Effects of automatic emergency braking systems on pedestrian crash risk

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ABSTRACT

Objective: Automatic emergency braking (AEB) that detects pedestrians has great potential to reduce pedestrian crashes. The objective of this study was to examine its effects on real-world police-reported crashes.

Methods: Two methods were used to assess the effects of pedestrian-detecting AEB on pedestrian crash risk. Vehicles with and without the system were examined on models where it was an optional feature. Poisson regression was used to estimate the effects of AEB on pedestrian crash rates per insured vehicle year, and quasi-induced exposure using logistic regression compared involvement in pedestrian crashes to a system-irrelevant crash type.

Results: AEB with pedestrian detection was associated with significant reductions of 25%–27% in pedestrian crash risk and 29%–30% in pedestrian injury crash risk. However, there was not evidence that that the system was effective in dark conditions without street lighting, at speed limits of 50 mph or greater, or while the AEB-equipped vehicle was turning.

Conclusions: Pedestrian-detecting AEB is reducing pedestrian crashes, but its effectiveness could be even greater. For the system to make meaningful reductions in pedestrian fatalities, it is crucial for it to work well in dark and high-speed conditions. Other proven interventions to reduce pedestrian crashes under challenging circumstances, such as improved headlights and roadway-based countermeasures, should continue to be implemented in conjunction with use of AEB to prevent pedestrian crashes most effectively.

Keywords: pedestrian detection system; pedestrian AEB; pedestrian crash prevention; advanced driver assistance system; light condition; speed limit

1. INTRODUCTION

Pedestrian deaths have risen alarmingly in the United States over the past decade. The 51% rise in pedestrian fatalities since 2009 resulted in 6,205 pedestrians losing their lives in 2019, making up 17% of all traffic fatalities. In that same year, approximately 76,000 additional pedestrians sustained nonfatal injuries in crashes with motor vehicles (Insurance Institute for Highway Safety [IIHS], 2021). Efforts to make travel safe have increasingly focused on preventing pedestrian crashes, injuries, and fatalities.

Pedestrian detection systems, which typically warn a driver when they are at risk of striking a pedestrian in front of their vehicle and apply the brakes if the driver does not respond, are a promising vehicle-based countermeasure for reducing pedestrian crashes. Some studies have predicted the potential of these systems by examining the proportion of pedestrian crashes that systems could possibly mitigate. Haus et al. (2019), for example, estimated automatic emergency braking (AEB) that detects pedestrians could potentially reduce U.S. pedestrian fatality risk by 84%–87% and serious injury risk by 83%–87% when optimally designed. Others have estimated a range of potential effects depending on assumptions regarding system specifications and crash scenarios addressed (Edwards et al., 2014; Hamdane et al., 2015; Jermakian & Zuby, 2011; Rosén et al., 2010; Yanagisawa et al., 2017).

Evaluations of the real-world effects of pedestrian detection systems are beginning to suggest they are delivering on this potential and reducing crashes. However, thus far studies have been limited to individual automakers and have not always reported robust effects. Wakeman et al. (2019) investigated the effects of Subaru's AEB system with pedestrian detection on rates of crashes where an insurance claim was filed to cover injury to a third party but no accompanying third-party vehicle damage claim was filed, which often signifies a pedestrian crash. Subaru's system was associated with a significant 35% reduction in U.S. pedestrian-related claim rates. Isaksson-Hellman and Lindman (2019) reported that car-to-pedestrian insurance claim rates were 21% lower among Volvos with AEB that detects pedestrians than those without in Sweden, but the number of crashes included was small and confidence intervals were wide. American studies of Toyota (Spicer, Vahabaghaie, Murakhovsky, Bahouth, et al., 2021) and

General Motors (Leslie et al., 2021) vehicles also found that pedestrian crash prevention systems were associated with reductions in pedestrian crash risk, although effects were not statistically significant.

For pedestrian detection systems to successfully prevent pedestrian fatalities, they need to work under the conditions where deaths commonly occur. Low light and high speed are key risk factors in pedestrian deaths (Kim et al., 2010; Sullivan & Flannagan, 2002; Tefft, 2013). Less than half of all U.S. pedestrian crashes in 2019 occurred in the dark, but more than three quarters of pedestrian fatalities were under dark conditions with 35% of deaths occurring in the dark without overhead street lighting. Similarly, 22% of all pedestrian crashes in 2019 with known speed limits occurred on roads with speed limits of 40–45 mph and 10% at 50 mph or greater, but over 60% of deaths were at speed limits of 40 mph or greater (IIHS, 2021). These conditions also represent where the largest increases in fatalities have occurred since reaching their low point in 2009. Hu and Cicchino (2018) reported that from 2009 to 2016, pedestrian fatalities increased by 20% in daylight and by 56% in the dark, and increases were also larger on higher speed arterial roads (67%) and on interstates and freeways (49%) than on lower-speed collectors and local roads (9%). Yet, tests of pedestrian AEB systems have demonstrated that they can struggle to perform well in the dark (American Automobile Association [AAA], 2019; IIHS, 2022), and owner manuals often note that systems are not designed to activate at higher speeds. Testing has also shown difficulty with other common but less deadly pedestrian crash scenarios, such as when a vehicle is turning (AAA, 2019).

The goal of this study was to examine the effects of AEB systems with pedestrian detection on pedestrian crashes while including a larger range of vehicle models than previous work. A second objective was to investigate pedestrian AEB crash effects by light condition, speed limit, and the driver’s maneuver prior to the crash (turning vs. not), to assess real-world performance under conditions that systems have struggled with in testing or that are strongly associated with fatality risk. These estimates could be used to establish the effects of current implementations of pedestrian-detecting AEB more robustly and also identify opportunities for improvement.

2. METHODS

The effects of AEB with pedestrian detection on pedestrian crashes were investigated using two methodologies. Effects on pedestrian crash rates per insured vehicle year were examined using Poisson regression while controlling for driver and vehicle risk factors. Quasi-induced exposure, where involvement in system-relevant crashes is compared with involvement in crashes unaffected by the system of interest as an exposure measure, is another method that has been used to study the effects of crash avoidance systems (e.g., Fildes et al., 2015; Keall et al., 2017; Leslie et al., 2021). While previous analyses of crash avoidance system effects from IIHS have examined rates of relevant crashes per insured vehicle year (e.g., Cicchino, 2017), the quasi-induced exposure method was introduced in the current study because it could better account for exposure to characteristics important to pedestrian crashes (light condition, speed limit, vehicle maneuver prior to the crash) that cannot be derived when using insured vehicle years as a measure of exposure. Quasi-induced exposure was used to evaluate the effects of AEB with pedestrian detection while accounting for driver, vehicle, and environmental risk factors, as well as to examine effects by crash characteristics. Additional analyses examined the effects of AEB on pedestrian injury severity among crashes that occur.

2.1 Vehicle feature data

The Highway Loss Data Institute (HLDI) collected data on the presence of AEB with pedestrian detection by make, series, model year, and trim for model year 2017–2020 vehicles. Study vehicles included series where AEB was an optional feature, its presence or absence could be determined by trim, and trim was discernable by the Vehicle Information Number (VIN). Additional vehicle feature data came from Nissan, who provided information on the presence of pedestrian crash prevention linked to unique VINs on the model year 2017–2018 Rogue. The population of study vehicles consisted of 79 make/series/model year combinations from Acura, Buick, Cadillac, Chevrolet, GMC, Honda, Hyundai, Kia, Mazda, Mitsubishi, Nissan, and Subaru (Table A1, Appendix).

IIHS headlight ratings were used as a covariate in the analyses. Headlights are rated good, acceptable, marginal, or poor based on measurements of the visibility illuminance of high and low beams on a straightaway and four curved approaches, with penalties for excessive glare. Vehicles can receive extra credit if they have high beam assist, which automatically switches between high and low beams in the dark based on the presence of other vehicles, if the high beams provide more visibility than the low beams on one or more approach. Because excess glare would not be thought to increase pedestrian crash risk, headlight ratings were adjusted to include only the visibility and high beam assist components and exclude the glare component. Brumbelow (2021) demonstrated that these components of the IIHS headlight ratings are associated with a reduction in nighttime pedestrian crash rates. Headlight ratings were linked to vehicles by make, series, model year, and trim. If more than one headlight type was available on a trim, the worst rating was used.

2.2 Crash data

Police-reported crash databases were obtained from 18 states during 2017–2020 that included full or partial VINs so that study vehicles could be identified. The involvement of pedestrians, maximum injury severity to a pedestrian in the crash, driver age, driver gender, light condition, speed limit, vehicle maneuver prior to the crash, and vehicle point of impact were derived from the state data sets and coded into a common format. Pedestrian crash involvements where the vehicle was backing were excluded from analyses. Variables for speed limit, vehicle maneuver, or point of impact were unavailable in six states for all or some years (Table 1), and data from state/year combinations without these variables were excluded in analyses where the variables were used.

Table 1. Police-reported crash data availability with variables for speed limit, vehicle maneuver, and vehicle point of impact by state and year

State and years available		Speed limit	Vehicle maneuver (turning)	Vehicle point of impact
CT	2017–2020		x	x
FL	2017–2019	x	x	x
GA	2017–2020	x	x	x
IL	2017–2020		x	x
LA	2017–2019	x	x	x
MD	2017–2020	x	x	x
MI	2017–2020	x	x	x
MN	2017–2019	x	x	x
MO	2017–2019	x	x	x
NC	2017–2019	x	x	x
NY	2017–2019		x	
OH	2017–2020	x	x	x
PA	2017–2020	x	x	x
TN	2017–2019	x	x	x
TX	2017–2020	x		x
UT	2017–2020	2017–2019 only	x	2018 only
WA	2017–2019	x	x	
WI	2018–2019	x	x	x

2.3 Insured driver data

HLDI provided data on the number of days vehicles were insured. Crash rates using these data are expressed as crashes per insured vehicle year, where one insured vehicle year is the equivalent to two vehicles insured for six months each or a single vehicle insured for one year, etc. Insured driver data included the state, age, and gender of the rated driver on the insurance policy and were matched to the crash data by vehicle, state, calendar year, driver age group, and driver gender.

2.4 Analyses

Poisson regression was used to evaluate the effects of AEB with pedestrian detection on pedestrian crash rates per insured vehicle year, with the log of insured vehicle years included as an offset term. Separate models were constructed for all pedestrian crashes, crashes where a pedestrian was injured, and crashes where a pedestrian sustained a serious or fatal injury (K or A on the KABCO scale). Models included covariates for state, calendar year, driver age group (< 25, 25–64, 65+, unknown), driver gender (male, female, unknown), and IIHS headlight visibility rating (good, acceptable, marginal, poor). An additional covariate coded for the combination of vehicle make/model/model year, to prevent confounding of AEB effects with other design differences between vehicles. Scale parameters were estimated within the Poisson models to account for potential overdispersion.

Quasi-induced exposure analyses were performed with logistic regression. Crashes in which the target vehicle was struck in the rear in a rear-end crash were used as the nonsensitive crash type, and thus logistic regression analyses examined the effects of AEB with pedestrian detection on the odds that a crash involved a pedestrian as opposed to a rear-struck involvement. Three models were constructed for each level of pedestrian injury severity (all severities, any injury, serious/fatal injury). In addition to the covariates used in Poisson regression models, the quasi-induced exposure analyses introduced other covariates where exposure per insured vehicle year could not be calculated: light condition (daylight, dark and lighted/dawn/dusk, dark and not lighted), speed limit (≤ 25 mph, 30–35 mph, 40–45 mph, 50+ mph), and vehicle maneuver prior to the crash (turning vs. not turning). Dark and lighted conditions refer to those where there is no natural light, but the area is illuminated by artificial overhead light. Crashes with dark and not lighted conditions have no overhead lighting present where the crash occurred. These analyses were limited to states with variables for speed limit, vehicle maneuver, and vehicle point of impact (to identify rear-end struck involvements).

Quasi-induced exposure was also used to investigate the effects of the system on pedestrian crashes by crash characteristics. Three separate logistic regression models were constructed to examine the effects of AEB by the crash characteristics of interest: light condition, speed limit, and vehicle maneuver. Each model included the same covariates as prior logistic regression models, plus interaction terms between the characteristic of interest and driver age, driver gender, state, calendar year, IIHS headlight rating, and the additional crash characteristic variables that were not the focus of the model among light condition, speed limit, and vehicle maneuver.

Interactions with driver age and gender were included to account for demographic differences in travel patterns that can affect crash circumstances. Older drivers are more likely to restrict their driving at night and on higher speed roads (Braitman & McCartt, 2008) and experience cognitive decline that results in over-involvement in turning crashes at intersections (Cicchino & McCartt, 2015), while younger and male drivers are more likely to crash at night (Massie et al., 1997; McCartt & Teoh, 2015). Because of differences in rurality and road type, the distribution of crashes by time of day, speed limit, and vehicle maneuver (due to density of intersections) vary by state. An interaction term with calendar year was included to control for the change in crash patterns seen in 2020 during the COVID-19 pandemic (Doucette et al., 2021; National Center for Statistics and Analysis, 2021). The interaction between the crash circumstance of interest and AEB was used to estimate the effects of AEB at each level of the characteristic and to compare differences in effects between levels.

An additional logistic regression model examined the effects of AEB on injury severity by examining the odds that a pedestrian crash resulted in a serious or fatal pedestrian injury, controlling for state, calendar year, driver age group, driver gender, IIHS headlight visibility ratings, make/model/model year, light condition, speed limit, and vehicle maneuver. This model excluded states without variables for speed limit or vehicle maneuver, but since rear-end struck involvements were not included as an exposure measure, it did not exclude states that were missing point of impact.

In all analyses, vehicle make/model/model year combinations involved in no pedestrian crashes of the severity examined were removed, as were vehicles involved in no crashes resulting in serious or fatal pedestrian injuries in models examining the odds of a serious/fatal injury in a pedestrian crash. Sparse levels of other covariates were combined in some analyses. Model parameters were exponentiated and interpreted as rate ratios (RRs) from Poisson regression models and odds ratios (ORs) from logistic regression models, and percent changes in these rates and odds associated with AEB were expressed by $100(exp(x) - 1)$, where x is the parameter estimate for AEB.

3. RESULTS

There were 1,483 pedestrian crashes, 1,381 pedestrian injury crashes, and 266 pedestrian serious injury or fatal crashes involving study vehicles across the 18 states. Pedestrian crash rates per insured vehicle year were lower among vehicles with AEB than those without at each severity level, and this pattern held for most vehicle makes (Table 2).

Table 2. Pedestrian crash rates, injury crash rates, and serious or fatal crash rates per insured vehicle year by make and equipment with AEB with pedestrian detection

Make	System	Pedestrian crashes		Pedestrian injury crashes		Pedestrian serious/fatal injury crashes	
		Crashes	Rate (x 100,000)	Crashes	Rate (x100,000)	Crashes	Rate (x 100,000)
Acura	AEB	1	10.5	1	10.5	0	0.0
	No AEB	7	25.7	7	25.7	2	7.3
Buick	AEB	0	0	0	0	0	0
	No AEB	1	37.0	1	37.0	0	0
Cadillac	AEB	25	41.0	23	37.8	3	4.9
	No AEB	11	26.6	11	26.6	2	4.8
Chevrolet Truck	AEB	1	15.6	1	15.6	1	15.6
	No AEB	1	16.9	1	16.9	0	0.0
GMC Truck	AEB	1	6.4	0	0.0	0	0.0
	No AEB	17	41.9	16	39.5	2	4.9
Honda	AEB	224	27.1	210	25.4	39	4.9
	No AEB	415	47.0	386	43.7	62	7.1
Hyundai	AEB	7	45.3	7	45.3	3	21.9
	No AEB	34	55.9	29	47.7	7	14.0
Kia	AEB	3	18.1	3	18.1	2	15.8
	No AEB	62	57.4	56	51.8	17	16.2
Mazda	AEB	1	10.0	0	0	0	0
	No AEB	3	41.1	3	43.9	0	0
Mitsubishi	AEB	1	109.1	1	109.1	0	0.0
	No AEB	5	99.3	5	99.3	1	21.5
Nissan	AEB	36	54.5	32	48.4	5	7.6
	No AEB	250	61.5	233	57.3	42	10.3
Subaru	AEB	154	17.9	140	16.2	28	3.3
	No AEB	223	25.2	215	24.3	50	5.8
All	AEB	454	24.0	418	22.1	81	4.4
	No AEB	1,029	41.6	963	38.9	185	7.7
	Total	1,483	34.0	1,381	31.7	266	6.3

Note: Because vehicle make/model/model year combinations were dropped from an analysis if they were involved in no pedestrian crashes of the severity examined, insured vehicle years vary slightly by injury severity.

Poisson regression model results for the effects of AEB with pedestrian detection on pedestrian crash rates per insured vehicle year are presented in Table 3. AEB was associated with reductions of 27% in pedestrian crash rates of all severities (RR, 0.73; 95% CI, 0.62–0.86, $p = 0.0002$), 30% in pedestrian injury crash rates (RR, 0.70; 95% CI, 0.60–0.83, $p < 0.0001$), and 21% in pedestrian serious/fatal injury crash rates (RR, 0.79; 95% CI, 0.57–1.09, $p = 0.14$); reductions were significant for pedestrian crashes of all severities and injury crashes.

Table 3. Poisson regression model results of pedestrian crash rates per insured vehicle year, by severity

	Rate ratio (95% confidence interval)		
Parameter	Pedestrian crashes (n = 1,483)	Pedestrian injury crashes (n = 1,381)	Pedestrian serious and fatal injury crashes (n = 266)
AEB with pedestrian detection	0.73 (0.62, 0.86)	0.70 (0.60, 0.83)	0.79 (0.57, 1.09)
Male driver (vs. female)	1.45 (1.28, 1.64)	1.46 (1.29, 1.65)	1.60 (1.25, 2.03)
Unknown driver gender (vs. female)	0.81 (0.51, 1.31)	0.70 (0.43, 1.14)	0.60 (0.20, 1.85)
Driver age < 25 (vs. 25–64)	2.04 (1.69, 2.47)	2.06 (1.70, 2.50)	2.12 (1.48, 3.05)
Driver age 65+ (vs. 25–64)	0.83 (0.71, 0.99)	0.87 (0.74, 1.03)	0.85 (0.62, 1.18)
Driver age unknown (vs. 25–64)	1.20 (0.76, 1.90)	1.24 (0.77, 2.00)	0.95 (0.31, 2.85)
Good headlight visibility rating (vs. poor)	0.74 (0.43, 1.28)	0.80 (0.46, 1.38)	0.96 (0.36, 2.55)
Acceptable headlight visibility rating (vs. poor)	0.78 (0.49, 1.26)	0.80 (0.50, 1.30)	0.69 (0.28, 1.72)
Marginal headlight visibility rating (vs. poor)	0.88 (0.57, 1.34)	0.87 (0.56, 1.33)	1.22 (0.53, 2.80)
2018 (vs. 2017)	0.91 (0.73, 1.13)	0.92 (0.75, 1.14)	1.04 (0.66, 1.66)
2019 (vs. 2017)	0.90 (0.72, 1.11)	0.91 (0.73, 1.12)	1.12 (0.71, 1.76)
2020 (vs. 2017)	0.66 (0.51, 0.87)	0.63 (0.48, 0.83)	0.88 (0.51, 1.51)

Note: Effects for state and make/model/model year combination are not shown.

Quasi-induced exposure analyses were limited to states with variables for speed limit, vehicle maneuver, and vehicle point of impact, so fewer pedestrian crashes were included. A total of 646 pedestrian crashes of all severities, 577 pedestrian injury crashes, and 130 pedestrian serious/fatal injury crashes occurred in states meeting the inclusion criteria, and 32,050 study vehicles were involved in the nonsensitive crash type of rear-end struck. Table 4 presents the results of logistic regression models examining the effects of AEB on the odds that a crash involved a pedestrian in comparison to being rear-end struck. In these analyses, pedestrian crash prevention was associated with significant reductions of 25% in the odds that a crash involved a pedestrian (OR, 0.75; 95% CI, 0.59–0.95, $p = 0.02$) and 29% in the odds that a crash involved an injured pedestrian (OR, 0.71; 95% CI, 0.55–0.91, $p = 0.008$). AEB was not associated with a change in the odds that a crash involved a seriously or fatally injured pedestrian (OR, 0.97; 95% CI, 0.60–1.56, $p = 0.90$).

Table 4. Logistic regression model results of quasi-induced exposure analyses examining the odds a crash involved a pedestrian, by severity

	Odds ratio (95% confidence interval)		
Parameter	Pedestrian crashes ($n = 646$)	Pedestrian injury crashes ($n = 577$)	Pedestrian serious and fatal injury crashes ($n = 130$)
AEB with pedestrian detection	0.75 (0.59, 0.95)	0.71 (0.55, 0.91)	0.97 (0.60, 1.56)
Male driver (vs. female)	1.32 (1.11, 1.58)	1.26 (1.05, 1.52)	1.51 (1.04, 2.19)
Unknown driver gender (vs. female)	1.54 (0.69, 3.44)	1.16 (0.46, 2.90)	2.61 (0.47, 14.59)
Driver age < 25 (vs. 25–64)	1.19 (0.90, 1.58)	1.25 (0.93, 1.69)	1.25 (0.71, 2.19)
Driver age 65+ (vs. 25–64)	1.70 (1.34, 2.14)	1.81 (1.42, 2.31)	1.68 (1.03, 2.75)
Driver age unknown (vs. 25–64)	10.15 (4.52, 22.80)	10.19 (4.12, 25.17)	4.74 (0.76, 29.61)
Good headlight visibility rating (vs. poor)	0.77 (0.36, 1.67)	0.92 (0.41, 2.11)	1.52 (0.39, 5.93)
Acceptable headlight visibility rating (vs. poor)	0.72 (0.37, 1.40)	0.76 (0.38, 1.54)	0.74 (0.18, 3.00)
Marginal headlight visibility rating (vs. poor)	0.98 (0.54, 1.76)	0.96 (0.52, 1.78)	1.55 (0.44, 5.48)
2018 (vs. 2017)	1.19 (0.86, 1.67)	1.15 (0.82, 1.62)	1.35 (0.63, 2.87)
2019 (vs. 2017)	1.25 (0.90, 1.73)	1.19 (0.85, 1.67)	1.56 (0.74, 3.25)
2020 (vs. 2017)	1.53 (1.05, 2.23)	1.36 (0.92, 2.02)	2.49 (1.09, 5.67)
Dark-lighted/dawn/dusk (vs. daylight)	2.59 (2.13, 3.15)	2.60 (2.11, 3.19)	3.83 (2.56, 5.74)
Dark-not lighted (vs. daylight)	6.44 (4.80, 8.65)	6.35 (4.64, 8.70)	11.42 (6.95, 18.76)
Speed limit 30–35 mph (vs. ≤ 25)	0.24 (0.20, 0.30)	0.23 (0.19, 0.29)	0.40 (0.24, 0.68)
Speed limit 40–45 mph (vs. ≤ 25)	0.10 (0.08, 0.13)	0.10 (0.08, 0.13)	0.22 (0.12, 0.38)
Speed limit 50+ mph (vs. ≤ 25)	0.04 (0.03, 0.06)	0.04 (0.03, 0.06)	0.16 (0.09, 0.30)
Turning (vs. not turning)	8.94 (7.26, 11.00)	9.30 (7.47, 11.58)	4.04 (2.39, 6.81)

Note: Effects for state and make/model/model year combination are not shown.

Logistic regression was used to investigate the odds that a pedestrian crash that occurred involved a serious or fatal pedestrian injury (Table 5). Controlling for driver, vehicle, and environmental factors, AEB was not associated with a significant change in pedestrian injury severity (OR, 1.09; 95% CI, 0.59–2.00, $p = 0.79$).

Table 5. Logistic regression analysis of the odds that a pedestrian in a crash sustained a serious or fatal injury ($n = 649$ pedestrian crashes)

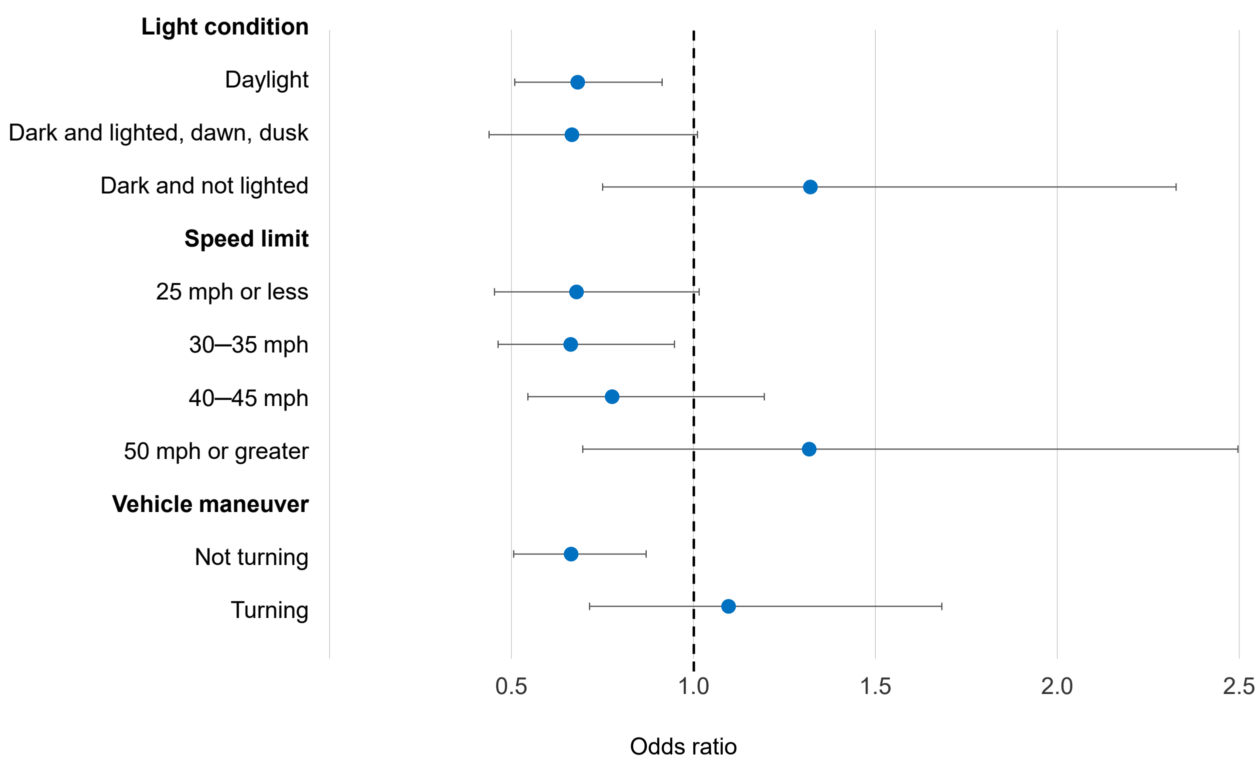
Parameter	Odds ratio (95% confidence interval)
AEB with pedestrian detection	1.09 (0.59, 2.00)
Male driver (vs. female)	0.93 (0.58, 1.50)
Unknown driver gender (vs. female)	3.85 (0.40, 37.10)
Driver age < 25 (vs. 25–64)	1.32 (0.63, 2.78)
Driver age 65+ (vs. 25–64)	1.08 (0.58, 2.02)
Driver age unknown (vs. 25–64)	0.23 (0.02, 2.23)
Good headlight visibility rating (vs. poor)	1.75 (0.26, 11.57)
Acceptable headlight visibility rating (vs. poor)	0.28 (0.04, 1.79)
Marginal headlight visibility rating (vs. poor)	0.86 (0.17, 4.34)
2018 (vs. 2017)	1.45 (0.60, 3.48)
2019 (vs. 2017)	1.44 (0.61, 3.41)
2020 (vs. 2017)	2.14 (0.77, 5.92)
Dark-lighted/dawn/dusk (vs. daylight)	1.95 (1.17, 3.27)
Dark-not lighted (vs. daylight)	2.23 (1.10, 4.52)
Speed limit 30–35 mph (vs. ≤ 25)	1.58 (0.86, 2.87)
Speed limit 40–45 mph (vs. ≤ 25)	2.31 (1.18, 4.52)
Speed limit 50+ mph (vs. ≤ 25)	6.45 (2.74, 15.20)
Turning (vs. not turning)	0.55 (0.31, 0.97)

Note: Effects for state and make/model/model year combination are not shown.

Of the 646 pedestrian crashes of all severities included in quasi-induced exposure analyses, 59% occurred during daylight, 4% during dawn or dusk, 26% during dark and lighted conditions, and 11% during dark and not lighted conditions; 34% were on roads with speed limits of 25 mph or lower, 37% with speed limits of 30–35 mph, 21% with speed limits of 40–45 mph, and 8% with speed limits of 50 mph or higher; and the driver of the subject vehicle was turning in 30%. The vehicle was proceeding straight in most crashes where it was not turning (in 60% of the 646 pedestrian crashes), and in the remaining crashes the vehicle was coded as making another maneuver (e.g., slowing, stopping, negotiating a curve) or the precrash maneuver was unknown.

AEB with pedestrian detection was associated with different effects by crash characteristics (Figure 1). In pedestrian crashes occurring during daylight (OR, 0.68; 95% CI, 0.51–0.91, $p = 0.01$) or during dawn, dusk, or dark and lighted conditions (OR, 0.67; 95% CI, 0.44–1.01, $p = 0.06$), it was associated with reductions in the odds of a pedestrian crash of 32% and 33%, respectively, but there was no reduction during dark and not lighted conditions (OR, 1.32; 95% CI, 0.75–2.33, $p = 0.33$). The effect during dark and not lighted conditions was significantly different from effects during daylight ($p = 0.03$) and dawn, dusk, or dark and lighted conditions ($p = 0.048$).

Figure 1. Effects of AEB with pedestrian detection on the odds a crash involved a pedestrian, by light condition, speed limit, and vehicle maneuver prior to the crash ($n = 646$ pedestrian crashes)



There was a 32% reduction in the odds that a crash was with a pedestrian associated with AEB at speed limits of 25 mph or less (OR, 0.68; 95% CI, 0.45–1.02, $p = 0.06$), a 34% reduction at speed limits of 30–35 mph (OR, 0.66; 95% CI, 0.46–0.95, $p = 0.02$), a 22% reduction at speed limits of 40–45 mph (OR, 0.78; 95% CI, 0.55–1.19, $p = 0.25$), and no reduction at speed limits of 50 mph or greater (OR, 1.32; 95% CI, 0.70–2.50, $p = 0.40$), although effects at lower speed limits did not differ significantly from 50+ mph (25 mph or less vs. 50+ mph: $p = 0.08$, 30–35 vs. 50+ mph: $p = 0.06$, 40–45 vs. 50+ mph: $p = 0.16$). Finally, AEB was associated with a 34% reduction in the odds of a pedestrian crash when a vehicle was not turning prior to the crash (OR, 0.66; 95% CI, 0.51–0.87, $p = 0.003$), but no reduction when it was turning (OR, 1.10; 95% CI, 0.71–1.68, $p = 0.67$); these effects were significantly different from each other ($p = 0.04$).

The analyses of the effects of pedestrian AEB on pedestrian crash rates and severity presented in Tables 3–5 were repeated excluding pedestrian crashes occurring in dark and not lighted conditions, at speed limits of 50 mph or greater, and where the subject vehicle was turning. Results are summarized in Table 6. In Poisson regression models, AEB with pedestrian detection was associated with significant reductions of 49% in rates of all pedestrian crashes (RR, 0.51; 95% CI, 0.38–0.68, $p < 0.0001$), 50% in rates of pedestrian injury crashes (RR, 0.50; 95% CI, 0.36–0.68, $p < 0.0001$), and 52% in rates of pedestrian serious or fatal injury crashes (RR, 0.48; 95% CI, 0.24–0.96, $p = 0.04$) per insured vehicle year. Quasi-induced exposure analyses revealed the odds of a pedestrian crash of any severity were 45% lower (OR, 0.55; 95% CI, 0.40–0.76, $p = 0.0003$), odds of a pedestrian injury crash were 47% lower (OR, 0.53; 95% CI, 0.38–0.75, $p = 0.0003$), and odds of a serious or fatal pedestrian crash were 44% lower (OR, 0.56; 95% CI, 0.28–1.13, $p = 0.11$) among vehicles with AEB. The odds of a pedestrian crash that occurred resulting in serious or fatal pedestrian injuries were 40% lower among vehicles with AEB (OR, 0.60; 95% CI, 0.22–1.65, $p = 0.32$), but this was not statistically significant.

Table 6

Effects of AEB with pedestrian detection on pedestrian crash involvement rates per insured vehicle year (Poisson regression), the odds that a crash involved a pedestrian (logistic regression), and the odds of a pedestrian crash resulting in a serious or fatal pedestrian injury (logistic regression), limited to crashes without dark and unlighted conditions, at speed limits < 50 mph, and where the subject vehicle was not turning.

Outcome and analysis	Pedestrian crash severity	Rate ratio (95% confidence interval)
Pedestrian crash involvement rate per insured vehicle year (Poisson regression)	All crashes (*n* = 391)	0.51 (0.38, 0.68)
	Injury crashes (*n* = 357)	0.50 (0.36, 0.68)
	Serious and fatal injury crashes (*n* = 74)	0.48 (0.24, 0.96)

Outcome	Crash severity	Odds ratio (95% confidence interval)
Odds a crash involved a pedestrian (quasi-induced exposure, logistic regression)	All crashes (*n* = 361)	0.55 (0.40, 0.76)
	Injury crashes (*n* = 328)	0.53 (0.38, 0.75)
	Serious and fatal injury crashes (*n* = 73)	0.56 (0.28, 1.13)
Odds of a pedestrian crash resulting in a serious or fatal pedestrian injury (logistic regression)	(*n* = 351)	0.60 (0.22, 1.65)

4. DISCUSSION

AEB with pedestrian detection is preventing crashes. This study demonstrates that AEB is associated with reductions of 25%–27% in the risk of a pedestrian crash and 29%–30% in the risk of a pedestrian injury crash. If these estimates were applied to the approximately 82,000 that sustained nonfatal or fatal injuries in motor vehicle crashes in the United States in 2019, more than 23,000 could have been prevented if all vehicles had pedestrian-detecting AEB. But its effectiveness could be even greater. There is not evidence that the system is preventing pedestrian crashes under dark conditions without street lighting, at speed limits of 50 mph or greater, or when the equipped vehicle is turning. Effectiveness estimates increased in crashes without these challenging characteristics, with reductions of 45%–49% in the risk of a pedestrian crash and 47%–50% in the risk of a pedestrian injury crash associated with the system.

Improving AEB to address high-speed and dark, unlighted conditions is especially important for addressing pedestrian deaths. Estimates of the potential of pedestrian detection have cautioned that its effectiveness in preventing fatalities would be hampered if it could not function in darkness and at high speeds (Jermakian & Zuby, 2011; Rosén, 2013). Consistent with those predictions, the quasi-induced exposure analysis in this study, which was better able to control for how driving exposure under difficult conditions may differ between vehicles with and without AEB, suggests that pedestrian detection is not having a meaningful effect on crashes resulting in serious or fatal pedestrian injuries. Because darkness and high speeds often co-occur in pedestrian crashes, both will need to be addressed for AEB to substantially reduce pedestrian fatalities. Rural roads, which tend to have higher speeds than urban roads (De Leonardis et al., 2018), are also more likely to lack street lighting (Lutkevich et al., 2012), and pedestrian crashes in the dark are more likely to occur on roads with higher speed limits (Sullivan & Flannagan, 2007). A total of 18% of U.S. pedestrian deaths in 2019 were in dark and not lighted conditions on roads with speed limits of 50 mph or greater, and nearly half (48%) occurred under either condition (IIHS, 2021).

Fatal pedestrian crashes do not frequently involve turning vehicles, but this crash type is common when considering pedestrian crashes of all severities. Over a third of U.S. police-reported pedestrian crashes in 2019 involved a vehicle that was turning (IIHS, 2021). The lack of effectiveness of AEB with pedestrian detection in turning scenarios is similar to what has been reported for AEB addressing vehicle-to-vehicle crashes. Cicchino and Zuby (2019) found that vehicles with AEB are more likely than vehicles without the system to be turning when they are the striking vehicle in a rear-end crash, suggesting that the system is not as effective at preventing rear-end crashes with turning configurations as other rear-end crash types, and Spicer, Vahabaghaie, Murakhovsky, Lawrence, et al. (2021) estimated that vehicle-to-vehicle AEB is less effective at intersections. These systems may not be designed to activate under turning scenarios because it is difficult to judge if drivers are unable to avoid a crash while they are providing steering input. It is important to balance increased functionality with avoiding unnecessary activations, which could reduce trust in the systems and potentially lead drivers to deactivate them (Kidd

& Reagan, 2019; Lee & See, 2004; Parasuraman & Riley, 1997). But because turning is a more common configuration in pedestrian crashes than in the rear-end crashes that vehicle-to-vehicle AEB is designed to address, improving performance while turning would have a comparatively larger impact for pedestrian-detecting AEB.

AEB could potentially mitigate the severity of a pedestrian crash by lowering the striking vehicle's speed even if the crash is not avoided entirely. The system did not reduce the odds that a pedestrian crash resulted in a serious or fatal injury in this study, which suggests that crashes that do occur involving vehicles with AEB are not less severe. This may be because the severity distribution in the crashes that remain skews upwards due to AEB's greater effectiveness in preventing the lower-speed and lighted crashes that are less likely to result in serious injuries. Furthermore, because pedestrians are at risk of sustaining serious injuries even at nonextreme speeds (e.g., Tefft [2013] estimated the average risk of a pedestrian sustaining an injury on the Abbreviated Injury Scale of 4 or more is 50% at an impact speed of 33 mph, 75% at 41 mph, and 90% at 48 mph), AEB may not slow a vehicle traveling at a high speed enough to prevent a serious pedestrian injury even when it does activate. AEB was associated with a reduction in the odds that a pedestrian crash resulted in a fatal or serious injury when crashes at high speed limits and under dark and not lighted conditions were excluded, albeit with a wide confidence interval.

A strength of this study was the convergent findings resulting from both analysis approaches for the effects of AEB on pedestrian crashes of all severities and with injuries. Equipment with AEB was identified by trim level on most study vehicles, and more expensive trims may differ from the base trim in where and how they are driven. Some of these differences were more carefully accounted for with the quasi-induced exposure method and by controlling for known environmental risk factors in pedestrian crashes in analyses using this method. There were not enough fatalities in the crash sample to directly examine system effects on them. Speed limit was used as a proxy for vehicle speeds, but actual vehicle speeds were unknown. Pedestrian crashes are underreported in police-reported data, especially among crashes not involving injury (Medury et al., 2019; Sciortino et al., 2005). It is evident the data used in the current study were subject to underreporting by how few noninjury crashes were included. It is unknown if or how this biased results, but there is not reason to think that underreporting would vary by the striking vehicle's AEB status.

Another limitation is that AEB and high beam assist were often packaged together on study vehicles. More than 70% of crash-involved study vehicles with AEB had high beam assist, while most crash-involved study vehicles without AEB did not have it equipped. Leslie et al. (2021) found that high beam assist was associated with a 26% reduction in the risk of nighttime crashes with animals, pedestrians, or cyclists. High beam assist is factored into the IIHS headlight visibility ratings that were a covariate in the analyses, but the presence of this technology specifically could not be controlled for because of its collinearity with AEB. High beam assist would not affect the benefits for AEB seen during daylight and did not boost system effects in dark and not lighted conditions. It could have inflated effects in dark and lighted conditions, however. Because locations with street lighting are less often rural, they are also where drivers are less likely to choose to use high beams (Reagan et al., 2017) and so are the conditions where high beam assist potentially has the most opportunity to impact nighttime crashes.

AEB with pedestrian detection appears to be effective in preventing crashes, but it could be even more effective if it operated well in low-light conditions, at high speeds, and in turning configurations. As systems improve to address a wider range of crash scenarios, other countermeasures to prevent crashes in these circumstances should continue to be implemented. Nighttime pedestrian crashes can be reduced with improved vehicle headlights (Brumbelow, 2021; Leslie et al., 2021) and increased use of roadway lighting (Elvik, 1995; Rea et al., 2009). Intersection improvements like leading pedestrian intervals and left-turn traffic calming can be implemented to prevent pedestrian crashes involving turning vehicles (Fayish & Gross, 2010; Hu & Cicchino, 2020a). Countermeasures such as automated speed enforcement, lowered speed limits, and traffic-calming roadway designs are associated with lower vehicle speeds (Hawkins & Hallmark, 2020; Hu & Cicchino, 2020b; Hu & McCartt, 2016), and could result in conditions where AEB is more likely to function well. AEB with pedestrian detection is a promising tool with the potential to considerably reduce pedestrian crashes as it becomes more widely adopted in the vehicle fleet, and it should operate in conjunction with other proven interventions to have the most substantial impact on pedestrian safety.

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7. APPENDIX

Table A1. Study vehicle series and model years

Make	Series	Model years
Acura	RDX	2017
Acura	TLX	2017
Buick	Enclave	2020
Cadillac	XT5 2WD	2017–2019
Cadillac	XT5 4WD	2018–2019
Chevrolet	Traverse 2WD	2020
Chevrolet	Traverse 4WD	2020
GMC	Acadia 2WD	2019
GMC	Acadia 4WD	2019
Honda	Accord 2D	2017
Honda	Accord 4D	2017
Honda	Civic 4D	2018
Honda	Civic 5D	2018
Honda	CR-V 2WD	2018–2019
Honda	CR-V 4WD	2018–2019
Honda	Fit	2018, 2020
Honda	Odyssey	2018–2020
Honda	Pilot 2WD	2017–2018
Honda	Pilot 4WD	2017–2018
Honda	Ridgeline Crew Cab	2019
Hyundai	Ioniq Hybrid	2019
Hyundai	Ioniq Plug-In Hybrid	2019
Hyundai	Kona 2WD	2019–2020
Hyundai	Kona 4WD	2019–2020
Hyundai	Santa Fe XL 2WD	2019
Hyundai	Santa Fe XL 4WD	2019
Hyundai	Sonata	2019
Kia	Optima	2019
Kia	Sorento 2WD	2020
Kia	Sorento 4WD	2020
Kia	Soul	2020
Kia	Sportage 2WD	2019
Kia	Sportage 4WD	2019
Kia	Stinger	2019
Mazda	3	2019
Mazda	CX-3 2WD	2018
Mazda	CX-3 4WD	2018

Make	Series	Model years
Mitsubishi	Eclipse Cross	2020
Mitsubishi	Outlander	2020
Mitsubishi	Outlander Sport	2019
Nissan	Altima 2WD	2019
Nissan	Altima 4WD	2019
Nissan	Rouge 2WD	2017–2018
Nissan	Rouge 4WD	2017–2018
Subaru	Crosstrek	2017–2020
Subaru	Forester	2017–2018
Subaru	Impreza 4D	2017–2020
Subaru	Impreza SW	2017–2019
Subaru	Legacy	2017–2018
Subaru	Outback	2017–2018
Subaru	WRX	2017–2020

Note: 2D=two-door, 4D=four-door, 5D=five-door, 2WD=two-wheel drive, 4WD=four-wheel drive, SW=station wagon.