PARTS
PARTNERSHIP FOR ANALYTICS
RESEARCH IN TRAFFIC SAFETY

A Study on Real-world Effectiveness of Model Year 2015–2023 Advanced Driver Assistance Systems

January 6, 2025

To learn more about the work of this partnership, visit NHTSA.gov/PARTS.

Acknowledgments

PARTS is deeply grateful for the following individuals' contributions of time and expertise – as well as the in-kind contributions of their respective organizations – to this study and report. Without your spirited collaboration, this groundbreaking work would not have been possible.

Special thanks to the PARTS Research Working Group members and partners for their countless hours, expertise, and attention to detail in leading the execution of the study. They are denoted with an asterisk (*).

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1 Executive Summary

The National Highway Traffic Safety Administration (NHTSA) estimates that 2.38 million people were injured in traffic crashes on United States (U.S.) roadways in 2022 and 40,990 people lost their lives on our roadways in 2023 [1] [2]. Advanced driver assistance systems (ADAS) in motor vehicles have the potential to reduce these crashes, prevent serious injuries, and save thousands of lives each year. As automobile manufacturers increasingly equip vehicles with ADAS, there is a growing need to study and understand the safety benefits of these technologies and identify opportunities to improve them [3]. The Partnership for Analytics Research in Traffic Safety (PARTS) was formed in 2018 as an independent, voluntary data sharing partnership among automobile manufacturers and the U.S. Department of Transportation's (USDOT) NHTSA to address this need.

Eleven original equipment manufacturers (OEM) currently participate in PARTS, including: American Honda Motor Company, Ford Motor Company, General Motors LLC, Hyundai Motor America, Kia America, Mazda North American Operations, Mitsubishi Motors R&D of America, Nissan North America, Stellantis (Fiat Chrysler Automobiles US LLC), Subaru Corporation, and Toyota Motor North America. The not-for-profit MITRE Corporation (MITRE) operates PARTS as an independent third party; MITRE conducted this study at the direction of and in collaboration with the PARTS partners.

Study Background

This study examined the real-world effectiveness of five ADAS features in passenger vehicles in reducing system-relevant crashes:

- Automatic emergency braking (AEB)
- Pedestrian automatic emergency braking (PAEB)
- Lane departure warning (LDW)
- Lane keeping assistance (LKA)
- Lane centering assistance (LCA).

Expanding on a previous PARTS analysis conducted in 2022 [4], this study evaluated:

- To what extent does AEB reduce front-to-rear crashes? Further, to what extent does AEB effectiveness change based on:
  - The striking vehicle's weight?
  - The struck vehicle's body class (e.g., motorcycle, tractor trailer)?
  - NHTSA's New Car Assessment Program (NCAP) testing performance results?
- To what extent does PAEB reduce single-vehicle frontal crashes with non-motorists? Further, to what extent is PAEB effectiveness at night influenced by auto-high beam (AHB) headlights?
- To what extent do LDW, LKA, and LCA reduce single-vehicle road-departure crashes?
- To what extent has the effectiveness across ADAS feature generations improved, as measured in model years?
- Does ADAS feature effectiveness vary under different driver, environmental, crash, or vehicle characteristics?

Study Data

This study generated the most comprehensive dataset on ADAS system-relevant crashes to date. It covered 98 million vehicles from 168 models spanning model years 2015–2023 contributed by nine OEM partners that were involved in 21.2 million police-reported crashes across 16 states from 2016–2023. The study linked standardized vehicle and crash data, resulting in 7.7 million crash-involved vehicles, 2.1 million of which were relevant to the ADAS features studied. Compared to the previous effort, this study included data from three additional states, three new model years, and 75 more vehicle models, nearly tripling the amount of study data available. This expanded dataset enabled more detailed analyses of system attributes and crash characteristics.

This cross-industry analysis included features with a range of capabilities and parameters that vary by OEM, vehicle model, model year, and trimline specifications and considered whether a vehicle was equipped with a given ADAS feature at the time of manufacture. It did not include whether that feature was on or activated at the time of crash.

Key Findings

The study measured a 49% reduction in front-to-rear crashes for vehicles equipped with AEB across all vehicle segments and model years. Further, the study measured a statistically significant improvement in the reduction of rear-end crashes, from 46% across model years 2015–2017 to 52% across model years 2021–2023, indicating that advancements in AEB over time have yielded tangible benefits.

For every 1,000-pound decrease in vehicle weight, the study measured an approximate 4% reduction in front-to-rear crashes for vehicles equipped with AEB. Understanding this effect is crucial as vehicle weight increases on U.S. roads [5].

The study also measured a 9% reduction in single-vehicle frontal crashes with non-motorists for vehicles equipped with PAEB, marking the first time PARTS has quantified a statistically significant measure of PAEB effectiveness.

Systems with active interventions (LDW + LKA and LDW + LKA + LCA) showed effectiveness in reducing single-vehicle road-departure crashes, although rates were low and varied with speed limit.

Future Growth

As a unique and evolving public-private partnership, PARTS is pioneering research approaches that are only possible through collaboration. The results of this study offer valuable insights into how, where, and when ADAS technologies are most effective, and where there are opportunities for improvement as the industry works toward manufacturing and fielding safer vehicles.

PARTS partners plan to further collaborate on research efforts, both expanding this analysis as ADAS deployment increases and exploring new research areas. Future work will measure crash severity reduction, an important aspect of ADAS effectiveness, and consider incorporating other data sources, such as telematics.

2 Background

Over the last decade, the automobile industry has deployed many innovative solutions, including ADAS, to improve traffic safety. The goal of these systems is to reduce the number and severity of traffic crashes, thereby preventing serious injuries and saving lives. Today, automobile manufacturers (or OEMs) equip their vehicles with an increasing number of ADAS features with ever-advancing capability. As some of these features are now predominantly standard in today's vehicles, there is a continued need to understand the evolving safety benefits of these technologies and identify opportunities to improve them.

PARTS was formed to address this need through a collaborative data sharing and analysis approach. By combining equipment data from millions of vehicles with millions of crash reports, PARTS has now completed its second in-depth analysis of ADAS effectiveness. The studied ADAS features included were automatic emergency braking (AEB), pedestrian automatic emergency braking (PAEB), lane departure warning (LDW), lane keeping assistance (LKA), and lane centering assistance (LCA).

PARTS conducted this study to further a collective, improved understanding of how these ADAS technologies perform in real-world operations to drive innovation and continuous improvements in safety performance, thereby further reducing crashes, serious injuries, and fatalities on roadways.

2.1 PARTS Overview

PARTS, established in 2018, is a public-private partnership between automobile manufacturers and NHTSA. The goal of this government-industry collaboration, operated by MITRE as an independent third party (ITP), is to advance traffic safety through the collaborative analysis of automotive safety technologies, with partners voluntarily sharing safety-related data for joint analysis.

Of the 11 OEMs participating in PARTS (see Figure 1), nine provided vehicle data for this study, accounting for more than 80% of the 2023 U.S. passenger car and light truck market sales [6].

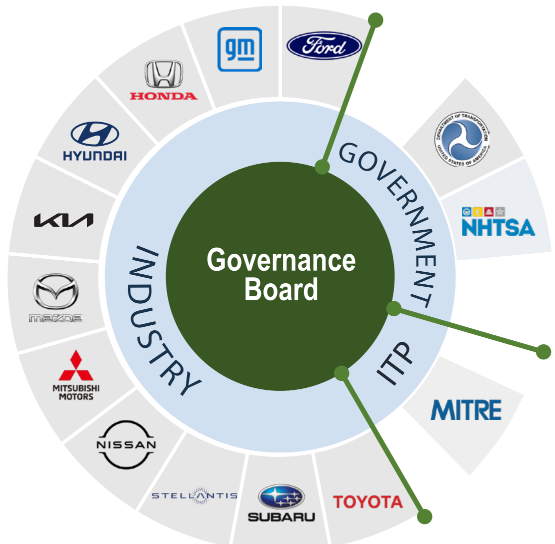


Figure 1. PARTS Participation

2.2 ADAS Effectiveness Study Overview

This 2024 ADAS Effectiveness Study is modeled after the 2022 PARTS Study and expands upon its breadth and scale. OEM partners provided vehicle equipment data for approximately 98 million passenger vehicles sold in the U.S., including 168 vehicle models from model years 2015–2023 and covering 10 vehicle segments (see Figure 4). This vehicle equipment data enabled the identification of ADAS features present on the vehicle at the time of manufacture. MITRE combined this data with police-reported crash data from 16 states, spanning from 2016 to 2023. This resulted in a dataset of 7.7 million crash-involved vehicles, 2.1 million of which were relevant to the ADAS features studied. Compared to the 2022 PARTS Study, the 2024 study included data from three additional states, three new model years, and 75 more vehicle models, nearly tripling the amount of study data available.

MITRE, in collaboration with the data-providing PARTS partners, used this linked and updated dataset to answer several initial research questions:

- To what extent does AEB reduce front-to-rear crashes?
- To what extent does PAEB reduce frontal non-motorist crashes?
- Does PAEB effectiveness at night change based on AHB headlights?
- To what extent do lane centering and departure features reduce single-vehicle road-departure crashes?

In addition, the study assessed whether a given ADAS feature's effectiveness changed under different driver, environmental, crash, or vehicle conditions (e.g., dark vs. dawn/dusk vs. daylight condition, speed limits, dry vs. wet roads, driver age and gender) and quantified the magnitude of the change where appropriate.

With a larger dataset than the previous 2022 study, PARTS partners expanded the research questions in this study to better understand AEB effectiveness across selected system attributes or crash characteristics, and to better understand ADAS effectiveness over time. These research questions included:

- Does AEB effectiveness differ based on striking vehicle weight?
- Does AEB effectiveness change by struck vehicle body type (e.g., motorcycle, tractor trailer)?
- Does AEB effectiveness differ based on NHTSA's NCAP testing performance results?
- Are we seeing measurable improvements to ADAS feature effectiveness across model years?

This study focused on the effectiveness of the ADAS systems in avoiding crashes rather than on reducing crash severity. Future research may explore how effective these systems are in mitigating injuries or reducing the severity of injuries during such crashes.

2.3 ADAS Features Studied

The study analyzed five ADAS features for system-relevant crashes, as shown in Figure 2. These ADAS definitions are consistent with names and definitions used in the 2022 PARTS Study.

All vehicles equipped with AEB in this study were also equipped with forward collision warning (FCW). Due to the low rate of newer models equipped solely with FCW, the study focused on vehicles with AEB rather than conducting a separate analysis of vehicles equipped only with FCW.

ADAS Feature (Acronym) Definition	Visual	System-relevant Crash
Automatic Emergency Braking (AEB) detects potential collisions with a vehicle ahead and automatically brakes to help avoid a collision or lessen the severity of impact.		Front-to-rear
Pedestrian AEB (PAEB) detects potential collisions with a pedestrian ahead and automatically brakes to help avoid a collision or lessen the severity of an impact.		Non-motorist
Lane Departure Warning (LDW) monitors the vehicle's position within the driving lane and can alert the driver as the vehicle approaches or crosses lane markers.		
Lane Keeping Assistance (LKA) provides momentary steering support to assist the driver in preventing the vehicle from departing the lane (when lanes are clearly marked).		Single-vehicle road-departure
Lane Centering Assistance (LCA) provides steering support to assist the driver in continuously maintaining the vehicle at or near the center of the lane.		

Figure 2. Five ADAS Features Included in this PARTS Study

2.4 Crash Types Studied

Each ADAS feature studied was mapped to a system-relevant crash type, as defined in Table 1. For example, in PAEB, the target population included single-vehicle frontal crashes with non-motorists (e.g., pedestrians, cyclists, scooters, and wheelchairs). In lane departure crashes where two vehicles were involved, the study was unable to distinguish which vehicle initially left its lane, due to data limitations. As such, this study focused on the effectiveness of LDW, LKA, and LCA in single-vehicle road-departure crashes rather than in sideswipe crashes involving vehicles traveling in the same or opposite directions.

As described in Section 3.4, the study used quasi-induced exposure (QIE) as the primary method to measure ADAS effectiveness. QIE compares vehicles equipped with the set of ADAS features under study against vehicles without those features, called control crashes. A control crash is assumed to be system irrelevant, meaning independent from and not related to the ADAS feature it is intended to measure. The control crash was the same (front-to-rear struck) for all ADAS features; it is described in the last row of Table 1. The system-relevant crash types and control crash type are the same as those used in the 2022 PARTS Study. The control crash type is the standard choice for these systems for QIE studies: [7] [8] [9].

Table 1. ADAS Feature System-relevant Crash Type and Control Crash Definitions

ADAS Features	Target Crash Type	Definition
AEB	Front-to-rear **Striking**	Manner of Crash = Front-to-rear AND Initial Contact Point[1] = [1, 12, 11] AND Motor Vehicle Maneuver Action NOT (backing or parked) AND Crash Vehicle Count = 2
PAEB	Single-vehicle Frontal Crashes with Non-motorists	Crash Pedestrian Count > 0 AND Crash Vehicle Count = 1 AND First Event or First Harmful Event = Pedestrian or Non-motorist AND Initial Contact Point = [1, 12, 11] AND Motor Vehicle Maneuver Action NOT (backing or parked)
Lateral (LDW, LKA, LCA)	Single-vehicle Road Departure	Crash Vehicle Count = 1 AND First Event or First Harmful Event = Ran Off Road, Cross Centerline, Cross Median, Collision with Fixed Objects, Rollover AND Vehicle Maneuver Action = any of {Going Straight, Negotiating a Curve, Leaving Traffic Lane, Ran Off Road}
Control	Front-to-rear **Struck**	Manner of Crash = Front-to-rear AND Initial Contact Point = [5, 6, 7] AND Motor Vehicle Maneuver Action NOT (backing or parked) AND Crash Vehicle Count = 2

[1] Most states included in this study use clock coordinates to indicate initial point of contact for crashes (where the front center of a vehicle is 12 o'clock). PARTS considered values of 5, 6, or 7 o'clock to be rear. Some states used descriptions such as "rear," "right rear bumper," and "rear – left." PARTS mapped related phrases and clock coordinates to the construct of "rear." PARTS used a similar mapping technique to harmonize the construct of "front" given varied state crash data.

3 Data and Methodology

3.1 Data Overview

This section provides an overview of the nature, scope, and size of the data sources used for this PARTS study and how these sources were prepared for analysis. Table 2 shows a summary of study data size and scope.

Table 2. Summary of Study Size and Scope

Number of vehicles	98 million sold in the U.S.
Total number of crash-involved vehicles	7.7 million crash-involved vehicles
System-relevant crash-involved vehicles	2.1 million crash-involved vehicles
Number of OEMs providing data	9
Number of vehicle models and vehicle segments	168 across 10 vehicle segments
Model years	2015–2023
Number of states and timeframe	16 states providing crash data from 2016–2023

To create the in-scope study dataset, multiple data sources were merged in preparation for analysis, as illustrated in Figure 3 below.

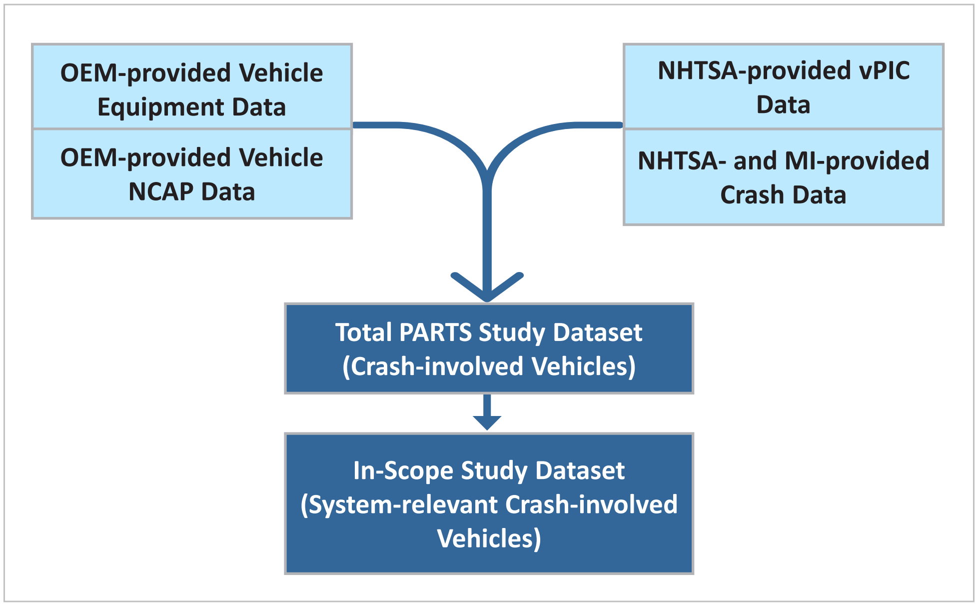


Figure 3. Data Sources

This PARTS study used four primary data sources:

- **Vehicle Equipment Data** included OEM-provided data on all passenger vehicles from model years 2015–2023 sold in the U.S. that met the selection guidance (see Section 3.1.1).
- **Crash Data** included police-reported crash data from 2016–2023 from 15 states (provided by NHTSA), and Michigan police-reported crash data from 2016–2022 (provided by Michigan State Police).
- **Vehicle NCAP Data** consisted of OEM-provided data on submissions to NHTSA's NCAP[2], including safety test results at the level of make, model, and model year for model years 2018–2023.
- **NHTSA's Vehicle Product Information Catalog (vPIC) Data** included vehicle type and body class (provided by NHTSA) that has been linked to NHTSA crash data.

3.1.1 Vehicle Equipment Data

Vehicle data included the ADAS features on each vehicle, build date, sold or customer delivery date, sales market (used to filter U.S.-only car market), and sale type (retail or fleet). This study's results are based on data from the following OEM partners:

- American Honda Motor Company – includes the Honda and Acura brands
- Ford Motor Company
- General Motors LLC – includes the Buick, Cadillac, Chevrolet, and GMC brands
- Hyundai Motor Company
- Mazda North American Operations
- Mitsubishi Motors R&D of America
- Stellantis (Fiat Chrysler Automobiles US LLC) – includes the Alfa Romeo, Chrysler, Dodge, Fiat, Jeep, and Ram brands
- Subaru Corporation
- Toyota Motor North America – includes the Toyota and Lexus brands.

The dataset included 98 million vehicles from 168 models, covering model years 2015–2023, manufactured on or before July 31, 2023. The vehicles were categorized into 10 segments based on their size and intended use, as shown in Figure 4: small car, midsize car, large car, small sport utility vehicle (SUV), midsize SUV, large SUV, midsize pickup, full-size light-duty pickup, full-size heavy-duty pickup, and minivan. PARTS determined these vehicle segments using the Insurance Institute for Highway Safety (IIHS)-Highway Loss Data Institute (HLDI) vehicle segment definitions, with some modifications.[3]

[2] NCAP references made in this report refer to the program before its November 2024 update on Advanced Driver Assistance Systems, which are effective for the 2026 model year [27].

[3] Modifications adjusted the segments to ensure there were at least three models within a segment; assigned model twins to the same segment when vehicle specifications were sufficiently similar based on OEM input about vehicle mass, structure, or other commonalities; and adjusted the midsize SUV criteria, which had the effect of moving some three-row SUVs from the small SUV to the midsize SUV segment.

	Original Equipment Manufacturer (OEM)									
	FORD	GM	HONDA	HYUNDAI	MAZDA	MITSUBISHI	STELLANTIS	SUBARU	TOYOTA	Total
Small Car	Fiesta Focus	ATS, CT4, Cruze, Volt, Bolt EV, Sonic, Spark	ILX (Integra) Civic, Fit, Insight	Accent Veloster	Mazda3-4Dr & HB	Mirage Mirage G4		Impreza WRX Crosstrek BRZ /GT86	Corolla 4Dr & HB, Prius, C-HR	27
Midsize Car	MKZ Fusion Mustang	Malibu Regal Verano CTS	TLX Accord	Elantra G70 Ioniq 6	Mazda6		Alfa Romeo Giulia Chrysler 200	Legacy Outback	Camry Lexus IS	19
Large Car	Taurus Continental MKS	Impala LaCrosse CT5, CT6, XTS		G80 G90 Sonata			Chrysler 300 Charger Challenger		Avalon ES LS Crown	18
Small SUV	EcoSport, Escape, Corsair, MKC, Bronco Sport	Equinox, Terrain, Envision, Encore, Encore, GX, XT4, Trailblazer, TRAX	RDX HR-V CR-V	GV60, Ioniq Kona Tuscon, Venue	CX-3, CX-5, CX-30, CX-50 MX-30 (EV)	Outlander Sport Eclipse Cross	Renegade Compass	Forester	RAV4, NX, Venza, Corolla Cross UX	38
Midsize SUV	Bronco, Edge Explorer, Nautilus, Aviator, Mustang Mach-E (EV)	Acadia, Enclave, Traverse, SRX, XT5, XT6, Blazer, Lyriq (EV)	MDX Pilot Passport	GV70 GV80 Palisade Sante Fe	CX-9	Outlander Outlander PHEV	Durango, Cherokee, Grand Cherokee, Stelvio, Wrangler 4DR	Ascent	Highlander RX, 4Runner, GX BZ4X/Solterra (EV)	35
Large SUV	Expedition Navigator	Tahoe, Yukon Yukon XL Suburban Escalade					Wagoneer Grand Wagoneer Gladiator		Sequoia	9
Midsize Pickup	Maverick Ranger	Colorado Canyon	Ridgeline	Santa Cruz			Jeep Gladiator		Tacoma	8
Full-Size Light Duty Pickup	F-150 F-150 Lightning (EV)	Sierra LD Silverado LD					Ram 1500		Tundra	6
Full-Size Heavy Duty Pickup	F-250 (Super Duty)	Sierra HD Silverado HD Hummer (EV)					Ram 2500			5
Minivan			Odyssey				Pacifica		Sienna	3
	26	44	14	19	9	6	18	8	24	168

Figure 4. Vehicle Data: Mapping Models to Segments

PARTS selected the models in Figure 4 based on the following guidelines:

- **Sufficient Sample Size:** The minimum sales threshold was 5,000 units per year and per model, which helped ensure a sufficient sample size for analysis.
- **ADAS Features:** At least one model year for each model was required to have at least one ADAS feature in scope for the analysis.
- **Study Scope:** Vehicle weight as measured by Gross Vehicle Weight Rating (GVWR) less than 10,000 pounds.
- **Non-attribution:** Among other data protection measures, PARTS required vehicle models from at least three OEMs in a vehicle segment in order to maintain anonymity of the results.

3.1.2 Crash Data

This study used police-reported crash data from 16 states. Data from 15 of these states was provided by NHTSA through its Consolidated State Crash (CSC) database, which consolidates police-reported crashes received from states through the new Electronic Data Transfer (EDT) process. In addition to the CSC data, Michigan crash data was provided by the University of Michigan Transportation Research Institute (UMTRI) with permission from the Michigan State Police. The data used in each case was a census of all police-reported crashes in those states. Data was limited by what was available in the original state-level crash report. Specific fields and data elements varied by state.

This study focused on crashes that occurred between January 2016 and September 2023, with some variation across the 16 states included in the analysis, as shown in Figure 5. Although additional states were available in the EDT-driven CSC data, they were not included in this study due to insufficient years of data or missing critical fields necessary for analysis.[4] The crash data encompassed a total of 21.2 million crashes involving 36.8 million vehicles across the 16 states.

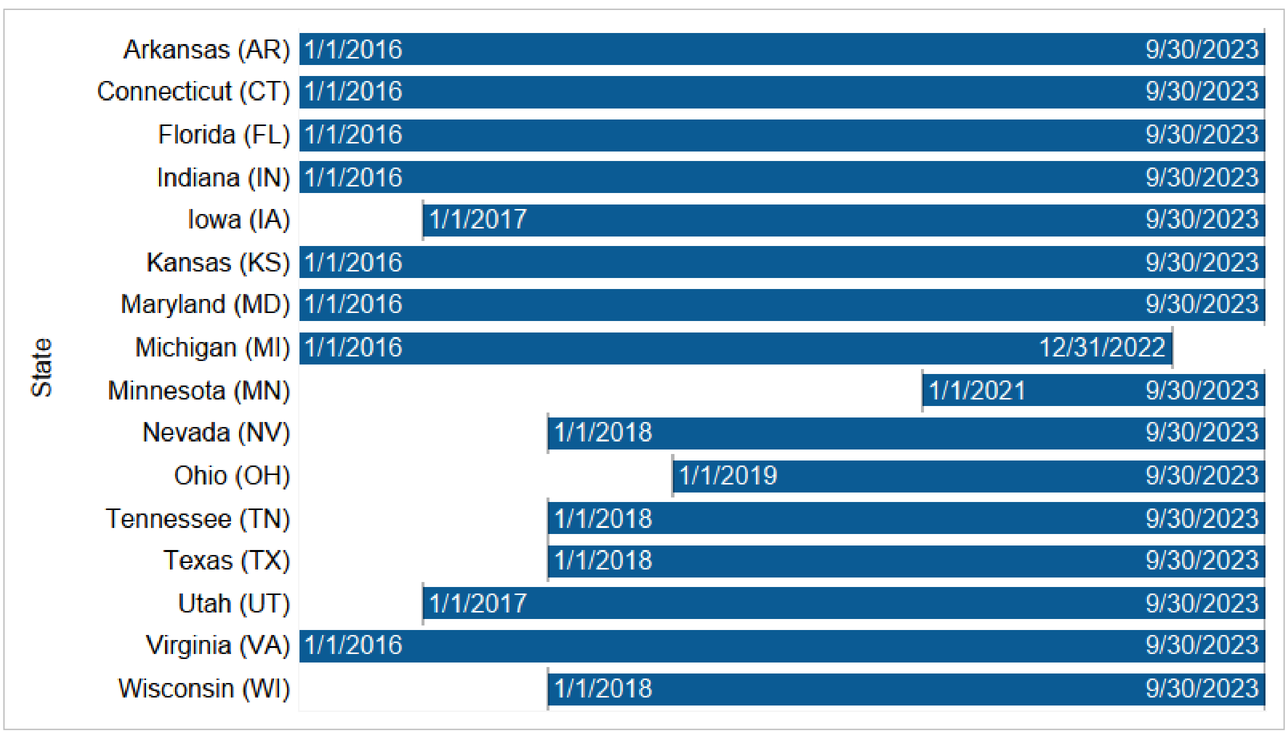


Figure 5. Crash Data by State and Time Period Covered

[4] States with available crash data that PARTS considered and ultimately decided not to use are California, Illinois, Maine, Nebraska, and Washington.

3.1.3 New Car Assessment Program (NCAP) Data

NHTSA's NCAP, which created the 5-Star Safety Ratings system, is a program designed to evaluate the safety performance of new vehicles and provide consumers with information to help them make informed purchasing decisions. NCAP conducts a series of crash tests on new vehicles, including frontal, side, and rollover tests, to assess their safety performance. The program also evaluates the availability and performance of advanced safety technologies [10].

The data is provided to NHTSA's NCAP program through a series of controlled crash tests per NCAP's test procedures conducted by OEMs and then selectively verified through independent testing by NHTSA. For this study, PARTS OEM partners provided the same data that were submitted to NCAP. OEM-provided vehicle NCAP data included performance test results by make, model, and model year covering a range of model years from 2018 to 2023. Specifically, the testing criteria and testing performance results from the NCAP Dynamic Brake Support (DBS) and Crash Imminent Braking (CIB) testing performance were used and standardized to facilitate linking with the other study data sources and to get the data in a usable form for analysis. DBS and CIB systems are part of the broader assessment of a vehicle's AEB capabilities. DBS systems increase braking effort initiated by the driver during collision-imminent situations if the driver's response is determined (by the system) to be insufficient to avoid the collision. CIB systems operate automatically to energize the brakes in crash-imminent situations if the driver does not respond to the warnings [11].

Unlike the vehicle equipment data, which was available at the VIN level, the NCAP data was provided at a broader level, encompassing the make, model, model year, and sometimes the trim or body type. To integrate the NCAP data with the vehicle equipment data, the entries were matched based on the make, model, and model year, and then aggregated at the trim or body type level. As a result, a few models and model years in the vehicle equipment database did not have a corresponding NCAP record, and therefore, those specific models and model years could not be linked to crash data at the VIN level.

3.1.4 NHTSA vPIC Data

The NHTSA vPIC is a comprehensive database that provides detailed information about vehicles registered in the U.S. It is intended to serve as a centralized source for basic VIN decoding, manufacturer information databases, manufacturer equipment plant identification, and associated data [12]. vPIC serves as a valuable tool for researchers who need accurate and detailed vehicle information for their studies. The crash data NHTSA provided through its CSC database was linked with the vPIC database via Crash ID and Crash Vehicle ID. The crash data received from Michigan contained fields similar to some of the fields found in the vPIC table from NHTSA. The specific data fields used in this study from the vPIC table included Vehicle Type and Body Class, which were combined into one field as "Vehicle Body Type" used in AEB attribute analysis (see Section 4.2.2). While the Vehicle Body Class information supplied in the Michigan data was available only for cargo and commercial vehicles, the Vehicle Type field aligned well with the vPIC information and was available for most of the vehicles in the dataset.

3.1.5 Preparing and Linking Data Sources

The data linkage process involved harmonization of crash and vehicle equipment datasets to enable comprehensive analysis. For crash data, raw values from police reports and state formats were mapped to standardized values, such as by using a clock-face reference for vehicle initial contact points. This process also added additional derived fields such as crash type and whether a vehicle was striking or struck. For vehicle equipment data, MITRE worked directly with OEMs to map their VIN-level records to standardized ADAS features, ensuring accuracy through consistent definitions and quality checks. The standardized datasets were then linked using the 17-digit VIN, resulting in a dataset with records for each crash-involved vehicle that matched the OEM-provided build data, totaling 7.7 million crash-involved vehicles, 2.1 million of which were relevant to the ADAS features studied.

An additional dataset was created that paired vehicles involved in the same front-to-rear crash, including both partner and non-partner vehicles. This dataset also included NCAP test results for partner vehicles and vehicle body type from the vPIC data. It contained 1.8 million crash records, enabling the AEB attribute analysis in front-to-rear crashes.

3.2 Descriptive Statistics of the Study Dataset

Figure 6 shows that the number of linked crashes generally increased over the years. The exceptions occurred in 2020, due to COVID-related lockdowns, and in 2023, because only part of the year was included in the study. It is also worth noting that the set of states also increased as the crash year increased, particularly in 2018 with the additions of Nevada, Tennessee, Texas, and Wisconsin. As model years advanced, the number of years available for observing crashes decreased. For instance, a 2015 model year vehicle could be involved in crashes from 2016 to 2023, while a 2023 model year vehicle could only be involved in crashes in 2022 or 2023. As a result, the crash sample used in the effectiveness analysis was biased toward crashes occurring later in the study period and involving older model year vehicles.

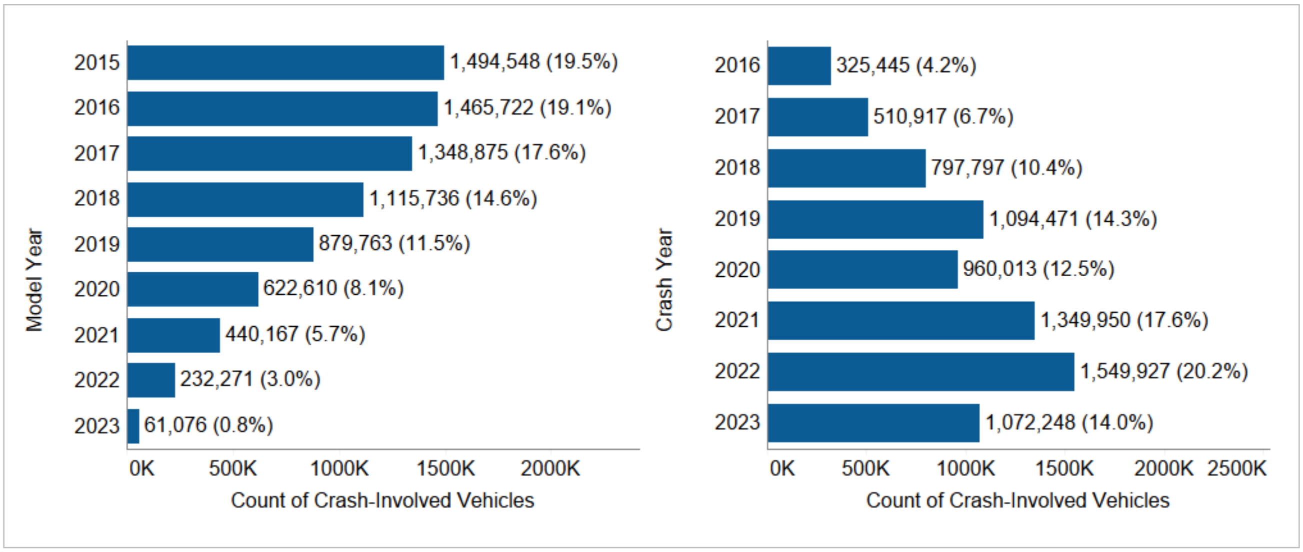


Figure 6. Linked Crash-involved Vehicle Counts Across All Crash Types by Crash Year and Model Year

The distribution of linked crashes by vehicle segment varied widely, as seen in Figure 7. For example, the small SUV segment made up a higher proportion of crashes in the sample than the full-size heavy-duty pickup segment. The largest reason for the difference is that the dataset included many more vehicles in the small SUV segment than the full-size heavy-duty pickup segment due to higher sale volumes. Differences in crash rates also may have contributed.

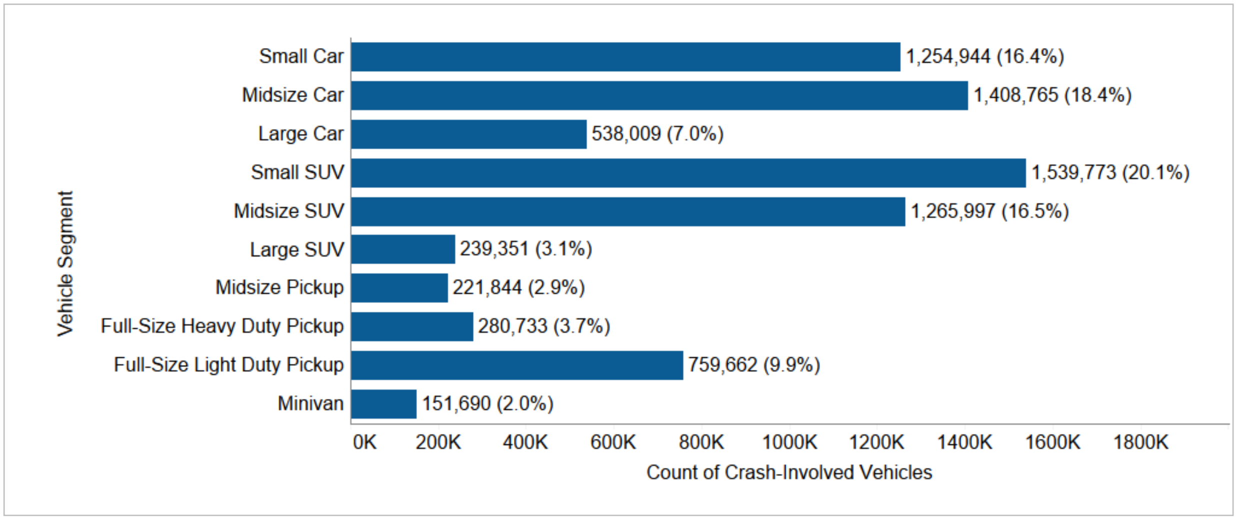


Figure 7. Distribution of Crash-involved Vehicles by Vehicle Segment

Figure 8 shows that the count of linked crashes can also vary widely by state. Half of the linked crashes occurred in Florida or Texas. While the primary contributor of the proportion of crashes by state is population, there are additional factors that may also account for these differences:

- The number of vehicles operating in each state
- The crash data provided by the states
- Reporting patterns between states
- The operating environments and demographics of the states
- Penetration of partner OEM vehicle sales in the states included.

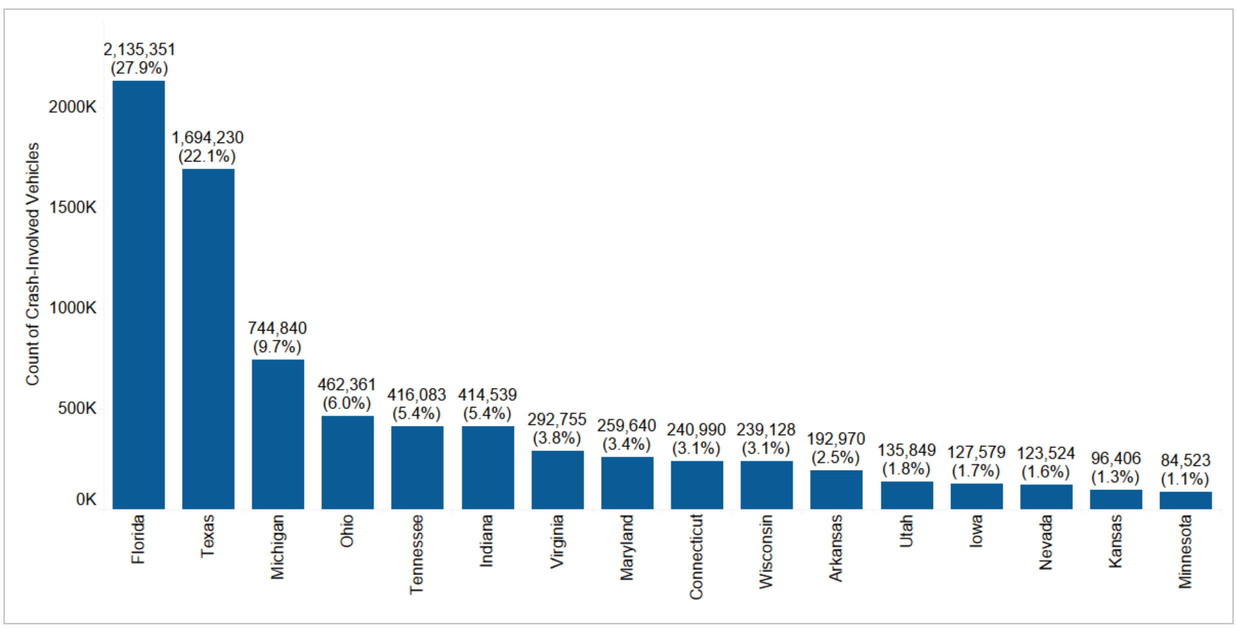


Figure 8. Distribution of Linked Crash-involved Vehicle Count by State

The penetration of ADAS features in linked crash-involved vehicles increased with model year progression, as shown in Figure 9. Although overall LDW equipage increased during the study period, the proportion of vehicles equipped with only LDW (lightest blue) actually decreased for newer vehicle models.

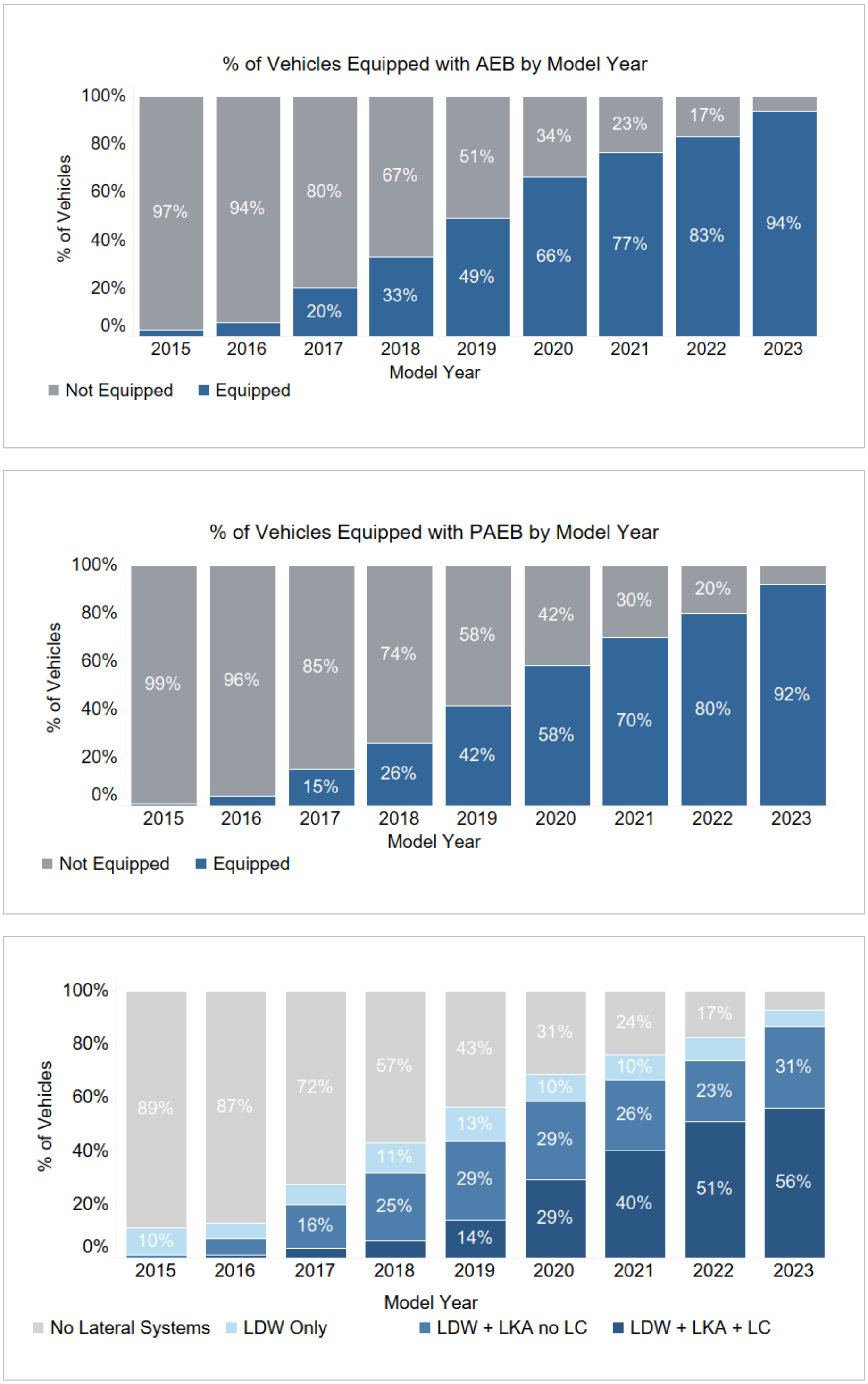


Figure 9. Percentage of Linked Vehicles Equipped by Model Year

Specific crash types are necessary to perform analyses, as shown previously in Table 1. Counts of these PARTS crash types are shown in Figure 10. The disparity between Front-to-Rear Striking and Front-to-Rear Struck is consistent with the disparity seen by other researchers. The disparity is due to the differing roles (i.e., striking vs. struck) of PARTS vehicles in these crash types and the distinct characteristics of PARTS vehicles compared to the general vehicle population. For instance, PARTS partners' vehicles are more likely to be equipped with AEB than the general population, which includes older vehicles manufactured before the introduction of AEB, leading to fewer Front-to-Rear Striking crashes. Additionally, PARTS vehicles tend to be newer than those in the general population. Other factors beyond these examples also contribute to the observed disparity.

The category “other,” which had the largest count, included crash types like vehicle turning left or right, backing, vehicle crashes involving more than two vehicles, etc. These types were not relevant to the ADAS features being studied and were therefore excluded from the study. Within the scope of this study, front-to-rear crashes had the largest counts (where front-to-rear struck crash is used as a control; see Table 1). The single-vehicle road-departure (SVRD) and pedestrian crashes had substantially lower counts.

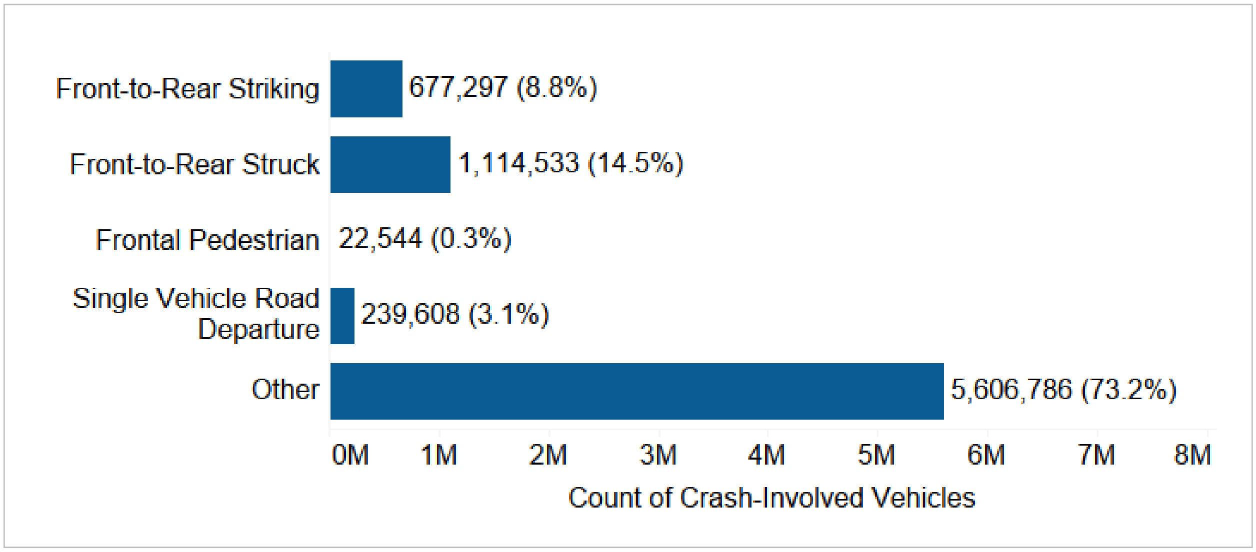


Figure 10. Linked Crash-involved Vehicle Counts by Defined Crash Type

The descriptive statistics by crash year, model year, and vehicle segment for the studied crash type are shown in Figures 11, 12, and 13.

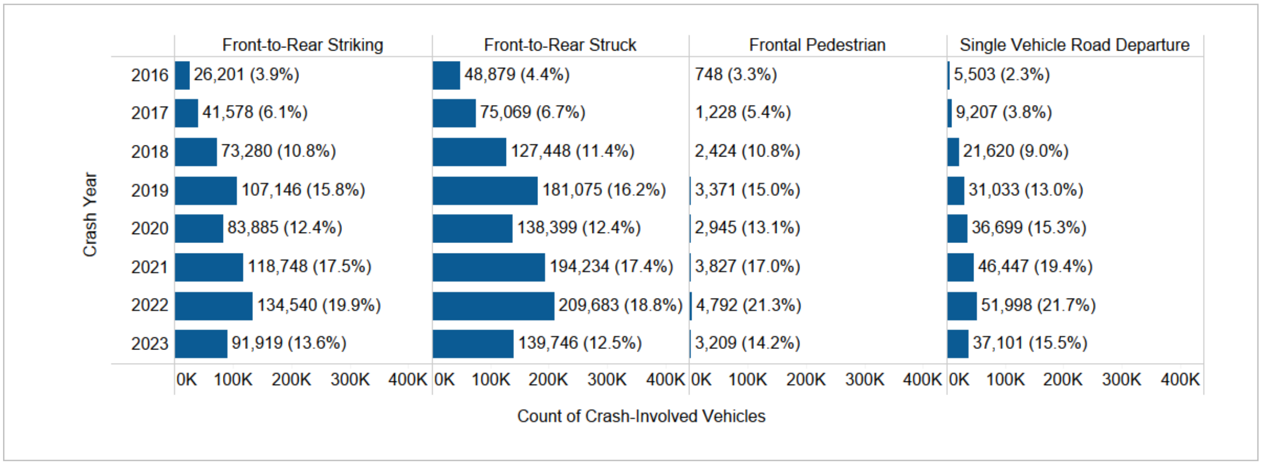


Figure 11. Linked Crash-involved Vehicle Counts for Studied Crash Types by Crash Year

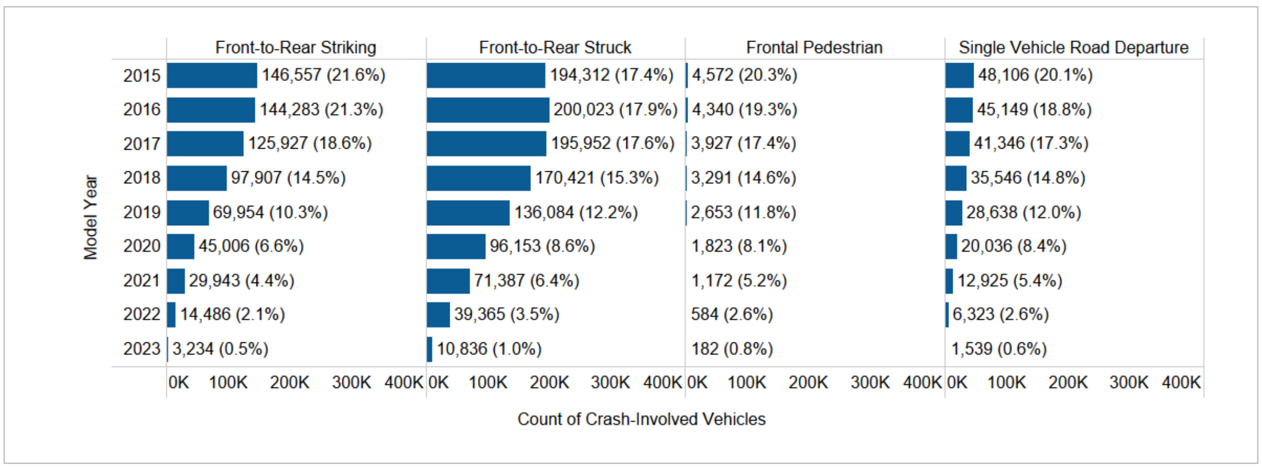


Figure 12. Linked Crash-involved Vehicle Counts for Studied Crash Types by Model Year

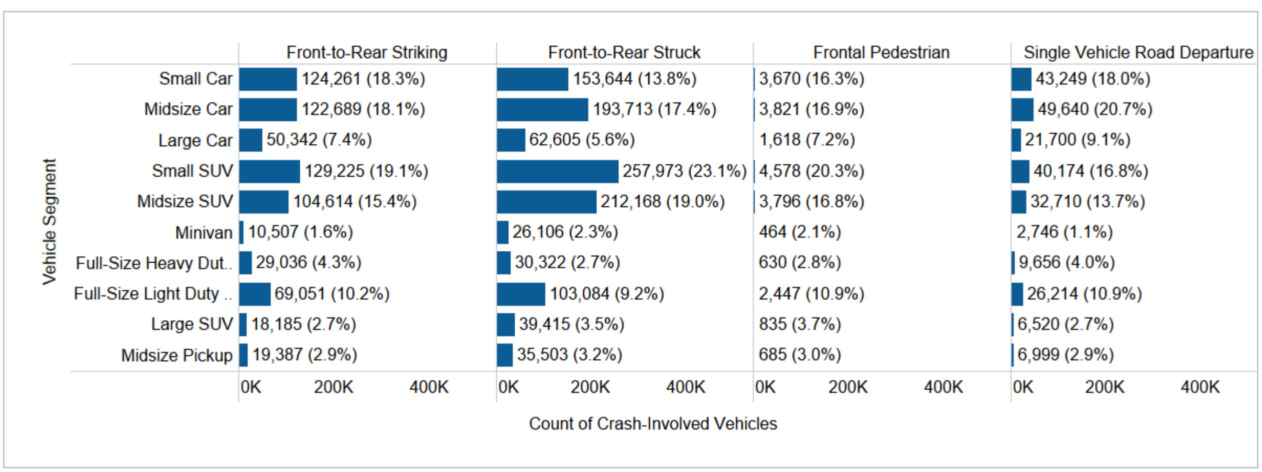


Figure 13. Linked Crash-involved Vehicle Counts for Studied Crash Types by Vehicle Segment

3.3 Comparison to the 2022 PARTS Study Dataset

Compared to the 2022 PARTS Study, this study presented several significant changes in both the vehicle and crash populations. Notably, the latest study included data from two new OEMs, Ford and Hyundai, while data from Nissan was absent. Furthermore, the study was updated to include the full model year 2021 and new model years 2022 and 2023. Unlike the 2022 study, which included only partial models from OEMs, the current study included all models that met the criteria outlined in Section 3.1.1. Additionally, the scope of the study was broadened to include three new vehicle segments – midsize pickups, full-size light-duty pickups, and heavy-duty pickups – and 75 new vehicle models. The crash data was also updated to cover the years 2021 to 2023 and expanded to include three new states: Kansas, Michigan, and Minnesota. These additions provided a more comprehensive and current analysis of ADAS features.

3.4 Methodology Overview

This study applied a similar methodology to the 2022 PARTS Study. It used QIE with logistic regression to estimate the reduction in system-relevant crashes for vehicles equipped with ADAS. The ADAS effectiveness in this study was measured by estimating the reduction in system-relevant crashes due to the presence of vehicles equipped with these systems. QIE measures crash rates relying only on crash data by using a control crash that is irrelevant to the equipage of the ADAS feature to account for potential exposure differences.[5] The methodology was modified to apply an adjustment for newer model year vehicles (model year 2020 and newer) because of a lack of unequipped vehicles (due to high equipage rates in newer vehicles).

Section 3.4.1 describes in detail the calculations of QIE and logistic regression model design.

3.4.1 Quasi-induced Exposure Calculations and Logistic Regression Model Design

QIE relies on an odds ratio comparing equipped to unequipped vehicles with respect to the number of system-relevant crashes relative to the number of control crashes. The QIE ADAS odds ratio is defined as:

$$\text{ADAS odds ratio} = \frac{\text{System-Relevant Crashes for Equipped Vehicles/Control Crashes for Equipped Vehicles}}{\text{System-Relevant Crashes for Unequipped Vehicles/Control Crashes for Unequipped Vehicles}}$$

If the ADAS odds ratio is less than one, then the ADAS feature is effectively reducing the number of system-relevant crashes, assuming no other influencing factors. Therefore, the ADAS effectiveness is stated as a reduction in odds:[5]

$$\text{ADAS Effectiveness} = 1 - \text{ADAS odds ratio}$$

In practice, odds ratios are estimated using logistic regression. The response variable in the logistic regression indicates whether a vehicle is involved in a system-relevant crash or a control crash. A binary explanatory variable represents whether the vehicle is equipped with ADAS. The exponentiated coefficient of this binary variable from the logistic regression provides the ADAS odds ratio. This method also allows for the inclusion of additional covariates that might affect the likelihood of system-relevant crashes compared to control crashes.

The covariates included in this study are listed in Table 3.

[5] See [26] and [15] for additional details on QIE.

Table 3. Covariates Included in the Study

Driver	Environment	Crash	Vehicle
• Driver Age • Alcohol/Drugs • Distracted • Driver Gender	• Weather • Road Surface Condition • Light Condition • Roadway Alignment • Intersection	• Crash State • Crash Year • Speed Limit	• Sales Type (Fleet vs. Retail) • Vehicle Segment • Vehicle Model Year • Automatic High Beams (AHB) in Dark Unlit (for PAEB)

The covariates included were the same as those used in the 2022 PARTS Study except for the addition of AHB during dark and unlit conditions for PAEB and some minor binning differences. The covariates were selected based on past research literature to identify key factors for ADAS effectiveness, discussions with partners to uncover other potential influencing factors, and data quality and availability.

Additionally, ADAS effectiveness was investigated for changes with respect to the covariates (i.e., interaction between covariate and binary ADAS variable). Each covariate was individually included as an interaction with the ADAS feature in the logistic regression. Bayesian Information Criteria (BIC) was used to identify whether the interaction (i.e., assuming changes in effectiveness for the covariate) added meaningful (i.e., unlikely to be due to random noise) information to the model (i.e., BIC is lower for logistic regression with interaction than without). BIC can be conservative in identifying changes in effectiveness (see the Discussion Section in the 2022 PARTS report), which would reduce the chance of false identification but could miss some differences that exist in truth. If identified by BIC, then estimates of each level are investigated with a 95% confidence interval (CI), Bonferroni[6] adjusted to control false positive rate within the covariate based on the number of levels.

Since the covariates were included as interactions with the ADAS system separately, the differences identified could be confounded by another factor (measured or unmeasured) if strong correlations exist between covariates (e.g., inclement weather and wet roads tend to be correlated).

3.4.2 Estimating Effectiveness when Limited Unequipped Vehicles Exist

New vehicles have a high penetration of ADAS features and tend to get in fewer crashes overall, which can lead to an overestimation of ADAS effectiveness.[7] While model year is controlled for in the logistic regression, it can be difficult to separate model year effects from ADAS feature effects when minimal unequipped vehicles exist in the population. To ensure that ADAS effectiveness overestimation did not occur, an adjustment factor was subtracted from the ADAS feature logistic regression coefficients for newer vehicle models (model years 2020+) to directly remove model year effects. This strategy (subtracting an adjustment factor for newer vehicles) is similar to the strategy used in [13] and [14] for studying electronic stability control once it became standard on most vehicles. For detailed information on the methodology, see Appendix B.

[6] A method for controlling for Type I (α) error due to multiple comparisons whereby α is divided by the number of comparisons for each individual comparison.

[7] See [13], [14], [28], [29].

4 Results

This section presents the results of the analysis on the effectiveness of three ADAS feature groupings in avoiding system-relevant crashes: AEB for front-to-rear crashes, PAEB for frontal crashes involving non-motorists, and lateral features (LDW/LKA/LCA) for single-vehicle road-departure crashes. For each group, the overall effectiveness is presented, along with the effectiveness for different model year subsets to assess changes over time and the variations in effectiveness based on covariates.

4.1 Automatic Emergency Braking Reduction in Front-to-rear Crashes

4.1.1 Automatic Emergency Braking Aggregate Results

In this study, vehicles equipped with AEB systems were estimated to statistically significantly (i.e., CI does not cover zero) reduce front-to-rear (F-R) crashes by 49% with a 95% CI of (48%, 50%), a finding consistent with the 2022 PARTS Study and other research [4] [15] [16] [17]. Detailed estimates, CIs (95%), and sample sizes are shown in Table 4. This effectiveness estimate is based on PARTS vehicles from model years 2015–2023, across all segments and crashes of any reported severity, as indicated by a KABCO injury classification in police reports, where K = fatal injury, A = suspected serious injury, B = suspected minor injury, C = possible injury, and O = no apparent injury [18].

Table 4. AEB Overall Effectiveness for Front-to-rear Striking Crashes

	Effectiveness (95% CI)	Sample Size		
Phase 3 MY2015-2023 (K,A,B,C,O, Unknown)	49% (48%, 50%)		F-R Striking (System Relevant)	F-R Struck (Control)
		Equipped	115,248	364,432
		Unequipped	467,649	618,350

4.1.2 Automatic Emergency Braking Effectiveness Over Time

The effectiveness of AEB was also evaluated for subsets of model years (2015–2017, 2018–2020, and 2021–2023), as shown in Figure 14. All combinations of subsets (2018–2020 vs. 2015–2017, 2021–2023 vs. 2015–2017, and 2021–2023 vs. 2018–2020) were tested to determine whether effectiveness was different over time. All subsets were found to be statistically significantly different (in all cases, p-values[8] < 0.001) at the 0.05 level.

[8] The comparison of time periods occurs in the log-odds space, making the estimate and confidence interval for the difference less interpretable. Therefore, the p-value for the test of difference between time periods is reported and the effectiveness estimate along with a 95% confidence interval of each time period presented. This is the case for PAEB and lateral features as well.

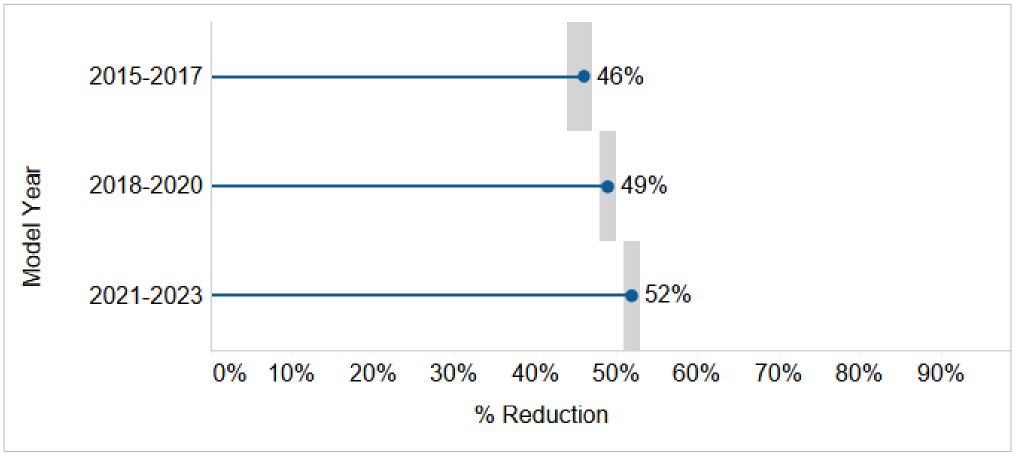


Figure 14. AEB Estimated Effectiveness Over Time (by subsets of Model Years) with 95% Confidence Intervals

4.1.3 Automatic Emergency Braking Effectiveness by Driver, Environment, Crash, and Vehicle Conditions

PARTS investigated whether there are differences in AEB effectiveness by covariates using BIC (i.e., if logistic regression including covariate interaction with AEB had lower BIC, as described in Section 3.4.1). Those covariates where AEB effectiveness was identified by BIC as having differences are bolded in Table 5. Additionally, the table includes observations about the estimates for the different levels of the covariate, although differences between specific combinations of covariate levels were not tested.

Table 5. AEB Effectiveness Interaction Results

	Covariate	AEB {K, A, B, C, O, Unk} Result
Driver	Driver Age	**Lower Effectiveness for Older Drivers**
	Alcohol/Drugs	*Not Identified as Differing*
	Distracted	*Not Identified as Differing*
	Driver Gender	**Lower Effectiveness for Male Drivers**
Environment	Weather	**Lower Effectiveness when Inclement Weather/Wet Roads**
	Road Surface Condition	
	Light Condition	**Lower Effectiveness when Darker**
	Roadway Alignment	**Lower Effectiveness when Road Curved**
	Intersection	**Lower Effectiveness when Occurring at Intersection**
Crash	Crash State	*Not Identified as Differing*
	Crash Year	*Not Identified as Differing*
	Speed Limit	**Lower Effectiveness when Speed Limits are Lower**
Vehicle	Sales Type (Fleet vs. Retail)	**Lower Effectiveness for Fleet Vehicles**
	Vehicle Segment	**Lower Effectiveness for Full-size Pickup Segments**

The covariates where AEB effectiveness differed in the previous PARTS study continued to show differences in the current analysis, and two new covariates – driver gender and vehicle segment – were identified. The previous PARTS study, which included only a limited sample of models from participating OEMs, did not observe differences in effectiveness across vehicle segments. However, this study found an interaction with vehicle segment, indicating lower performance for full-size pickup trucks. Unique challenges regarding AEB effectiveness in full-size pickups were also found in [16]. Additionally, the study examined AEB effectiveness based on the weight of the striking vehicle, as detailed in Section 4.2.1. More research is needed to explain drivers of measured effectiveness differences due to the confounding of weight, vehicle segment, and other factors.

For additional details on the effectiveness by covariates, see Appendix C.

4.2 Automatic Emergency Braking Attribute Results

The study aimed to explore variation in real-world effectiveness of AEB by examining specific attributes and crash characteristics. For this study, four attributes were selected based on hypothesized impact on AEB performance and the availability of relevant data. The weight of the striking vehicle, NCAP DBS, and NCAP CIB attributes were studied in the same manner as interactions with the covariates mentioned previously. The struck vehicle body type was studied by fitting separate logistic regressions for each struck vehicle where only system-relevant crashes that included the struck vehicle in the specific category were included in the logistic regression.

4.2.1 Weight of Striking Vehicle

The researchers hypothesized that AEB effectiveness would increase with each unit decrease in vehicle weight. The actual weight of the vehicle at the time of crash was not available, so to estimate the weight of the vehicle, researchers used Gross Vehicle Weight Rating (GVWR), which was provided by OEMs at the VIN level. GVWR means the value specified by the manufacturer as the loaded weight of a single vehicle, which includes the weight of the vehicle and its cargo carrying capacity, including occupants [19]. When an OEM-provided GVWR was missing at the VIN level, the average GVWR reported in OEM-provided NCAP data – categorized by trim, model, and model year – was used to fill the missing GVWR.

The GVWR was included as a continuous variable in the logistic regression and interacted with the AEB variable, producing an estimated slope parameter. The findings indicated that for every 1,000 pounds decrease in GVWR, AEB effectiveness was increased by approximately 4%, as shown in Figure 15. The researchers interpret the interaction slope parameter (GVWR interaction with AEB) as "For every 1,000 lbs. decrease in GVWR, AEB effectiveness increases by approximately 4%." The heavy-duty pickup segment had the potential to overly influence the analysis results given both its much lower effectiveness (see Appendix C) and heaviest weight. Therefore, to ensure the relationship between weight and effectiveness was not solely driven by heavy-duty pickups, that segment was excluded from the analysis. As mentioned above in Section 4.1.3, more research is needed to explain drivers of measured effectiveness differences due to the confounding of vehicle segment, weight, and other factors.

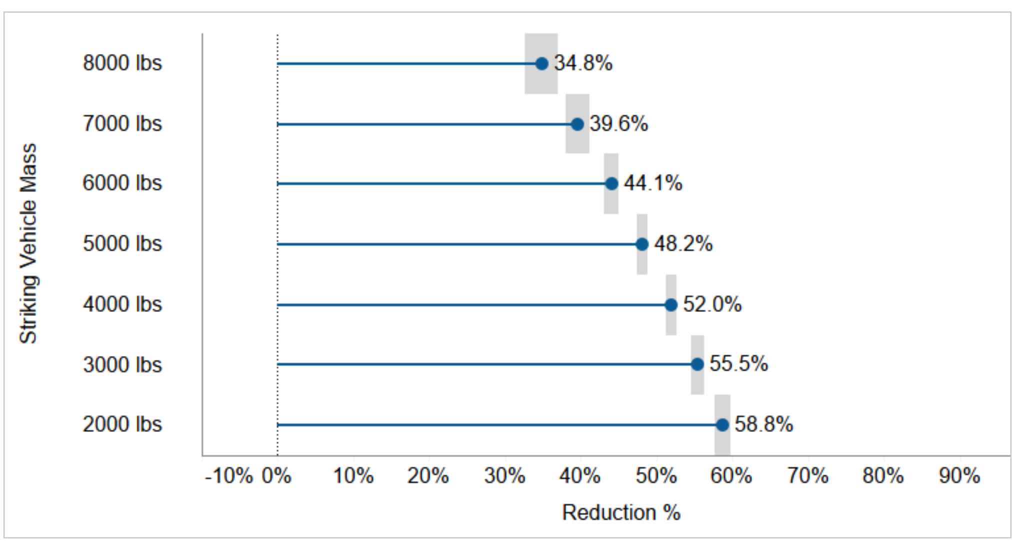


Figure 15. AEB Effectiveness by Striking Vehicle Weight

4.2.2 Struck Vehicle Body Type

The Struck Vehicle Body Type attribute measured whether AEB effectiveness differed based on the type of struck vehicle in front-to-rear crashes. Data sources used for this analysis were NHTSA's vPIC "Vehicle Type" and "Body Class" tables. The specific data categorization is shown in Table 6 below.

Table 6. Struck Vehicle Body Type Categorization

Name	Definition
Motorcycle	Vehicle Type = Motorcycle
Passenger Car	Vehicle Type = Passenger Car
Multipurpose Vehicle	Vehicle Type = Multipurpose Vehicle and not {Body Class = Van and GVWR >7,000 lbs.}
Pickup	Vehicle Type = Truck and Body Class = Pickup
Full-Size Van	Vehicle Type = Bus and Body Class = Van or Vehicle Type = Truck and Body Class = {Van or Cargo Van} or Vehicle Type = Multipurpose Vehicle and Body Type = Van and GVWR >7,000 lbs
Bus	Vehicle Type = Bus and not Body Class = Van
Truck (non-pickup)	Vehicle Type = Trailer or Vehicle Type = Truck and not Body Class = {Van or Cargo Van or Pickup}
Incomplete	Vehicle Type = Incomplete Vehicle

Low-speed vehicles[9] were excluded from analysis due to low sample size and the difficulty and complexity of mapping to a standard taxonomy. "Incomplete" refers to a vehicle for which the manufacturer was uncertain about its final type when assigning the VIN [20] and includes, for example, bare truck chassis without a cab or cargo box intended for ambulance outfitting or other specialized body installations by a third-party upfitter.

Results in Figure 16 indicate that the effectiveness of AEB systems was reduced when the struck vehicle type was non-passenger, such as a motorcycle, bus, non-pickup truck, or incomplete vehicle.

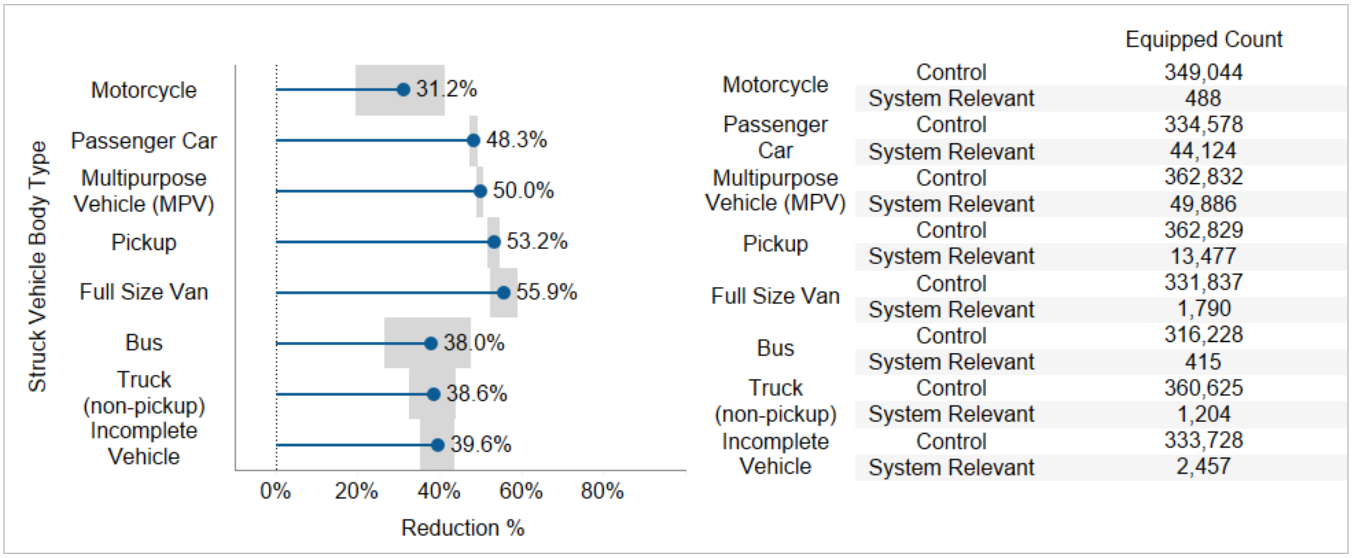


Figure 16. AEB Effectiveness Results by Struck Vehicle Body Type

[9] A low-speed vehicle is a 4-wheeled motor vehicle that can attain a speed of more than 20 miles per hour but not more than 25 miles per hour on a paved, level surface, and has a GVWR of less than 3,000 pounds. https://vpic.nhtsa.dot.gov/ManufacturerHandbook.pdf

4.2.3 New Car Assessment Program (NCAP) Dynamic Braking Support (DBS) Testing Criteria

This analysis addressed the research question: “Does AEB effectiveness differ by system performance in NCAP DBS testing criteria?” The NCAP DBS testing measures how well a vehicle’s DBS system performs according to the criteria set by the NCAP, which involves testing the system’s ability to detect potential collisions and effectively assist in braking to reduce the severity of a crash or avoid it altogether. The DBS testing scenarios include Lead Vehicle Stopped, Lead Vehicle Moving Slower, and Lead Vehicle Decelerating [21].

The data used for this analysis came from the OEM-provided NCAP data field “Does the DBS system meet NCAP performance criteria?”[10] DBS testing data was categorized for a given model and model year, as shown in Table 7. Model years 2018–2023 were included.[11]

Table 7. DBS Testing Criteria Data Categorization

Category	Definition
Meet	All systems and trims reported as “Yes”
Does Not Meet	One or more systems or trims reported as “No”
No Testing Results	Vehicle models in PARTS study with a matched NCAP record but no testing results provided in the NCAP sheets, or labeled as “Testing Pending,” “Not Tested,” or “To Be Tested.”
No Matched NCAP Record	Vehicle models and model years in PARTS study without a matched NCAP record and therefore no linked crash record
Unequipped	No DBS system on this vehicle

Results showed that AEB effectiveness was lower for models and model years that did not meet NCAP DBS testing criteria, as shown in Figure 17. The “No Testing Results” category showed higher estimated effectiveness than the overall AEB effectiveness, and the category of “No Matched NCAP Record” showed a higher center estimate effectiveness.

It is important to note that the absence of testing results could be attributed to various factors, such as the timing and version of the NCAP data provided by the OEMs. The unmatched NCAP records originated from a small number of models and seem to be randomly distributed across different OEMs and model years, although the total number of crash-involved vehicles might not be insignificant. Discrepancies in the model names listed in the NCAP data may have prevented accurate linkage to the vehicle equipment data. Consequently, some models might have met the NCAP DBS performance standards, but this was not reflected in the available data. The categories of “No Testing Results” and “No Matched NCAP Record” were included in the analysis to reflect the available data but, given the ambiguity of these categories, the researchers recommend caution when interpreting the estimated effectiveness values.

[10] Model years 2015–2017 were not included in the analysis because the NCAP started to collect DBS testing results beginning with model year 2018.

[11] The adjustment for newer model years (2020+) was applied and was the same as in the previously described analyses; see Section 3.4.2 and Appendix B.

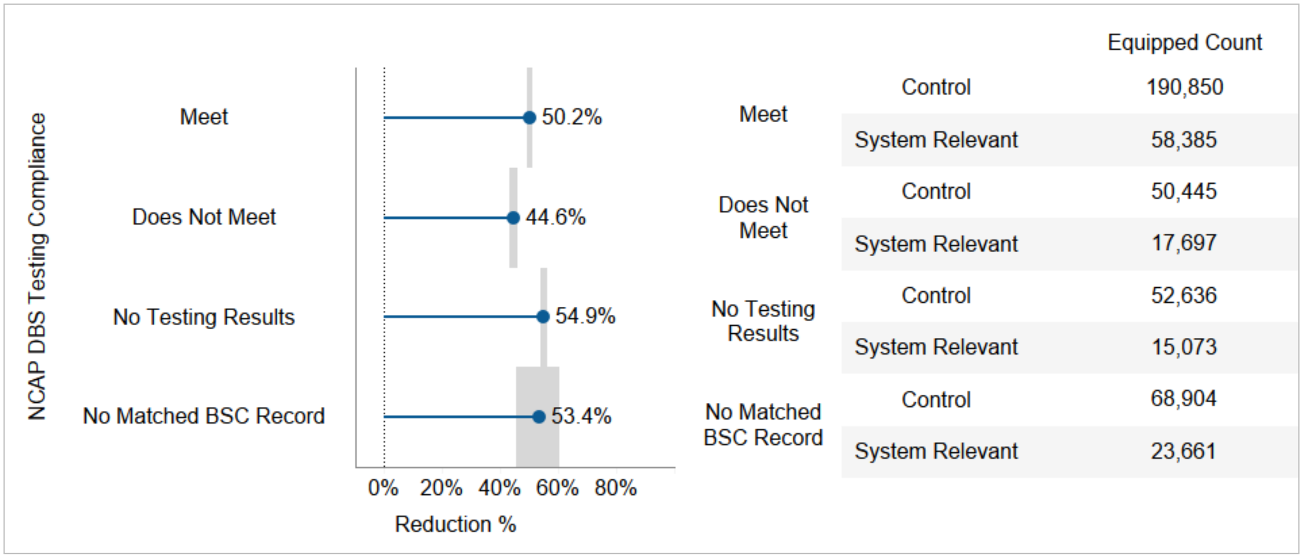


Figure 17. NCAP DBS Test Criteria AEB Effectiveness Results

4.2.4 New Car Assessment Program (NCAP) Crash Imminent Braking (CIB) Testing Performance

Lastly, the NCAP CIB testing performance Lead Vehicle Moving (LVM) 45/20 was used to address the research question: “Does AEB effectiveness differ by system performance on NCAP CIB testing?” Contrary to the DBS testing, where the driver initiates braking, for the CIB test the vehicle must automatically brake without driver input to reduce the impact speed by a specified amount, although contact with the test target can occur. The CIB testing data provides speed reduction information by miles per hour, allowing for a comparison between vehicles that meet the minimum speed reduction with target contact and those that fully reduce speed without contact.

The CIB LVM 45/20 testing specifically evaluates the ability of the CIB system to detect and respond to a slower-moving lead vehicle in the forward path of the subject vehicle at the constant speed of 20 mph, with the subject vehicle following at 45 mph. This testing procedure was selected because of (1) its relevance to real-world scenarios; (2) the comparability to DBS (the test is directly comparable with vehicles that meet DBS no-contact requirements); and (3) data availability (the 45/20 test results data have already been standardized and are readily available for analysis).

OEMs provided the model years 2018–2023 NCAP data field, “CIB LVM 45/20 test results,” for use in the analysis. LVM 45/20 testing results were categorized for a given model and model year, as shown in Table 8.

Results indicated that AEB-equipped vehicle models/model years categorized as “Does Not Meet” had lower estimated effectiveness than the overall effectiveness (see Figure 18). In line with the DBS results, the “No Testing Results” category showed higher estimated effectiveness than the overall effectiveness, and the “No Matched NCAP Record” category had a higher center estimate. As with the DBS testing criteria, the “No Testing Results” and “No Matched NCAP Record” categories were included in the analysis to reflect the available data but, given the ambiguity of these categories, the researchers recommend caution when interpreting the estimated effectiveness values.

Table 8. CIB LVM 45/20 Testing Performance Data Categorization

Category	Definition
Meet No Contact (Full Speed Reduction)	“No contact” or “avoid” stated, only 1 or 2 runs contacted, or delta-V is reported > 23 mph
Meet With Contact (Minimum Speed Reduction)	“Contact” stated, more than 2 runs contacted, or delta-V is reported as < 23 mph
Does Not Meet	One or more systems or trims does not meet the LVM 45/20 requirements with or without contact: “No” is stated in the NCAP submission
No Testing Results	Vehicle models in PARTS study with a matched NCAP record but no test results provided in NCAP data, or labeled as “Testing Pending”, “Not Tested,” “To be Tested”, or “Pass” without indication of contact status
No Matched NCAP Record	Vehicle models and model years in PARTS study without a matched NCAP record and therefore no linked crash record
Unequipped	No CIB system on this vehicle

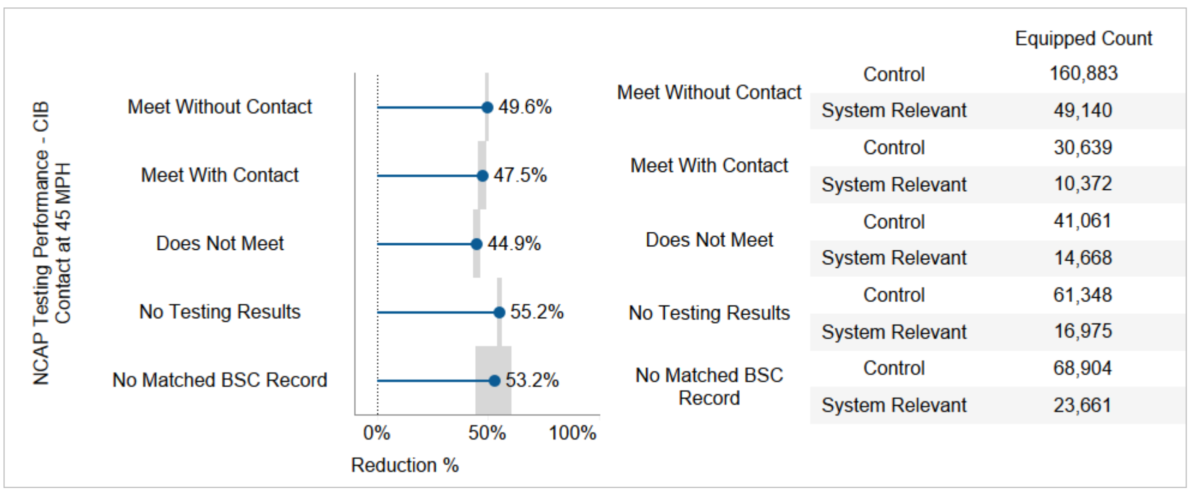


Figure 18. NCAP Testing Performance – CIB Contact at 45 MPH AEB Effectiveness Results

4.3 Pedestrian Automatic Emergency Braking Reduction in Single-vehicle Frontal Crashes with Non-motorists

4.3.1 Pedestrian Automatic Emergency Braking Aggregate Results

Vehicles equipped with PAEB systems were estimated to have had a statistically significant (i.e., the CI does not cover zero) reduction of 9% – with a 95% CI of (3%, 14%) – for single-vehicle frontal crashes with non-motorists. Detailed estimates, 95% CIs, and sample sizes are shown in Table 9. The effectiveness estimate is based on PARTS vehicles from model years 2015–2023, across all segments and crashes of any reported injury severity, as indicated by a KABCO injury classification of {K, A, B, C} in police reports. Crashes with the highest KABCO reported injury level of "O" (Not Injured) or "Unknown" were excluded due to known underreporting of incidents involving pedestrians or other non-motorists; see the 2022 PARTS Study report for discussion on the topic [4]. Note that in this study, there were no vehicles that were equipped with PAEB without also having AEB, but there were vehicles equipped with AEB without PAEB. Vehicles equipped with PAEB were compared to those not equipped with PAEB.

Table 9. PAEB Overall Effectiveness for Single-vehicle Frontal Crashes with Non-motorists

	Effectiveness (95% CI)	Sample Size		
			Pedestrian (System Relevant)	F-R Struck (Control)
Phase 3 MY2015-2023 (K,A,B,C)	9% (3%, 14%)	Equipped	4,168	290,485
		Unequipped	12,883	660,072

4.3.2 Pedestrian Automatic Emergency Braking Effectiveness Over Time

The effectiveness of PAEB was additionally evaluated for subsets of model years (2015–2019 and 2020–2023), as shown in Figure 19. However, the subsets of model years were tested for a difference that yields a p-value of 0.065, which is not statistically significant at a level of 0.05.

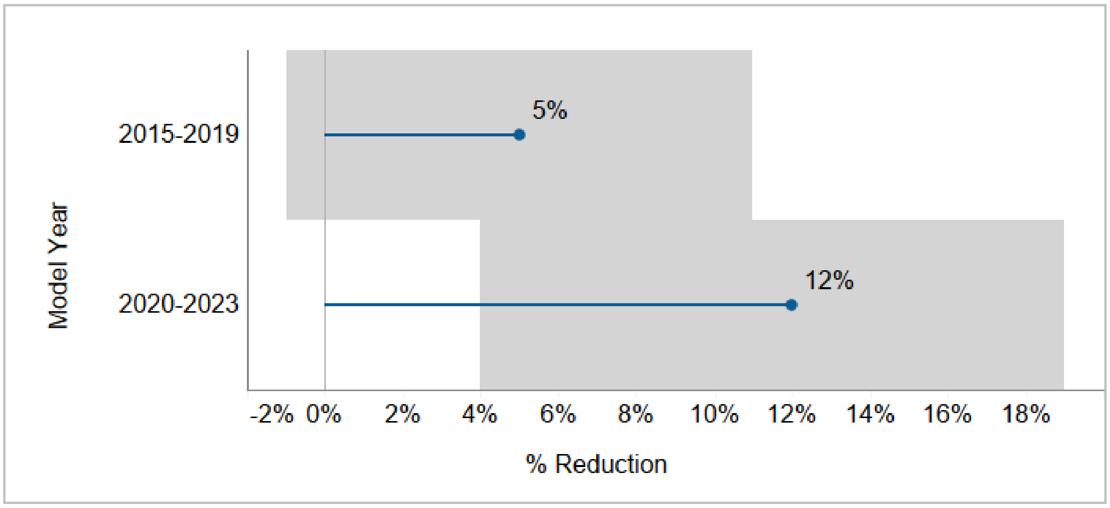


Figure 19. PAEB Estimated Effectiveness Over Time (by subsets of Model Years) with 95% Confidence Intervals

4.3.3 Pedestrian Automatic Emergency Braking Effectiveness by Driver, Environment, Crash and Vehicle Conditions

PAEB effectiveness was not identified by BIC as changing by any covariates examined (see Table 10). This could be due to PAEB not changing with respect to these covariates or as a function of a lack of statistical power (e.g., due to sample size and choice of criteria) to detect differences.

Table 10. PAEB Effectiveness by Covariates

	Covariate	PAEB {K, A, B, C} Result
Driver	Driver Age	Not Identified as Differing
	Alcohol/Drugs	Not Identified as Differing
	Distracted	Not Identified as Differing
	Driver Gender	Not Identified as Differing
Environment	Weather	Not Identified as Differing
	Road Surface Condition	
	Light Condition (including AHB in dark unlit)	Not Identified as Differing
	Roadway Alignment	Not Identified as Differing
	Intersection	Not Identified as Differing
Crash	Crash State	Not Identified as Differing
	Crash Year	Not Identified as Differing
	Speed Limit	Not Identified as Differing
Vehicle	Sales Type (Fleet vs. Retail)	Not Identified as Differing
	Vehicle Segment	Not Identified as Differing

4.4 Lateral Feature Reduction in Single-vehicle Road-departure Crashes

4.4.1 Lateral Feature Aggregate Results

The study estimated the reduction in single-vehicle road-departure crashes when the vehicle was equipped only with LDW (LDW Only), with LDW + LKA (no LCA), and with LDW + LKA + LCA. These were compared against vehicles equipped with none of these lateral ADAS features, using data from PARTS vehicles from model years 2015–2023. The analysis covered all vehicle segments and crashes of any reported severity, as indicated by the KABCO injury classification in the police report. For vehicles equipped with LDW + LKA + LCA, the system may or may not have been integrated with other SAE Level 2[12] active systems, depending on the vehicle model and model year that was involved in the crash.

Vehicles equipped with LDW Only did not have a statistically significant estimated reduction for single-vehicle road-departure crashes. Vehicles equipped with a lateral ADAS feature (LDW + LKA or LDW + LKA + LCA) had an estimated statistically significant reduction for single-vehicle road departures, with similar estimated reductions of 5% (with 95% CI of 3%, 8%) and 4% (with 95% CI of 1%, 8%), respectively. Detailed estimates, 95% CIs, and sample sizes are shown in Table 11.

Table 11. Lateral ADAS Feature Overall Effectiveness for Single-vehicle Road-departure Crashes

	Systems	Effectiveness (95% CI)	Sample Size		
				SVRD (System Relevant)	F-R Struck (Control)
Phase 3 MY2015-2023 (K,A,B,C,O, Unknown)	LDW Only (No LKA, No LCA)	2% (-1%, 5%)	Equipped	20,530	98,405
			Unequipped	133,761	586,899
	LDW + LKA (No LCA)	5% (3%, 8%)	Equipped	31,408	202,283
			Unequipped	133,761	586,899
	LDW + LKA + LCA	4% (1%, 8%)	Equipped	17,819	131,119
			Unequipped	133,761	586,899

[12] SAE International Surface Vehicle Recommended Practice, "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles," SAE Standard J3016, Rev. April 2021.

4.4.2 Lateral Feature Effectiveness Over Time

The effectiveness of nested combinations of the lateral features were estimated for subsets of model years (2015–2019 and 2020–2023), see Figure 20, and tested for differences over time. Groupings by model year were not statistically different at level 0.05 (with p-values of 0.20, 0.65, and 0.07 respectively), meaning that no change over time was observed.

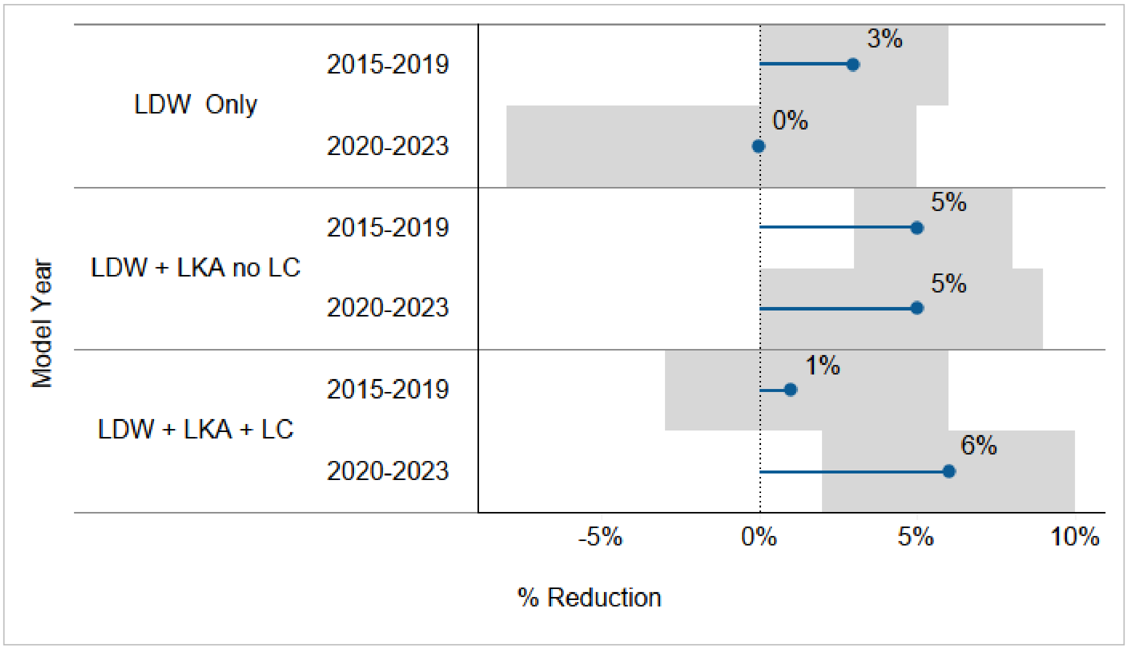


Figure 20. Lateral ADAS Feature Estimate of Effectiveness Over Time (by subsets of Model Years) with 95% Confidence Intervals

4.4.3 Lateral Feature Effectiveness by Driver, Environment, Crash, and Vehicle Conditions

Covariates where the effectiveness of combinations of the lateral ADAS features differed as identified by BIC are noted in bold in Table 12. Additionally, Table 12 notes observations about the estimates for the different levels of the covariate (although differences between specific combinations of covariate levels were not tested). For more details on the effectiveness by covariate for lateral ADAS features, see Results for All Identified Interactions in Appendix B.

The results of posted speed limits for lateral systems in Table 12 are unintuitive. Vehicles equipped with LDW + LKA + LCA systems showed varying effectiveness by speed limits, with the lowest effectiveness in zones with speed limits over 65 mph. In contrast, LDW Only vehicles showed lower effectiveness for speed limits under 25 mph and higher effectiveness over 65 mph. It is important to note that the posted speed does not necessarily equate to travel speed [22], and roads with a posted speed limit below 25 mph include residential areas, school zones, and alleys [23], where lateral systems are typically not designed to activate. Speed limits under 25 mph were included in the analysis to reflect the available data, but the researchers recommend caution when interpreting the estimated effectiveness value.

Table 12. Lateral ADAS Feature Effectiveness by Covariates

	Covariate	MY 2015–2023 {K,A,B,C,O, Unk} Result		
		LDW Only (No LKA, No LCA)	LDW + LKA (no LCA)	LDW + LKA + LCA
Driver	Driver Age	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
	Alcohol/Drugs	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
	Distracted	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
	Driver Gender	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
Environment	Weather	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
	Road Surface Condition	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
	Light Condition	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
	Roadway Alignment	*Not Identified as Differing*	*Not Identified as Differing*	**Identified as Differing**
	Intersection	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
Crash	Crash State	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
	Crash Year	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*
	Speed Limit	**Lower Effectiveness for <25, Higher Effectiveness for 65+**	*Not Identified as Differing*	**Lower Effectiveness for 65+**
Vehicle	Sales Type (Fleet vs. Retail)	*Not Identified as Differing*	**Lower Effectiveness for Fleet**	*Not Identified as Differing*
	Vehicle Segment	*Not Identified as Differing*	*Not Identified as Differing*	*Not Identified as Differing*

5 Discussion

The PARTS 2024 Study produced one of the most comprehensive datasets on ADAS system-relevant crashes. The 2024 dataset was nearly three times the size of the one used in the previous study. It incorporated data from three additional states, three new model years, and 75 more vehicle models. The study assessed the effectiveness of ADAS features through their ability to prevent crashes. In addition to corroborating previous research, the study's unprecedented size allowed for analysis that uncovered novel insights. This section highlights these new discoveries and identifies areas where further research could be particularly beneficial.

5.1 Automatic Emergency Braking (Front-to-rear Crashes)

The effectiveness of AEB systems in reducing front-to-rear crashes has been consistently validated through extensive research and data analysis. With access to a much larger and more comprehensive dataset, this study found a 49% reduction in such crashes with a tight CI of (48%, 50%) and confirmed the results of prior studies [4] [15] [16] [17]. As AEB systems proliferate across an increasing portion of the U.S. fleet, these results underscore the reliability of these systems in significantly reducing front-to-rear crashes – one of the most common crash types in the U.S. – and highlight AEB's critical role in improving traffic safety.

The expanded dataset, including vehicles from more model years and almost all passenger vehicle segments, allowed the PARTS study to find a statistically significant improvement in AEB effectiveness over time. The most recent models in this study, model years 2020–2023, are now preventing more than half the rear-end striking crashes, at 52% effectiveness.

The methodology employed in this study was refined to account for the high equipage rates in newer model years, with the goal of mitigating overestimation of effectiveness for newer vehicle models. Other research areas that face the same limitations can apply this novel adjustment methodology for newer model years when limited unequipped vehicles exist for comparison.

In contrast to the previous PARTS study, which included only a limited sample of models from participating OEMs, this study found that the vehicle segment of full-size pickup trucks had a lower effectiveness. The heavier weight of these vehicles may adversely impact system performance, as shown in the attribute study in Section 4.2, as this weight factor can affect the braking distance and the overall responsiveness of the system, potentially leading to reduced effectiveness. Given these findings, future research should study full-size pickups separately from other vehicle segments. This approach would allow for a more tailored analysis specific to this important vehicle segment, potentially leading to less biased covariate parameter estimates and the inclusion of additional covariates that are relevant to the unique characteristics of full-size pickups.

Another novel finding was the increase in AEB crash-reduction effectiveness as vehicle weight decreases; effectiveness increases by approximately 4% for every 1,000 pounds lighter the striking vehicle is. This is the first time AEB effectiveness has been found to correlate with vehicle weight. It is important to understand the relationship between vehicle weight and AEB effectiveness as vehicle sizes increase on U.S. roads [5]. Future research that incorporates other measures of vehicle weight or weight at time of crash into the analysis would better account for accurate vehicle weight.

This is also the first time in which AEB effectiveness across different types of struck vehicles was studied in real-world scenarios. This study found that the effectiveness of AEB was reduced when the struck vehicle was an irregular or non-passenger vehicle type, such as a motorcycle, bus, non-pickup truck, or incomplete vehicle. These findings may have been influenced by the small sample sizes for these vehicle types. Therefore, it may be helpful in future research efforts to estimate effectiveness separately for passenger and non-passenger struck vehicles. To provide a more comprehensive understanding of the results, future studies should consider the unique driving patterns of motorcycles and additional details related to motorcycle crashes. Additional research is also needed on the detection and identification of non-standard vehicles.

Overall, the increased size of the study dataset enabled novel, deeper dives into AEB performance-related attributes, including different crash contexts, vehicle characteristics, and laboratory crash testing results. In the future, PARTS will continue to refine the existing attributes and expand to new attributes, such as vehicle powertrain type (e.g., traditional internal combustion engine versus electric vehicles).

5.2 Pedestrian Automatic Emergency Braking (Frontal Crashes with Non-motorists)

The PAEB analysis demonstrated a statistically significant reduction of 9% for single-vehicle frontal crashes with non-motorists. A statistically significant PAEB effectiveness is notable since police-reported pedestrian and other non-motorist impacts are rare. Demonstrating that current systems effectively avoid such crashes is important because they represent some of the most severe events in terms of injuries and fatalities [24].

Given the relatively small number of system-relevant crashes (i.e., 4,100), this study was not able to detect statistical significance at the more granular covariate level, including automatic high beams in dark, unlit conditions. In the future, PARTS will continue to increase the statistical power to investigate differences in effectiveness by increasing the scope of the crash and vehicle data included in the analysis.

More research is needed to explore factors contributing to crashes involving non-motorists, such as the intersection of poor lighting and insufficient infrastructure with driver behaviors (e.g., speeding, impairment) and non-motorist factors (e.g., wearing dark clothing, impairment). Additionally, more research is needed to better understand the specific capabilities and generations of PAEB systems, especially those designed to detect other non-motorists, such as cyclists or scooter users. This will help in more accurately identifying relevant crashes to include in the study.

5.3 Lateral ADAS Features (Single-vehicle Road-departure Crashes)

The analysis of lateral systems revealed that those with active interventions – LDW + LKA (No LCA) and LDW + LKA + LCA – demonstrated effectiveness significantly different from zero for single-vehicle road-departure crashes, although the effectiveness rates remained in the single digits.

A significant limitation of the study is an assumption that if a vehicle was equipped with a feature, the driver had enabled that feature and it was activated at the time of crash. One possible reason for the findings of lower effectiveness of LDW and LKA is that drivers may be turning off the systems, especially for early model years [25]. Lane keeping systems are intended to assist a driver in remaining in the travel lane but can be overridden by the driver. Police reports do not provide adequate information to interpret driver actions or intent.

Another limitation is that the study did not incorporate information about OEM-specific implementations of lane management systems, to include the type of warning systems (e.g., auditory vs. haptic feedback) or the operational design domain that defines the limits of that feature's functional capability. For example, the systems are not typically designed to activate at lower speeds. This analysis was limited by lack of roadway information at the time of crash – for example, there was no information about the existence or condition of lane markings, the number of lanes, or the exact amount of road curvature to understand how these lane management features perform in the real world under different roadway conditions.

In future studies, PARTS may continue to refine the lateral system effectiveness study by:

- Incorporating system activation status through other data sources, such as telematics
- Refining our understanding of the speed limit covariate, and better understanding operating domains and system limitations to support interpretation of results
- Better understanding the effects of system usage, travel speeds, variation of system implementation, and road types and curvature.

5.4 Summary of Study Limitations

This section summarizes the major limitations of this study identified by PARTS members.

First, the study considered vehicles equipped with ADAS features at the time of manufacture but did not account for actual ADAS usage. It did not capture whether drivers had enabled or disabled ADAS features at the time of crash or whether the features activated during the crash event.

Second, the study did not directly account for all driving behaviors and their effect on ADAS effectiveness. While some covariates, such as age, gender, and vehicle models, were included as proxies for driving behavior, they might not have fully captured the nuances of how different drivers operate their vehicles.

Third, the use of police-reported crash reports as a primary source of data presented a series of well-known challenges. For instance, these reports may be incomplete, may not capture the driver's decisions in the moment before a crash, and/or have variations in coding protocols across different states. Furthermore, there is also a tendency for police-reported crashes not to contain minor traffic incidents, as those are frequently unreported. This underreporting can lead to a gap in the data, as less severe crashes may not be documented at all or not with the same rigor as more serious crashes. Consequently, the full scope of crash occurrences and their potential implications for ADAS effectiveness may not be fully captured in the available data. In addition, police-reported crashes often lack detailed information on vehicle dynamics and other relevant factors, such as pre-crash movement, visibility conditions, actual speed, and lane markings. This absence of detailed data can result in imprecise definitions of system-relevant crashes, making it challenging to accurately assess the circumstances under which safety features are most effective.

Fourth, the control crashes may not fully account for all variables and conditions present in real-world scenarios. While front-to-rear struck crashes are widely used in the literature to account for exposure, they may be imperfect for certain aspects of analysis. These imperfections can influence the estimates of effectiveness.

Lastly, the effect of model year on vehicle safety features remains uncertain for model years 2020–2023, primarily due to the limited availability of unequipped vehicles for comparison. As a result, the model year effect for these years is assumed to be linear in the log-odds space and consistent with the trends observed in model years 2015–2019. However, if these assumptions prove to be inaccurate, the model year effect may not be properly adjusted, leading to potential inaccuracies in the effectiveness estimates.

5.5 Suggestions for Future Research

The data sharing and analysis partnership of PARTS is truly unique. PARTS was able to complete this study because of each partner's willingness to share data and collaborate on the analysis, a commitment that the partners remain dedicated to and plan to further. PARTS partners plan to proceed with their co-designed research roadmap to close research gaps identified with this study, reiterate this study as ADAS deployment continues to increase, and expand the research into new areas. Opportunities include the following:

- **Injury Mitigation:** While this study focused on the effectiveness of ADAS features in avoiding crashes and not the crash severity reduction, it is crucial to address scenarios where crashes are unavoidable. In these situations, the role of ADAS features may be to reduce the impact speed, potentially decreasing the severity of injuries. Future research should explore how effective these systems are in mitigating injuries or reducing the severity of injuries during such incidents.
- **Expansion to Newer and Emerging Features:** As automotive technology evolves, it is important to include newer and emerging ADAS features, such as intersection AEB, and to investigate their effectiveness.
- **Refinement and Expansion of AEB Attributes:** Future studies that refine and add attributes beyond those studied here – such as weight of the striking vehicle, struck vehicle body type, and NCAP DBS and NCAP CIB attributes – are essential for a deeper understanding of AEB performance.
- **Methodological Innovations:** As an increasing number of vehicles are equipped with many standard ADAS features, it is important to continue to explore new methodologies in the absence of a control group of unequipped vehicles.
- **Standardized Crash Data Sources:** Providing feedback to crash data collection activities at the state and federal levels can help address data variation and limitations. This, in turn, can enhance safety by improving

the accuracy and reliability of crash mapping and facilitating a better understanding of vehicle dynamics during a crash.

- **Data Expansion:** Repeating the analysis using a larger dataset – to include more OEMs, newer model years, additional crash years, and a wider range of states – could lead to more statistically significant findings and a deeper understanding of the conditions that most influence feature effectiveness.
- **Incorporation of Telematics Data:** Integrating telematics data into ADAS effectiveness research can address key limitations and provide valuable insights into on/off status and system activation at the time of crash.

As a data sharing public-private partnership, PARTS is an innovative approach for continuously testing and proving out new ways for collaborating on safety. Working together, government and industry can contribute to enhancing the safety of our roads.

Abbreviations and Acronyms

Term	Definition
ADAS	Advanced Driver Assistance Systems
AEB	Automatic Emergency Braking
AHB	Auto-High Beam
BIC	Bayesian Information Criteria
CI	Confidence Interval
CIB	Crash Imminent Braking
CSC	Consolidated State Crash
DBS	Dynamic Brake Support
EDT	Electronic Data Transfer [system]
ESC	Electronic Stability Control
FARS	Fatality Analysis Reporting System
FCW	Forward Collision Warning
FHWA	Federal Highway Administration
F-R	Front to Rear
GM	General Motors
GVWR	Gross Vehicle Weight Rating
HLDI	Highway Loss Data Institute
IIHS	Insurance Institute for Highway Safety
ITP	Independent Third Party
LCA	Lane Centering Assistance
LDW	Lane Departure Warning
LKA	Lane Keeping Assistance
LVM	Lead Vehicle Moving
MITRE	The MITRE Corporation
MPH	Miles per Hour
NCAP	New Car Assessment Program
NHTSA	National Highway Traffic Safety Administration
OEM	Original Equipment Manufacturer
PAEB	Pedestrian Automatic Emergency Braking
PARTS	Partnership for Analytics Research in Traffic Safety
PII	Personally Identifiable Information
QIE	Quasi-induced Exposure
SUV	Sport Utility Vehicle
SVRD	Single Vehicle Road Departure
UMTRI	University of Michigan Transportation Research Institute
U.S.	United States
USDOT	United States Department of Transportation
VIN	Vehicle Identification Number
vPIC	NHTSA's Vehicle Product Information Catalog

References

[1] NHTSA, "Overview of Motor Vehicle Traffic Crashes in 2022," June 2024. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813560. [Accessed December 2024].

[2] NHTSA, "Early Estimate of Motor Vehicle Traffic Fatalities in 2023," April 2024. [Online]. Available: https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813561. [Accessed December 2024].

[3] PARTS, "Market Penetration of Advanced Driver Assistance Systems (ADAS)," September 2024. [Online]. Available: https://www.mitre.org/sites/default/files/2024-09/PR-24-2614-PARTS-Market-Penetration-Advanced-Driver-Assistance-Systems-0917.pdf. [Accessed December 2024].

[4] PARTS, "Real-world Effectiveness of Model Year 2015-2020 Advanced Driver Assistance Systems," 9 November 2022. [Online]. Available: https://www.mitre.org/sites/default/files/2022-11/pr%2022-3734-PARTS-real-world-effectiveness-model-year-2015-2020-advance-driver-assistance-systems_0.pdf. [Accessed December 2024].

[5] A. Hula, A. Maguire, A. Bunker, T. Rojeck and S. Harrison, "The 2020 EPA Automotive Trends Report," EPA, 2021.

[6] Statista, "Estimated U.S. market share held by selected automotive manufacturers in 2023," 2024. [Online]. Available: https://www.statista.com/statistics/249375/us-market-share-of-selected-automobile-manufacturers/. [Accessed 10 August 2022].

[7] A. J. Leslie, R. J. Kiefer, C. A. Flannagan, B. A. Schoettle and S. H. Owen, "Analysis of the Field Effectiveness of General Motors Model Year 2013-2020 Advanced Driver Assistance System Features," University of Michigan Transportation Research Institute, Ann Arbor, 2022.

[8] Jessica B. Cicchino, "Effects of automatic emergency braking systems on pedestrian crash risk", Accident Analysis & Prevention, Volume 172, 2022, 106686, ISSN 0001-4575, https://doi.org/10.1016/j.aap.2022.106686. (https://www.sciencedirect.com/science/article/pii/S0001457522001221).

[9] R. Spicer, A. Vahabaghale, D. Murakhovsky, S. St. Lawrence, B. Drayer and G. Bahouth, "Do driver characteristics and crash conditions modify the effectiveness of automatic emergency braking?," SAE International, 2021.

[10] NHTSA, "Resources Related to NHTSA's New Car Assessment Program," [Online]. Available: https://www.nhtsa.gov/ratings/resources-related-nhtsas-new-car-assessment-program#procedures--reports. [Accessed 6 January 2025].

[11] NHTSA, "Active Braking Technologies," 26 November 2024. [Online]. Available: https://www.nhtsa.gov/research-data/crash-avoidance/active-braking-technologies.

[12] "NHTSA Product Information Catalog and Vehicle Listing," [Online]. Available: https://vpic.nhtsa.dot.gov/.

[13] C. Farmer, "Effect of electronic stability control on automobile crash risk," *Traffic Injury Prevention,* pp. 317-25, 2004.

[14] C. Farmer, "Effects of Electronic Stability Control: An Update," *Traffic Injury Prevention,* pp. 319-324, 2006.

[15] A. J. Leslie, R. J. Kiefer, M. R. Meitzner and C. A. Flannagan, "Field effectiveness of General Motors advanced driver assistance and headlighting systems," *Accident Analysis and Prevention,* 2021.

[16] J. B. Cicchino, "Effects of forward collision warning and automatic emergency braking on rear-end involving pickup trucks," IIHS, Arlington, VA, November 2022.

[17] R. Shannon-Spicer, A. Vahabaghaie, D. Murakhovsky, G. Bahouth, B. Drayer and S. St. Lawrence, "Effectiveness of Advanced Driver Assistance Systems in Preventing System-Relevant Crashes," SAE International, 2021.

[18] NHTSA, "MMUCC Guideline: Model Minimum Uniform Crash Criteria Fifth Edition," National Highway Traffic Safety Administration, Washington, DC, 2017.

[19] CFR, "571.3 Definitions," 26 November 2024. [Online]. Available: https://www.ecfr.gov/current/title-49/subtitle-B/chapter-V/part-571/subpart-A/section-571.3.

[20] CFR, "Code of Federal Regulations Title 49," 02 12 2024. [Online]. Available: https://www.ecfr.gov/current/title-49/subtitle-B/chapter-V/part-568/section-568.4.

[21] NHTSA, “New Car Assessment Program (NCAP) [Docket No. NHTSA-2015-0006].”

[22] S. L. Skszek, “Actual Speeds on the Roads Compared to the Posted Limits,” Arizona Department of Transportation, Phoeniz, Arizona, 2004.

[23] FHWA, “Speed Limit Basics,” 02 12 2024. [Online]. Available: https://highways.dot.gov/safety/speed-management/speed-limit-basics.

[24] N. Lubbe, Y. Wu and H. Jeppson, “Safe speeds: fatality and injury risks of pedestrians, cyclists, motorcyclists, and car drivers impacting the front of another passenger car as a function of closing speed and age,” *Traffic Safety Research,* p. Vol 2, 13 April 2022.

[25] A. E. Cox, I. J. Reagan and J. B. Cicchino, "Drivers’ use of front crash prevention, lane departure warning and prevention, and speed warning systems," Insurance Institute for Highway Safety, Arlington, VA, 2024.

[26] M. Keall and S. Newstead, “Selection of Comparison Crash Types for Quasi-Induced Exposure Risk Estimation,” *Traffic Injury Prevention,* pp. 10:23-29, 2009.

[27] *New Car Assessment Program Final Decision Notice – Advanced Driver Assistance Systems and Roadmap,* 2024.

[28] K. N. Poindexter, "Passenger Vehicle Crash Involvement Rates by Vehicle Model Year," National Center for Statistics and Analysis, Washington, D.C., 2003.

[29] S. Blows, R. Q. Ivers, M. Woodward, et al., "Vehicle year and the risk of car crash injury," *Injury Prevention: Journal of the International Society for Child and Adolescent Injury Prevention*, vol. 9, no. 4, pp. 353-356, 2003.

Appendix A Preparing and Linking Data Sources

A standardization process was applied to the key data fields from each source to enable their use in analysis. For crash data, this involved mapping raw values of equivalent meaning to the same standardized value, accounting for nuances in individual law enforcement reports and individual state formats. For example, raw data on the location of impact on the vehicle included values such as "front bumper and hood," "12 clock point," and "front center bumper." These examples all were mapped to the standardized value of "12," referencing the location of impact relative to a clock face with the vehicle front end pointing toward 12 o'clock. After raw values were standardized, they were used to derive additional fields, such as the type of crash (e.g., front-to-rear) and whether the vehicle was striking or struck.

For vehicle equipment data, manufacturers provided VIN-level records that described vehicle content, often using their own formats and feature names. Some manufacturers group multiple ADAS features under one name, and these groups can change by model or model year. To ensure accuracy, MITRE worked directly with each manufacturer to map their features to standardized ADAS features. A consistent definition of each feature was applied to derive a standardized true/false value indicating whether a vehicle was equipped with the ADAS feature of interest or not. Data completeness and accuracy were carefully assessed. Standardized quality checks and reports were reviewed with the data providers, and any identified quality issues were addressed. For privacy and de-identification purposes, a series of anonymization processes were applied to any incidental personally identifiable information (PII) and VINs used to join datasets for analysis.

The standardized crash and vehicle equipment datasets were joined based on the 17-digit VIN. The resulting linked dataset contained one record for each partner vehicle that was involved in a crash and included key fields from each source. The build dataset had 98 million vehicle records, and the state crash dataset had 36.8 million crash-vehicle records. The linked dataset was limited to the crash-involved vehicles having a match in the OEM-provided build dataset and included 7.7 million crash vehicles.

An additional dataset was prepared with pairs of vehicles involved in the same front-to-rear crash based on the linked dataset described above (with crash-involved vehicles manufactured by OEM partners) and other vehicles from the state crash dataset. Having characteristics of both the striking and struck vehicles aligned in a single data record enabled the analysis of AEB effectiveness relative to vehicle attributes. Each record in the paired file included one partner vehicle and one other vehicle that may or may not have been manufactured by a PARTS OEM partner. For the partner vehicle, the NCAP test result dataset was joined in, enabling analysis of NCAP test performance as part of the AEB attribute study. This paired striking-struck file had 1.8 million crash records.

Appendix B Details of Adjustment for Model Years 2020+

The model year adjustment factor is calculated based on unequipped vehicles from older model years (2015–2019) when enough unequipped (approximately half of crashes vehicles were still unequipped in 2019) vehicles existed. A model year slope parameter is fit in a logistic regression containing only unequipped vehicles to ensure that the influences of ADAS features are removed. The logistic regression formula to calculate the adjustment is:

$$\log(odds) = \beta_0 + \beta_{adjust} * model\ year + \beta_1 * covariate_1 + \cdots + \beta_p * covariate_p$$

The adjustment factor is β_{adjust} in the above equation.

With the adjustment factor calculated, the next step is to fit a logistic regression to estimate the effectiveness by model year. For model years 2015–2019, both equipped and unequipped vehicles are included in the logistic regression. For model years 2020+, only equipped vehicles are included in the logistic regression. (This was done to ensure that model year effects were not partially removed in the logistic regression, which would cause the adjustment factor to double penalize.) The logistic regression is then fit with an ADAS variable that is mixed with model year, as defined in the following bulleted list, instead of the binary equipped and unequipped.

- Reference: Unequipped Model Year 2019
- Unequipped Model Year 2015
- Equipped Model Year 2015
- Unequipped Model Year 2016
- Equipped Model Year 2016
- Unequipped Model Year 2017
- Equipped Model Year 2017
- Unequipped Model Year 2018
- Equipped Model Year 2018
- Equipped Model Year 2019 (no corresponding unequipped since reference level)
- Equipped Model Year 2020
- Equipped Model Year 2021
- Equipped Model Year 2022
- Equipped Model Year 2023

Model year 2019 unequipped is used as reference since the adjustment factor starts to be applied for model year 2020+.

The logistic regression formula is as follows:

$$\begin{aligned} \log odds = {} & \propto_0 + \propto + \propto_{equipped,2015} + \cdots \ \propto_{unequipped,2018} + \\ & \propto_{\ equipped,2018} + \propto_{equipped,2019} + \propto_{equipped,2020} + \cdots + \propto_{equipped,2023} + \propto_1 \\ & * covariate_1 + \cdots + \propto_p * covariate\_p \end{aligned}$$

Note that in the above equation, the coefficient notation is expanded such that each coefficient corresponds to the level of a covariate rather than using more condensed notation.

To calculate the estimated ADAS effectiveness by model year for 2015–2019, the unequipped coefficient is subtracted from the equipped, as shown for model year 2015 below:

$$\propto_{equipped,2015} - \propto_{unequipped,2015}$$

The estimated effectiveness for model year 2019 is $\propto_{equipped,2019}$ since the reference level is unequipped model year 2019.

To calculate the estimated ADAS effectiveness by model year for 2020–2023, the coefficient has an adjustment factor subtracted. Since unequipped 2019 is the refence and model years 2020–2023 do not have an unequipped level, the $\propto_{equipped,model\ year}$ is the effectiveness of ADAS for that model year and also any model year effect. The adjustment factor is subtracted to remove the model year effect, which is done as follows:

$$\propto_{equipped,model\ year} - \ \beta_{adjust} * (model\ year - 2019)$$

This method assumes the reduction in crash rates (regardless of equipage) for newer vehicles in model years 2020 forward and follows a linear trend in the log-odds space that is identical to that observed in model year 2015–2019 unequipped vehicles.

To match to previous research, the weighted average (based on proportion of equipped vehicles in each model year of the control crash) of effectiveness for each model year is calculated to arrive at an overall effectiveness. This weighting can be different from that used in previous pooled effectiveness results, potentially leading to variations between the current estimate and past pooled estimates.

Appendix C Results for All Identified Interactions

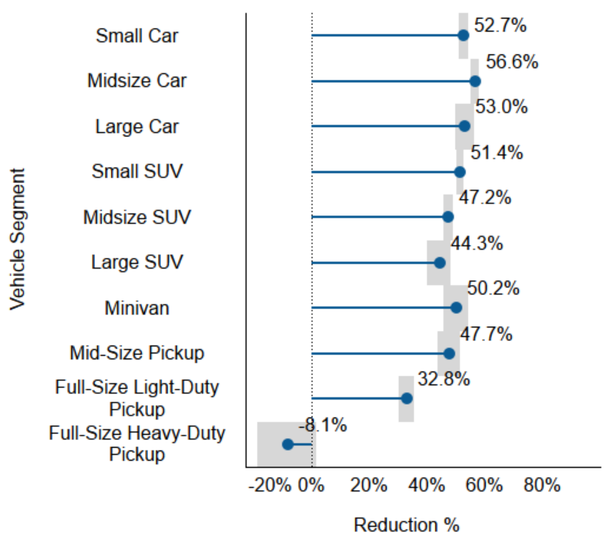
This appendix includes detailed results for all identified interactions across the ADAS features. Each covariate was separately included in the logistic regression as an interaction with the ADAS feature and BIC used to identify whether the interaction added meaningful information (i.e., BIC lower for logistic regression with interaction than without).

For each covariate identified by BIC, this section displays the effectiveness estimates by covariate level along with a 95% Bonferroni-corrected (based on number of levels of the covariate) CI. Additionally, the sample sizes for each level are also displayed.

Appendix C.1 Automatic Emergency Braking Identified Interactions

AEB by Vehicle Segment

It is noteworthy that in vehicle segments, full-size pickups generally exhibited lower effectiveness compared to the overall average. Full-size heavy-duty pickups did not show a statistically significant estimated reduction on front-to-rear striking crashes, as indicated by the 95% CI covering zero. PARTS also examined AEB effectiveness based on the weight of the striking vehicle, which is likely correlated with vehicle segment and may partially explain the differences in effectiveness.

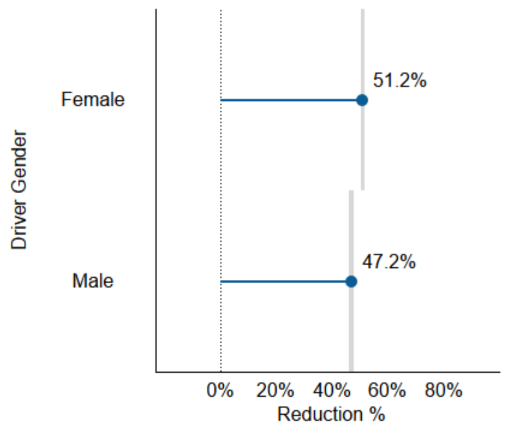


		Equipped	Unequipped
Small Car	Control	50,488	91,920
	System-Relevant	21,490	92,918
Midsize Car	Control	62,769	113,437
	System-Relevant	18,452	91,033
Large Car	Control	11,080	42,298
	System-Relevant	4,021	38,496
Small SUV	Control	100,276	135,054
	System-Relevant	27,604	86,982
Midsize SUV	Control	73,778	115,513
	System-Relevant	19,028	71,030
Large SUV	Control	21,305	7,159
	System-Relevant	7,573	4,560
Minivan	Control	9,243	10,760
	System-Relevant	2,165	5,926
Mid-Size Pickup	Control	11,057	17,558
	System-Relevant	3,514	11,340
Full-Size Light-Duty Pickup	Control	22,287	64,016
	System-Relevant	9,555	46,127
Full-Size Heavy-Duty Pickup	Control	2,127	20,635
	System-Relevant	1,846	19,237

Figure 21. Estimated AEB Effectiveness by Vehicle Segment

AEB by Driver Gender

Unlike past PARTS studies, the current study identified AEB effectiveness as changing for driver gender, with effectiveness found to be lower for male drivers. Other factors, such as driving behavior and vehicle segment, may have confounded this finding.



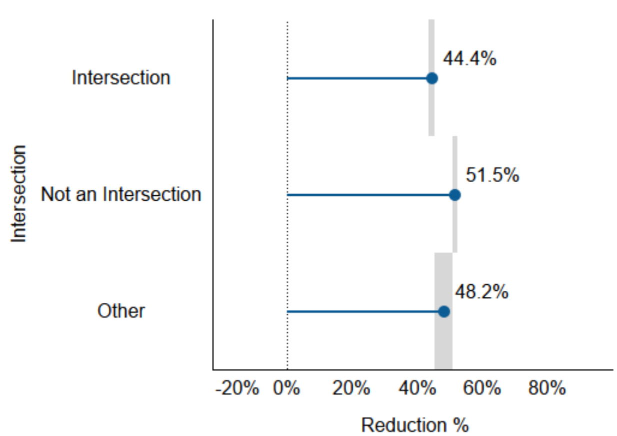
		Equipped	Unequipped
Female	Control	197,570	318,010
	System-Relevant	55,473	221,228
Male	Control	166,840	300,340
	System-Relevant	59,775	246,421

Figure 22. Estimated AEB Effectiveness by Driver Gender

The remaining covariates identified during this phase were also identified by PARTS in the previous study, with the estimates showing similar direction and magnitudes. Therefore, the remaining interaction effectiveness estimates are presented with limited discussion; see the 2022 PARTS Study for more detailed discussion of effectiveness by these covariates.

AEB by Crash Location at Intersection or Not

Estimated AEB effectiveness was found to be lower for crashes occurring at an interaction than the overall estimated effectiveness.

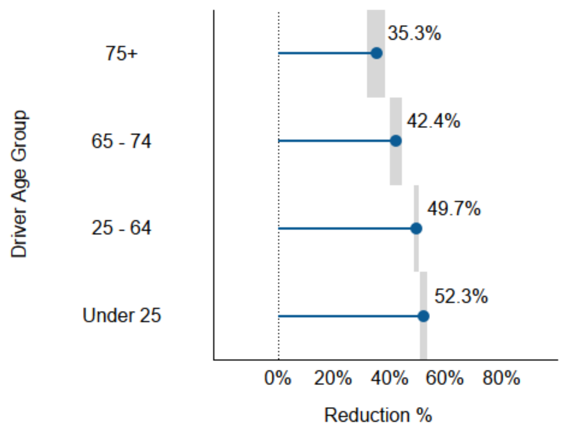


		Equipped	Unequipped
Intersection	Control	119,429	208,895
	System-Relevant	40,182	155,017
Not an Intersection	Control	234,880	391,869
	System-Relevant	71,715	299,358
Other	Control	10,101	17,586
	System-Relevant	3,351	13,274

Figure 23. Estimated AEB Effectiveness by Crash Location at Interaction or Not

AEB by Driver Age

Estimated AEB effectiveness was found to be lower for drivers 65–74 and older than 75.

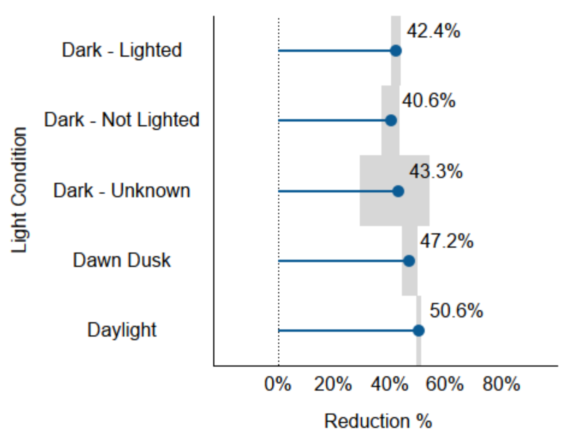


		Equipped	Unequipped
75+	Control	13,181	17,033
	System-Relevant	5,654	12,916
65 - 74	Control	34,416	48,247
	System-Relevant	8,631	24,403
25 - 64	Control	279,057	474,020
	System-Relevant	77,451	310,033
Under 25	Control	37,756	79,050
	System-Relevant	23,512	120,297

Figure 24. Estimated AEB Effectiveness by Driver Age

AEB by Light Condition

Estimated AEB effectiveness was found to be lower for crashes occurring when it was dark (lighted or not lighted) than the overall estimated effectiveness.

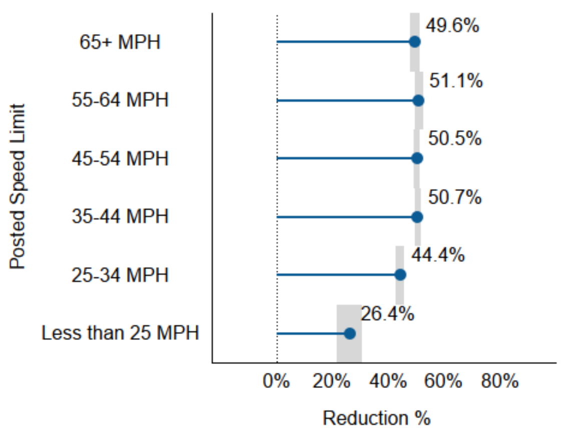


		Equipped	Unequipped
Dark - Lighted	Control	43,824	76,875
	System-Relevant	16,687	60,019
Dark - Not Lighted	Control	10,490	21,152
	System-Relevant	4,434	18,222
Dark - Unknown	Control	679	1,252
	System-Relevant	259	995
Dawn Dusk	Control	13,123	24,476
	System-Relevant	4,340	18,193
Daylight	Control	296,294	494,595
	System-Relevant	89,528	370,220

Figure 25. Estimated AEB Effectiveness by Light Condition

AEB by Posted Speed Limit

Estimated AEB effectiveness was found to be lower for crashes occurring on roads with lower posted speed limits (25–34) than the overall estimated effectiveness. Effectiveness was even lower with posted speed limits under 25 mph.

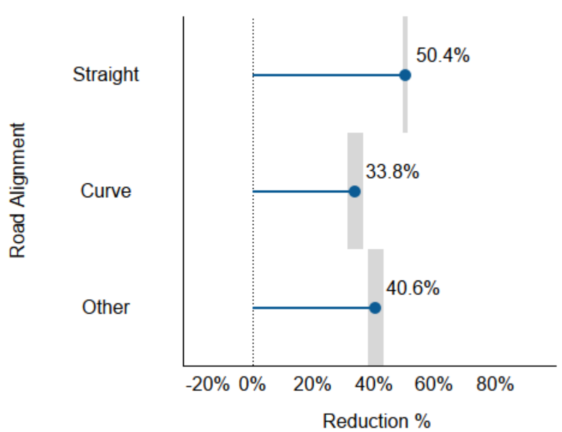


		Equipped	Unequipped
65+ MPH	Control	40,476	66,397
	System-Relevant	13,411	53,281
55-64 MPH	Control	50,498	85,819
	System-Relevant	15,412	65,685
45-54 MPH	Control	108,885	182,799
	System-Relevant	33,779	137,964
35-44 MPH	Control	106,659	184,377
	System-Relevant	31,935	136,882
25-34 MPH	Control	48,891	85,921
	System-Relevant	16,300	63,357
Less than 25 MPH	Control	9,001	13,037
	System-Relevant	4,411	10,480

Figure 26. Estimated AEB Effectiveness by Posted Speed Limit

AEB by Road Alignment

Estimated AEB effectiveness was found to be lower for crashes occurring on curved roads than the overall estimated effectiveness.

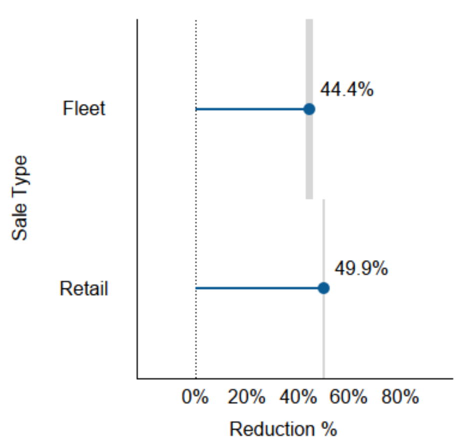


		Equipped	Unequipped
Straight	Control	333,855	551,320
	System-Relevant	103,112	419,078
Curve	Control	17,326	28,367
	System-Relevant	7,787	23,168
Other	Control	13,229	38,663
	System-Relevant	4,349	25,403

Figure 27. Estimated AEB Effectiveness by Road Alignment

AEB by Sales Type

Estimated AEB effectiveness was found to be lower for fleet vehicles than the overall estimated effectiveness.

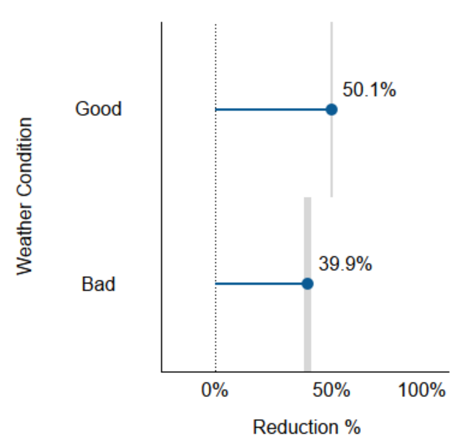


		Equipped	Unequipped
Fleet	Control	43,667	116,483
	System-Relevant	16,654	96,203
Retail	Control	320,743	501,867
	System-Relevant	98,594	371,446

Figure 28. Estimated AEB Effectiveness by Sales Type

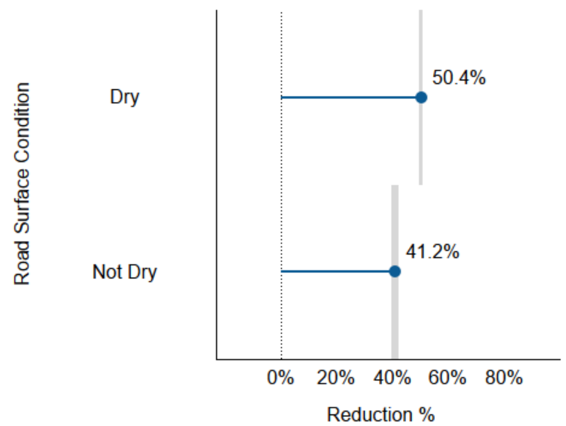
AEB by Weather and Road Surface Conditions

Estimated AEB effectiveness was found to be lower for crashes occurring when the road was not dry or during adverse weather (e.g., rain, frozen precipitation, fog, wind) than the overall estimated effectiveness. Weather and road surface are presented together in the next two figures because they are highly correlated (i.e., known confounding factors).



		Equipped	Unequipped
Good	Control	325,243	543,546
	System-Relevant	103,290	421,393
Bad	Control	39,167	74,804
	System-Relevant	11,958	46,256

Figure 29. Estimated AEB Effectiveness by Weather Condition



Road Surface Condition	Group	Equipped	Unequipped
Dry	Control	308,632	512,039
	System-Relevant	98,266	401,031
Not Dry	Control	55,778	106,311
	System-Relevant	16,982	66,618

Figure 30. Estimated AEB Effectiveness by Road Surface Condition

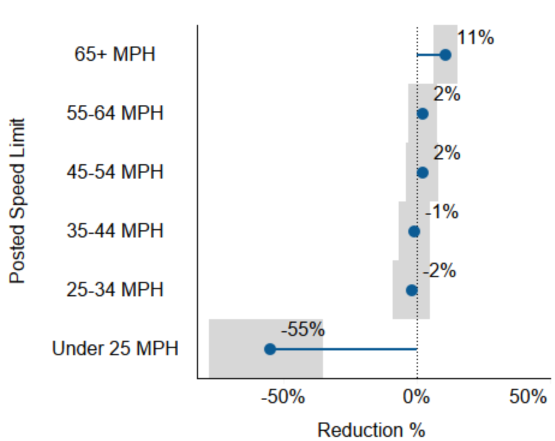
Appendix C.2 Pedestrian Automatic Emergency Braking Identified Interactions

PAEB effectiveness was not identified as differing by any covariates.

Appendix C.3 Lateral ADAS Feature Identified Interactions

LDW Only by Posted Speed Limit

LDW Only effectiveness was found to be lower than the overall estimated effectiveness for crashes occurring on roads with a posted speed limit under 25 mph, and higher for roads with a posted speed limit of 65+ mph. The higher effectiveness for 65+ was intuitive to the PARTS partners since roadway markings are often better maintained and more standard on roads with those posted speed limits. As mentioned in Section 4.4.3, posted speed does not necessarily equate to travel speed [22], and roads with a posted speed limit below 25 mph include residential areas, school zones, and alleys [23], where lateral systems are typically not designed to activate. Speed limits under 25 mph were included in the analysis to reflect the available data, but the researchers recommend caution when interpreting the estimated effectiveness value.

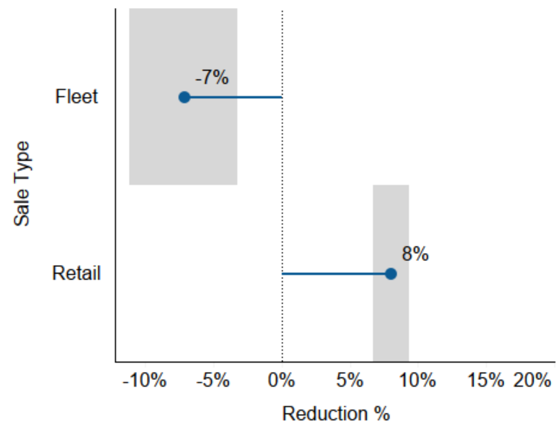


Posted Speed Limit	Group	Equipped	Unequipped
65+ MPH	Control Group	11,378	62,941
	System Relevant Group	5,437	35,421
55-64 MPH	Control Group	14,311	81,405
	System Relevant Group	4,921	32,766
45-54 MPH	Control Group	29,197	173,561
	System Relevant Group	2,972	19,875
35-44 MPH	Control Group	28,473	175,110
	System Relevant Group	3,361	22,699
25-34 MPH	Control Group	13,123	81,316
	System Relevant Group	2,957	19,025
Under 25 MPH	Control Group	1,923	12,566
	System Relevant Group	882	3,975

Figure 31. Estimated LDW Only Effectiveness by Posted Speed Limit

LDW + LKA by Sales Type

LDW + LKA estimated effectiveness was found to be lower for fleet vehicles than the overall estimated effectiveness.

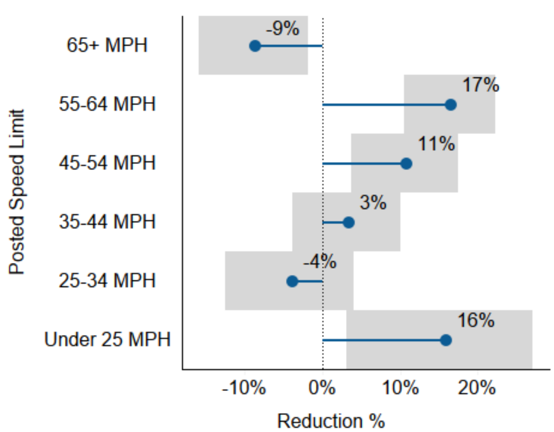


		Equipped	Unequipped
Fleet	Control Group	31,232	103,571
	System Relevant Group	6,608	28,325
Retail	Control Group	171,051	483,328
	System Relevant Group	24,800	105,436

Figure 32. Estimated LDW + LKA Effectiveness by Sales Type

LDW + LKA + LCA by Posted Speed Limit

LDW + LKA + LCA estimated effectiveness was found to be lower for crashes occurring on roads with a posted speed limit of 65+. The effectiveness being lower for posted speed limits 65+ shows a different behavior than LDW Only effectiveness and is not intuitive for the PARTS partners. More research is required to fully understand the results for posted speed limit.

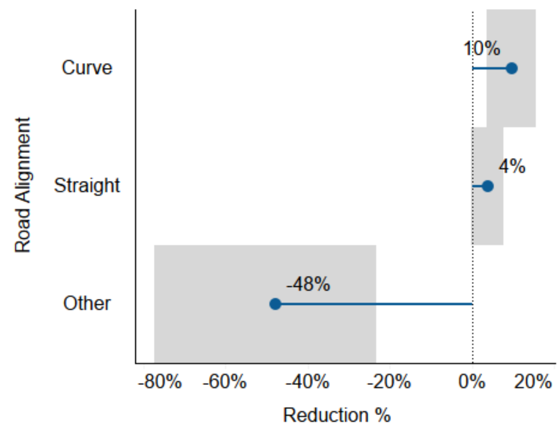


		Equipped	Unequipped
65+ MPH	Control Group	14,379	62,941
	System Relevant Group	5,405	35,421
55-64 MPH	Control Group	18,192	81,405
	System Relevant Group	3,701	32,766
45-54 MPH	Control Group	39,121	173,561
	System Relevant Group	2,454	19,875
35-44 MPH	Control Group	38,186	175,110
	System Relevant Group	2,923	22,699
25-34 MPH	Control Group	17,648	81,316
	System Relevant Group	2,648	19,025
Under 25 MPH	Control Group	3,593	12,566
	System Relevant Group	688	3,975

Figure 33. Estimated LDW + LKA + LCA Effectiveness by Posted Speed Limit

LDW + LKA + LCA by Road Alignment

LDW + LKA + LCA estimated effectiveness was also found to be lower for crashes where road alignment was “other” (not reported or reported in a manner that did not allow categorization in “curve” or “straight”) than the overall effectiveness estimate. It is important to note that the “other” category generally represented a small percentage of the crashes. Future research should investigate whether reporting patterns for the “other” category changed over time or differed by state and the influence that may have on the estimated effectiveness.



		Equipped	Unequipped
Curve	Control Group	6,415	27,264
	System Relevant Group	4,641	34,983
Straight	Control Group	121,840	524,598
	System Relevant Group	12,933	96,166
Other	Control Group	2,864	35,037
	System Relevant Group	245	2,612

Figure 34. Estimated LDW + LKA + LCA Effectiveness by Road Alignment

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