EFFECTS OF A BICYCLIST DETECTION SYSTEM ON POLICE-REPORTED BICYCLE CRASHES

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ABSTRACT

Research Question/Objective
Automatic emergency braking (AEB) is effective at preventing vehicle-to-vehicle rear-end crashes and pedestrian crashes. Subaru's driver assistance system that includes AEB, called EyeSight, could detect bicycles in parallel configurations in the United States in its first and second generations, and added bicyclist detection in perpendicular configurations in its third generation. The purpose of this study was to evaluate whether the first and second generations of EyeSight reduced bicycle crashes in the real world.

Methods and Data Sources
The presence or absence of EyeSight was identified through Vehicle Identification Numbers for model year 2013–2020 Subaru models where the system was optional. All bicycle crashes and single-vehicle single-bicyclist crashes with parallel and perpendicular configurations involving these vehicles were extracted from the police-reported crash databases of 16 U.S. states during calendar years 2014–2020.

The association of EyeSight with bicycle crash rates per insured vehicle year was examined with negative binomial regression controlling for calendar year, state, vehicle model year and series, and driver age group and gender. Quasi-induced exposure analyses using logistic regression compared involvement in a bicycle crash to the nonsensitive crash types of being rear-end struck or side-struck, using the same covariates as the negative binomial regression models. These analyses included crash data from 14 states where rear-end-struck and side-struck vehicles could be identified.

Results
Study vehicles were involved in 856 bicycle crashes, of which 283 had parallel configurations and 387 had perpendicular configurations. EyeSight was associated with a statistically significant 29% reduction in parallel crash rates per insured vehicle year (Rate ratio [RR], 0.71; 95% confidence interval [CI], 0.53–0.96, $p = 0.03$), and nonsignificant reductions of 5% in perpendicular crash rates (RR, 0.95; 95% CI, 0.74–1.21, $p = 0.66$) and 9% in overall bicycle crash rates (RR, 0.91; 95% CI, 0.77–1.08, $p = 0.28$). Effects of similar magnitudes were seen in the quasi-induced exposure analyses.

Discussion and Limitations
An early version of EyeSight reduced bicycle crashes in the parallel configurations it was designed to detect but did not have much effect on bicycle crashes overall. Crash configuration was identified by bicyclist and vehicle direction of travel when they were available. In states where direction of travel was unavailable, bicyclist precrash actions of cycling along the roadway with or against traffic and crossing were used as proxies for parallel and perpendicular configurations, respectively. The actual configurations of crashes in these states were unknown.

Conclusions and Relevance to Session Submitted
Although it is promising that an initial bicyclist detection system prevented crashes in parallel configurations, a minority of bicycle crashes are of this type. AEB systems will need to increase functionality and detect perpendicular crash configurations to meaningfully reduce bicycle crashes.

INTRODUCTION

Automatic emergency braking (AEB) systems, which typically warn drivers of an impending collision and apply the brakes if they do not respond to the warning, have been demonstrated to be effective in reducing vehicle-to-vehicle rear-end crashes [1-4] and crashes with pedestrians [5]. Because of its effectiveness, 20 U.S. automakers committed to make vehicle-to-vehicle AEB a standard feature on virtually all new passenger vehicles as of September 2022 [6], and the United States Department of Transportation [7] has pledged to begin rulemaking by 2024 to mandate AEB with pedestrian detection on new passenger vehicles.

Bicyclist detection is another feature that is being added to AEB. In the United States, this functionality is needed as a tool to potentially curb the increase in bicyclist fatalities that has occurred over the past decade. An estimated 985 pedalcyclists were killed in U.S. motor vehicle crashes in 2021 [8], which represents a 58% increase from the 623 cyclists who lost their lives in 2010. The number of U.S. bicyclists treated in emergency departments and admitted to hospitals has similarly risen over time [9].

Studies have estimated the potential benefits of AEB systems that detect cyclists [10,11], but little is known about their real-world effects on crashes. Recently, Kullgren et al. [12] reported that AEB with bicyclist detection was associated with a 21% reduction in bicyclist crash risk in Sweden. The goal of the current study was to investigate the effects of the first and second generations of Subaru's EyeSight, an AEB system that includes bicyclist detection, on bicyclist crash risk in the United States.

METHODS

Two approaches were used to examine the effects of EyeSight on bicyclist crash risk. First, the relationship of the system to bicycle crash rates per insured vehicle year was investigated. The second approach used the quasi-induced exposure technique to compare involvement in a bicycle crash with involvement in a crash type not relevant to EyeSight between vehicles that were and were not equipped with the system. The nonsensitive crash type in quasi-induced exposure is used as a proxy for driving exposure [13] and is thought to better account for differences in driving distance and conditions that are not captured when using insured vehicle years as the exposure measure.

EyeSight System

Study vehicles were model year (MY) 2013–2020 U.S. Subaru models that offered the first- or second-generation versions of EyeSight as an optional feature, including the MY 2013–2018 Legacy and Outback, 2014–2018 Forester, 2015–2019 Impreza, 2015–2020 Crosstrek, and 2016–2020 WRX. In its first and second generations in the United States, EyeSight was designed to detect cyclists in parallel scenarios but not in perpendicular ones. EyeSight is a feature that is discernable from the Vehicle Identification Number (VIN), and its presence or absence on vehicles was identified from decoding the VINs associated with crashes and insured vehicles.

Crash Data

Key variables from the crash databases of 16 U.S. states during calendar years 2014–2020 were coded into a common format for analysis (Appendix, Table A1). Bicycle crashes were defined as crashes involving one or more bicyclists in which the subject vehicle was not backing. Single-vehicle single-bicyclist crashes were further classified as having parallel or perpendicular crash configurations in two ways, depending on variable availability in each state. Configuration was based on the vehicle and bicycle directions of travel prior to the crash in the eight states where these variables were available. The crash had a parallel configuration if both the vehicle and cyclist were traveling along the same path (e.g., both east/west or both north/south), and a perpendicular one if they were traveling in intersecting paths (e.g., the vehicle was traveling north/south and cyclist east/west, or the vehicle was traveling east/west and the cyclist north/south).

The bicyclist's action prior to the crash was used as a surrogate for configuration in other states, with crashes where the cyclist was riding along the roadway with or against traffic categorized as parallel scenarios, and crashes where the cyclist was crossing considered to be perpendicular scenarios. When both variables were available, the configuration was established by the direction of travel, and bicyclist precrash action was considered when direction was missing. Nearly all single-vehicle single-bicyclist crashes were classified as having perpendicular or parallel configurations in states where vehicle/bicycle direction of travel were available unless direction was unknown. In states where bicyclist precrash action was used as a proxy for configuration, about one fourth of the bicyclists were coded with another precrash action (e.g., cycling on the sidewalk, adjacent to the roadway, playing in the roadway) and weren't included in analyses of crash configurations.

Rear-end-struck and side-struck crash involvements were also identified for use in the quasi-induced exposure analyses. A vehicle was considered rear-end struck if the manner of collision was a rear end and the point of impact was to the rear (5-, 6-, or 7 o'clock), and was side struck if the subject vehicle was impacted on the side (2-, 3-, 4-, 8-, 9-, or 10 o'clock) in a two-vehicle crash where the manner of collision was not a rear end by another vehicle with a frontal impact (11-, 12-, or 1 o'clock).

Insured Driver Data

Data on the number of days vehicles were insured were obtained from the Highway Loss Data Institute. Crash rates are expressed as crashes per insured vehicle year, with a single vehicle insured for 1 year or two vehicles insured for si6 months each equaling one insured vehicle year. 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.

Analyses

Analyses examining the relationship of EyeSight to bicycle crash rates per insured vehicle year used negative binomial regression models that controlled for vehicle model year and series combination, state, calendar year, driver age group (< 25, 25–64, 65 years and older), and driver gender.

Quasi-induced exposure analyses were performed using logistic regression with the same covariates as the negative binomial regression models. These analyses were limited to 14 states with variables for vehicle point of impact so that struck vehicles could be identified. The two states without these variables were large (New York and Washington), and so sample sizes were considerably smaller without them.

Rear-end-struck crash involvements were initially selected as the nonsensitive crash type. This crash type has been shown to vary close to linearly with exposure [13] and has been used in other quasi-induced exposure analyses examining the crash effects of AEB [2,3,5,12]; however, Cicchino [1] found that AEB was associated with a 20% increase in rear-end-struck crash-involvement rates per insured vehicle year, possibly due to more instances of hard braking when AEB is activated. If AEB increases the risk of being struck in the rear, treating that crash type as nonsensitive in the quasi-induced exposure analyses could result in biasing effect estimates towards showing a benefit. EyeSight was associated with a small (3%) but statistically significant increase in rear-end-struck crash rates per insured vehicle year in the current data set (Rate ratio [RR], 1.03; 95% confidence [CI], 1.00–1.06, $p = 0.04$). Thus, a second crash type, side-struck crash involvements, was used as the nonsensitive crash type in an additional set of quasi-induced exposure analyses.

Both methods were used to separately examine the association of EyeSight with (1) all bicycle crashes, (2) single-vehicle single-bicyclist crashes with parallel configurations, and (3) single-vehicle single-bicyclist crashes with perpendicular configurations. Vehicle series/model year combinations were removed from an analysis if they were involved in no bicycle crashes of the type examined (e.g., vehicles involved in no bicycle crashes with parallel configurations were excluded from analyses of parallel crash scenarios). Model parameters were exponentiated and interpreted as rate ratios (RRs) from negative binomial 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 EyeSight.

RESULTS

Study vehicles were involved in 856 bicycle crashes. A total of 822 of these were single-vehicle single-bicyclist crashes, of which 283 (34%) had parallel configurations and 387 (47%) had perpendicular configurations. Crash rates per insured vehicle year were lower for vehicles with EyeSight than without, with the largest difference seen in parallel-configuration crashes (Table 1).

Table 1.
Bicycle crash rates per insured vehicle year among Subaru vehicles with and without EyeSight

System	**Parallel configuration**		**Perpendicular configuration**		**All bicycle crashes**	
	Number	**Rate (x 100,000)**	**Number**	**Rate (x 100,000)**	**Number**	**Rate (x 100,000)**
With EyeSight	68	4.2	113	6.9	242	14.8
Without EyeSight	215	5.9	274	7.6	614	16.9
Total	283	5.4	387	7.4	856	16.3

Negative binomial regression revealed that when accounting for covariates, bicycle crash rates in parallel configurations were 29% lower among vehicles with EyeSight compared with the same models without the system (RR, 0.71; 95% CI, 0.53–0.96, $p = 0.03$; Table 2). In contrast, there were smaller and nonsignificant differences of 5% in rates of perpendicular (RR, 0.95; 95% CI, 0.74–1.21, $p = 0.66$) and 9% of all (RR, 0.91; 95% CI, 0.77–1.08, $p = 0.28$) bicycle crashes per insured vehicle year between vehicles with and without EyeSight.

Table 2.
Model results of association of EyeSight with bicycle crash risk

Analysis	**Parallel configuration**	**Perpendicular configuration**	**All bicycle crashes**
	RR (95% CI)	**RR (95% CI)**	**RR (95% CI)**
Negative binomial regression	0.71 (0.53, 0.96)*	0.95 (0.74, 1.21)	0.91 (0.77, 1.08)
	OR (95% CI)	**OR (95% CI)**	**OR (95% CI)**
Quasi-induced exposure (rear-end-struck nonsensitive crash type)	0.72 (0.49, 1.05)$^{+}$	0.99 (0.73, 1.35)	0.93 (0.76, 1.15)
Quasi-induced exposure (side-struck nonsensitive crash type)	0.69 (0.47, 1.00)$^{+}$	0.95 (0.70, 1.29)	0.87 (0.71, 1.08)

Abbreviations: CI, confidence interval; OR, odds ratio; RR, rate ratio.
$^{*}p < 0.05$. $^{+}p < 0.10$.

Analyses using quasi-induced exposure included 571 total bicycle crashes, 181 with parallel configurations, and 259 with perpendicular configurations. Study vehicles in the quasi-induced exposure states were involved in 34,593 rear-end-struck crashes and 10,105 side-struck crashes. Effect sizes in quasi-induced exposure analyses were similar to models examining crash rates per insured vehicle year (Table 2), but the association of EyeSight with parallel configurations was no longer statistically significant ($p = 0.09$ for analysis using rear-end-struck crashes as nonsensitive crash type, $p = 0.05$ for analysis using side-struck crashes). The smaller sample sizes in the quasi-induced exposure analyses limited statistical power, especially when examining crash configurations.

DISCUSSION

The first and second generations of EyeSight were effective in the United States at reducing bicycle crashes in the parallel configuration they were designed to detect, but this did not translate into a consequential decline in bicycle crashes overall. It is well-documented that while parallel scenarios are overrepresented in fatal bicycle crashes, they are not the most frequent scenario when considering bicycle-motor vehicle crashes of all severities. MacAlister and Zuby [14] reported that in the United States during 2008–2012, the cyclist was in-line or against traffic in 28% of single-vehicle crashes involving the fronts of passenger vehicles and was crossing traffic in 54%. Crossing crashes similarly make up the majority of bicycle-motor vehicle crash scenarios in Europe [15,16]. AEB with bicyclist detection will need to respond in perpendicular scenarios as well as parallel ones to reduce bicycle crashes meaningfully.

Fortunately, systems with this functionality currently exist in production. The third generation of EyeSight, which was introduced in the United States on the MY 2022 Forester and WRX, adds detection of cyclists traveling in a path perpendicular to the vehicle. The MY 2023 Subaru Outback, Legacy, and Ascent are available with a third mono camera that expands the field of view of EyeSight and could potentially detect cyclists sooner in crossing scenarios. Euro NCAP [17] tests AEB with bicyclist detection in both crossing and longitudinal scenarios, which encourages automakers in the European market to equip vehicles with systems that perform well in both configurations. Future research can examine the real-world effects of these systems in the United States when enough crash data amass to study them.

AEB has been shown to struggle in some challenging vehicle-to-vehicle and pedestrian crash circumstances, which could also limit the potential effectiveness of AEB with bicyclist detection. Cicchino [5] found that AEB with pedestrian detection is not associated with pedestrian crash risk reductions in the dark, and Kullgren et al. [12] reported that a lack of efficacy in the dark extends to AEB with bicyclist detection in Sweden. Like with pedestrians, bicyclist fatalities disproportionally occur in the dark [14], and so AEB systems will need to work well in the dark to prevent deaths. Cyclists are at a greater fatality risk when involved in crashes with higher vehicle speeds, which has also been associated with lower efficacy for AEB with pedestrian detection [5]. Crashes where the subject vehicle is turning are challenging for vehicle-to-vehicle and pedestrian AEB [5,18], and while this scenario is not associated with increased injury severity, it is common; in U.S. national crash data, vehicle-turning scenarios make up more than 40% of single-vehicle bicycle crashes involving the fronts of passenger vehicles [14].

The constraints on situations where AEB with bicyclist detection may be effective underscore the need to implement other vehicle features, policies, and roadway design modifications that improve safety for cyclists. Better headlights [19] and roadway lighting [20] make it easier for drivers to see cyclists at night and lower nighttime crash risk. Treatments that lower vehicle speeds, such as traffic calming or lowering speed limits in urban areas, have been demonstrated to reduce injury risk for cyclists [21,22]. Geometric design features, like smaller curb radii, and pavement markings can decrease driver conflicts with cyclists while turning at intersections [23]. Raised bicycle crossings are associated with fewer bicycle-motor vehicle crashes at unsignalized intersections [24] and could reduce bicycle-motor vehicle crashes in perpendicular scenarios. Multiple types of countermeasures need to be used so that bicyclists can operate within a safe system.

Limitations

Data elements collected in police reports vary by state in the United States, and information pertaining to bicycle crashes is known to be inconsistent among states [25]. The classification scheme for identifying bicycle crashes as having occurred in parallel and perpendicular scenarios was meant to be an approximation for the actual crash configuration to focus the analysis on crash types that were likely (parallel) and unlikely (perpendicular) to be detected by the first and second generations of EyeSight. It is expected, though, that there were errors in these classifications. For example, direction of travel is meant to capture the cyclist's and vehicle's direction prior to the crash, but the direction recorded when the cyclist or vehicle was turning may not be consistently coded. Codes for bicyclist action prior to the crash do not account for the driver's action, and while it seems logical that crashes where the police coded the bicyclist as crossing were unlikely to be in parallel configurations, in-depth information on actual crash configurations was not available in state crash databases. The percentage of single-vehicle single-bicyclist crashes in this study that were categorized as parallel was higher than what would be expected from U.S. national crash statistics, and the percentage categorized as perpendicular was lower, suggesting that parallel configurations were overcounted and perpendicular ones undercounted. If this were the case, the effect estimate for EyeSight in parallel scenarios may have been underestimated.

EyeSight was an optional system on the vehicle models studied in this analysis, and drivers who chose to purchase it may drive differently than those who did not. Using the quasi-induced exposure technique and controlling for driver demographic characteristics in the analyses may have accounted for some aspects of driving exposure differences between these groups. Although rear-end-struck crashes are frequently used as the nonsensitive crash type in quasi-induced exposure analyses of AEB effects, Subaru vehicles with EyeSight experienced a rear-end-struck crash rate per insured vehicle year that was 3% higher than vehicles without the system, which may have inflated effect size estimates in the analysis using this crash type. It is encouraging that corroborating results were found in the analysis examining bicycle crash rates per insured vehicle year and in the quasi-induced exposure analysis using side-struck crash rates as the nonsensitive crash type. The small sample size by crash configuration is an additional limitation, especially in the quasi-induced exposure analysis, which restricted statistical power.

CONCLUSION

AEB systems that detect bicyclists have great potential to prevent motor vehicle crashes with bicyclists, but they need to be able to detect the most common crash configurations to make a difference in the overall crash picture. Currently available systems that can detect cyclists in perpendicular scenarios, including the third generation of EyeSight in the United States, should be more effective at reducing bicycle crashes as a whole than the first and second generations of EyeSight.

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APPENDIX

Table A1.
Police-reported crash data availability with variables for vehicle and bicyclist direction of travel, bicyclist action prior to the crash, and vehicle point of impact by state and year

U.S. state	Years available	Vehicle and bicycle direction of travel	Bicyclist action prior to crash	Vehicle point of impact
Connecticut	2017–2020		X	X
Florida	2014–2019		X	X
Idaho	2014–2020	X	X	X
Illinois	2014–2020		X	X
Maryland	2014–2020		X	X
Minnesota	2016–2020		X	X
Missouri	2014–2020	X		X
New Jersey	2014–2020	X		X
New Mexico	2014–2020	X		2019–2020 only
New York	2014–2019	X	2014–2015 only	
Ohio	2017–2020	X		X
Pennsylvania	2014–2020	X		X
Utah	2014–2019		X	2014–2016, 2018 only
Washington	2014–2020		X	
Wisconsin	2014–2019	2014–2016 only	2017–2019 only	X
Wyoming	2014–2020		X	X