensor technology, as well as changes in the nature of AEB design as automobile manufacturers have generally gone away from earlier lidar-based systems to current systems that fuse data from multiple sensors, including radar and mono-, stereo-, or tri-cameras.

TABLE 4. Logistic regression model results for vehicle-to-vehicle (AEB) tests

Variable	Coeff.	S.E.	p-value	Odds Ratio
Intercept	-9.43	1.372	<0.001	n/a
12 mph (baseline)	n/a	n/a	n/a	n/a
25 mph	-7.09	0.511	<0.001	0.001
AEB activation time (/tenth of a second)	0.52	0.068	<0.001	1.673
Maximum deceleration rate (ft/s^2)	0.30	0.031	<0.001	1.354
2013 model year (baseline)	n/a	n/a	n/a	n/a
2014 model year	-0.64	1.053	0.543	0.527
2015 model year	1.09	1.068	0.309	2.966
2016 model year	2.33	1.038	0.025	10.264
2017 model year	3.61	1.031	<0.001	37.087
2018 model year	4.48	1.127	<0.001	88.155
2019 model year	4.76	1.156	<0.001	116.217
2020 model year	4.72	1.348	<0.001	112.210
2021 model year	6.27	1.308	<0.001	527.196
2022 model year	7.19	1.542	<0.001	1326.857
Random Effect	**Coeff.**	**S.E.**	**p-value**	**Odds Ratio**
Intercept (variance)	7.12	0.975	<0.001	n/a

Note: n/a = not applicable

Table 5 presents results separately for the perpendicular (top) and parallel (bottom) crossing scenarios, respectively. Starting with the perpendicular tests, the direction and magnitude of effects in the perpendicular tests tended to be similar irrespective of whether the target was an unobstructed adult or an obstructed child pedestrian. However, the odds of a successful test were approximately 71% lower for the child pedestrian as compared to the adult. Turning to the other variables of interest, the trends were generally quite similar to what was shown for the vehicle-to-vehicle AEB tests. Considering the vehicle-perpendicular adult or child scenario, the likelihood of collision avoidance decreased at the higher testing speed and increased with AEB activation time. Increasing the maximum deceleration by 1 ft/s^2 was associated with an increase in the likelihood of collision avoidance by about 55%. With an obstructed child as the target, the collision was about 29% less likely to be avoided when compared to an unobstructed adult.

The same parameters were also explored for the parallel events (CPLA-25) as shown in the bottom of Table 5. This was also the one test scenario that included nighttime conditions in addition to the normal daytime tests. As mentioned previously, the nighttime tests began with model year 2021 vehicles and, as such, only the three most recent years of vehicles (2021-2023) were included in the analysis. The testing results were largely stable over this time period. Interestingly, if the earlier model years are included, there were substantive improvements from model years 2018 through 2020 before this plateau effect occurred.

TABLE 5. Logistic regression model results for vehicle-to-pedestrian (P-AEB) tests

Vehicle-to-perpendicular adult or child scenario (CPNA-25/CPNC-50)

Variable	Coeff.	S.E.	p-value	Odds Ratio
Intercept	-12.26	0.984	<0.001	n/a
Adult target with no obstruction (Baseline)	n/a	n/a	n/a	n/a
Child target with obstruction	-1.24	0.150	<0.001	0.288
12 mph (baseline)	n/a	n/a	n/a	n/a
25 mph	-4.13	0.215	<0.001	0.016
AEB activation time (0.1 s)	0.50	0.034	<0.001	1.642
Maximum deceleration rate (ft/s^2)	0.44	0.028	<0.001	1.554
Random Effect Covariance	**Coeff.**	**S.E.**	**p-value**	**Odds Ratio**
Intercept (variance)	2.99	0.483	<0.001	n/a
Vehicle-to-parallel adult scenario (CPLA-25)				
Variable	**Coeff.**	**S.E.**	**p-value**	**Odds Ratio**
Intercept	-13.86	1.743	<0.001	n/a
25 mph (baseline)	n/a	n/a	n/a	n/a
37 mph	-5.74	0.337	<0.001	0.003
AEB activation time (0.1 s)	0.21	0.037	<0.001	1.238
Maximum deceleration rate (ft/s^2)	0.52	0.046	<0.001	1.678
Daytime (baseline)	n/a	n/a	n/a	n/a
Nighttime	-1.31	0.534	0.014	0.269
Random Effect	**Coeff.**	**S.E.**	**p-value**	**Odds Ratio**
Intercept (variance)	7.21	1.218	<0.001	n/a

Note: n/a = not applicable

As in the other tests, results were much less favorable at higher tests speeds. In this case, the increase from 25 to 37 mph resulted in a dramatic decrease in the likelihood of a successful test. The time at which the AEB activated was a significant determinant of success in all types of pedestrian tests; however, the perpendicular tests were significantly more sensitive to changes in AEB activation (odds ratio of 1.642 compared to 1.238). In contrast, the deceleration rate tended to have similar impacts across the tests. Interestingly, the nighttime results showed a 27% decrease in the likelihood of successfully stopping. These results are supported by Rosen et al. (*43*), who suggested that the performance of AEB systems may be negatively impacted by lighting conditions.

CONCLUSIONS

This study provides strong evidence in support of the crash and injury prevention potential of automatic emergency braking systems, both for vehicle-to-vehicle and vehicle-to-pedestrian scenarios. Both AEB and P-AEB systems have the potential to significantly reduce collision risks under various scenarios. As a case in point, the AEB systems tended to activate 0.77 s after the forward collision warning (FCW). In the P-AEB tests, this time difference ranged from 0.31 s to 0.58 s. Collectively, these activation times are less than average driver reaction times of around 1.0 s to 1.2 s and significantly less than conservative highway design values of 2.2 s to 2.5 s (*51*). Similarly, the AEB and P-AEB systems decelerate at rates from 27 ft/s^2 to 31 ft/s^2, significantly faster than typical values for human drivers, which range from 11 ft/s^2 to 23 ft/s^2. (design value of 11.2 ft/s^2) (*51*).

Also promising is the fact that the effectiveness of these systems has improved markedly over just the past 10 years since the systems were first introduced. Figure 2 shows a graphical representation of the probability of a vehicle successfully stopping as a function of the vehicle model year and test speed for the vehicle-to-vehicle AEB collision avoidance test. Figure 3 provides a similar summary for P-AEB performance.

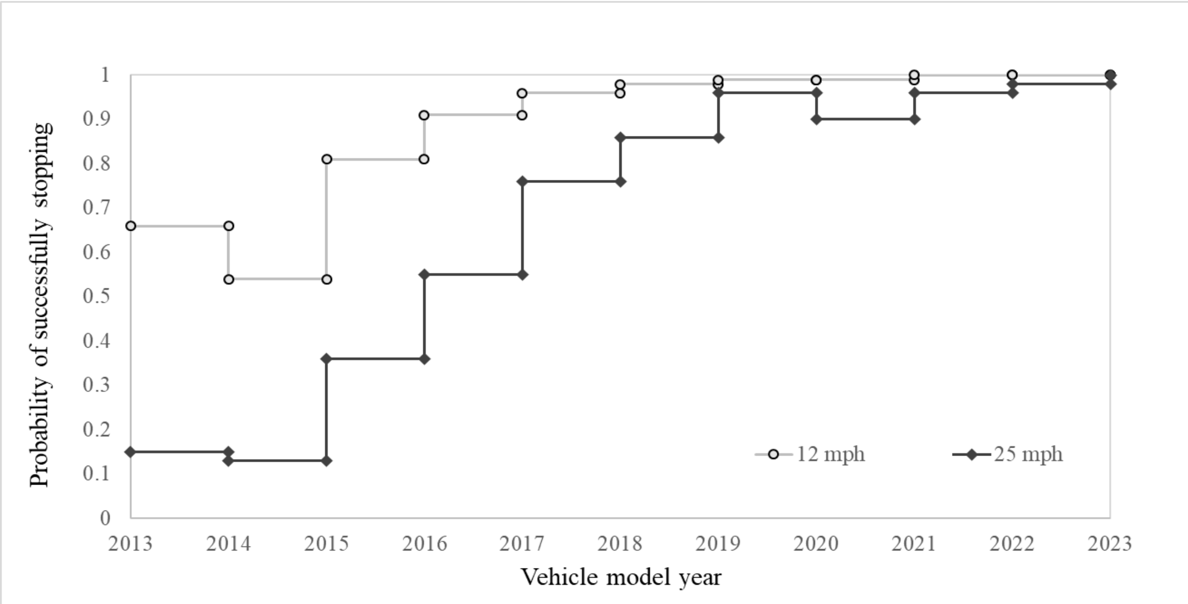

FIGURE 2 Improvements in vehicle-to-vehicle (AEB) tests over time.

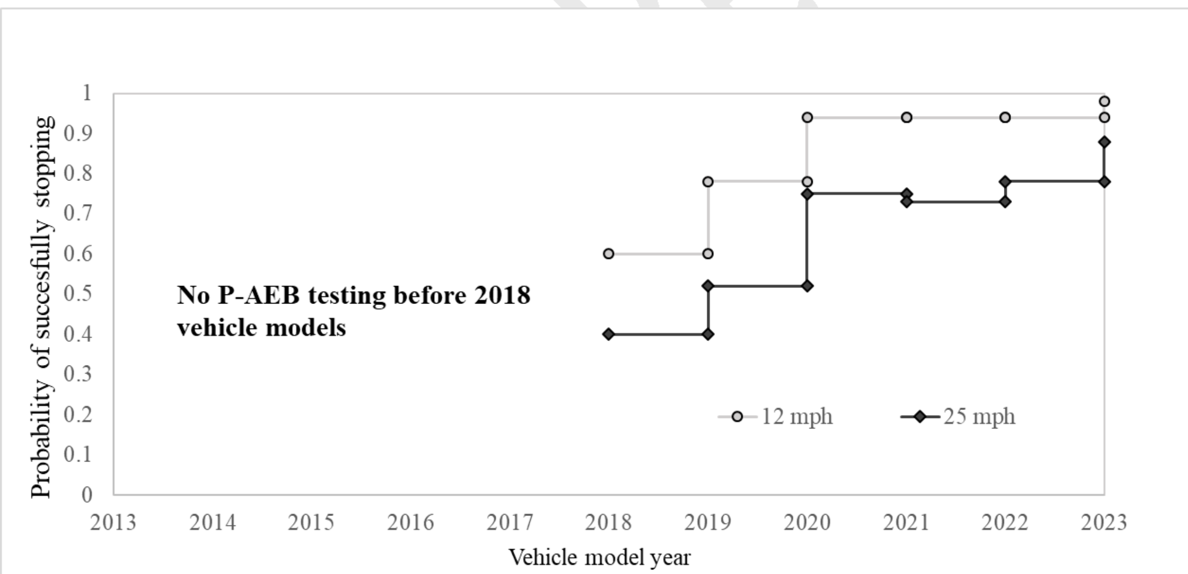

FIGURE 3 Improvements in pedestrian-to-vehicle (P-AEB) tests over time.

Collectively, these results are reflective of the improvements that have occurred in senor design, artificial intelligence, and other aspects of AEB system design. Despite this progress, there are still some important limitations and areas that warrant further investigation. For example, Figure 2 and Figure 3 also clearly show two other trend from the tests: (1) P-AEB performance, though improved, is still significantly worse than AEB in vehicle-to-vehicle tests; and (2) performance is found to degrade persistently at higher speeds. While these gaps have closed in recent model years, it is important to emphasize the nature of the IIHS tests, which are conducted under clear weather conditions on flat, straight roads.

The recently introduced nighttime pedestrian tests have played an important role in helping to improve the effectiveness of these systems under challenging contextual environments. However, it is important to note that the same types of environments and scenarios that are challenging for human drivers are also more challenging for AEB systems. This includes areas with limited sight distance, such as horizontal and vertical curves, where camera and radar systems lose their lines of sight/echo. The same is true of higher speed environments and, collectively, these are some of the same areas where fatalities have recently increased coming out of the COVID-19 pandemic. The recent notice of proposed rulemaking from NHTSA highlights some of the challenges that automobile manufacturers face.

Moving forward, additional testing protocols are likely to be developed to help advance the effectiveness of emerging systems under more challenging conditions. There are also additional insights that may be gained from further analysis of the IIHS data. For example, the nighttime CPLA tests include runs with both low beam and high beam headlights. While the samples were too small for a meaningful analysis as a part of this paper, this represents one area of inquiry that is warranted. The type and location of sensors is also an area of promise for further investigation. Preliminary work conducted as a part of this study has shown significantly better performance for more sophisticated sensor systems. This helps to explain some of the marked advances shown in Figures 2 and 3 as lidar has been replaced by radar-camera sensor fusion designs. Unfortunately, some aspects of sensor design and system performance are very difficult to address because AEB technology and algorithms are generally proprietary or custom to each manufacturer (*44*, *45*), making it challenging to investigate their effectiveness by a third party.

Vehicle-to-vehicle (V2V) communications technologies also have the potential to advance AEB development (*54–56*). Implementing these systems presents challenges as they require varying degrees of collaboration among stakeholders in the competitive automotive industry. However, programs such as NHTSA's Partnership for Analytics Research in Traffic Safety (PARTS) demonstrate that this type of collaboration is feasible.

Finally, the results from this study support some prior research that has demonstrated vehicles equipped with AEB technologies have lower collision rates and/or insurance claims as compared to those without AEB. However, additional investigation is needed to better understand the reasons, as well as the circumstances under which these trends are stronger or weaker.

DISCLAIMER

The opinions expressed in this paper are those of the author and are based on the result of analyses carried out using publicly available IIHS/HLDI collision avoidance data. They are not intended to endorse any brand or automaker directly or indirectly.

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CONTRIBUTION

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Peter Savolainen; draft manuscript preparation: Akinfolarin Abatan, Hisham Jashami, and Peter Savolainen. All authors reviewed the results and approved the final version of the manuscript.

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