REAL-WORLD EFFECTIVENESS OF LANE KEEPING ASSISTANCE SYSTEMS USING FARS

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ABSTRACT
The study explored methods for estimating the real-world effectiveness of lane keeping assistance features in reducing system-relevant crashes involving a fatality. The study combined National Highway Traffic Safety Administration's Fatality Analysis and Reporting System data from crash years 2019 – 2023 with original equipment manufacturer supplied vehicle equipment data from 9 manufacturers including 98 million vehicles representing 168 vehicle models from model years 2015 – 2023. The study defined system-relevant crash scenarios using pre-crash scenario mappings developed by the United States Department of Transportation's Volpe National Transportation Systems Center and estimated effectiveness by equipage status of lane keeping assistance technology features using Poisson regression models with exposure approximated using vehicle miles traveled adjusted for COVID-19 years and driver demographics.

The study focused on lane keeping assistance effectiveness in fatal crashes, given that fatal crashes comprise an important segment of all vehicle crashes. Unexpectedly significant estimated reductions in fatal rear-end struck crashes related to feature equipage suggested that the methods investigated in this study are limited in their ability to isolate effectiveness specific to lane keeping assistance. These findings highlighted the ever-increasing challenge of isolating the impacts and effectiveness of specific Advanced Driver Assistance Systems functions in the real world. Future research to understand the effectiveness of advanced driver assistance systems on the most severe crashes will require new approaches that capture more of the complexities involved.

Keywords: Advanced Driver Assistance Systems, Lane Keeping Assistance, Traffic Fatalities

INTRODUCTION

Study Background

In 2023, traffic crashes were responsible for 40,901 fatalities on United States roadways according to the National Highway Traffic Safety Administration (NHTSA) [1]. Recent research has shown that Advanced Driver Assistance Systems (ADAS) are associated with reduced system-relevant crash rates [2] [3] [4]. ADAS are vehicle-based systems that assist drivers with the driving task. Some systems warn the driver when they are moving into a safety-critical situation (e.g., Lane Departure Warning) or intervene in order to avoid or mitigate a potential crash (e.g., Automatic Emergency Braking (AEB) and Lane Keeping Assistance (LKA)). Other systems provide ongoing assistance in basic driving tasks such as speed-keeping, lane-centering, and following (e.g., Adaptive Cruise Control (ACC) and Lane Centering Assistance (LCA)).

Over the past 15 years, numerous studies have examined the effectiveness of advanced safety systems in preventing crashes and reducing injuries, consistently showing technological improvements reflected in rising effectiveness estimates. A prime example is AEB, which has become widely available in new vehicles over the last decade [5] thanks to a voluntary commitment by OEMs. Early evaluations indicated that AEB could reduce rear-end striking crashes by nearly 43% [4]. More recent data reveals that the effectiveness of AEB continues to improve with advancing implementations in newer vehicle model years: 2021-2023 models demonstrate an increased effectiveness of approximately 52% [2]. This upward trend highlights the ongoing maturation and enhanced performance of AEB technology over time.

One of the challenges in assessing the field performance of these systems is the need for large amounts of crash and vehicle data to support statistical confidence in analysis. The studies that estimate effectiveness use linked crash and vehicle-equipage data to identify the crash experience of vehicles with and without the technology. For example, Leslie et al. [3] linked GM vehicle equipage data with police-reported crash data from 14 states, while the Insurance Institute for Highway Safety (IIHS) linked vehicle content data to police reports and insurance information [4]. As more vehicles are equipped, it becomes more feasible to generate sufficient sample sizes, and importantly, the larger the sample, the more it is possible to make increasingly granular estimates, especially of effectiveness on crashes with different levels of injury outcome.

This study aimed to evaluate methods for determining whether there is a difference in system-relevant fatal crash rates for vehicles equipped with LKA compared to unequipped vehicles. Lane keeping was selected for this study as it is historically less studied than AEB and the system-relevant crash types associated with lane keeping systems are responsible for a higher proportion of fatal crashes than the crash types associated with other ADAS features. The study leverages Fatality Analysis and Reporting System (FARS) data from crash years 2019 – 2023 and vehicle equipment data from 98 million vehicles representing 168 vehicle models from model years 2015 – 2023. System-relevant crash scenarios are defined using pre-crash scenario mappings developed by the U.S. Department of Transportation's (USDOT) Volpe National Transportation Systems Center [6]. Effectiveness is estimated using approximated Vehicle Miles Traveled [7] (VMT) to measure exposure and modeled using Poisson regression.

FARS is a census of fatal motor vehicle crashes derived from police report data and includes a set of data files documenting all qualifying fatalities that occurred within the 50 States, the District of Columbia, and Puerto Rico since 1975. To qualify as a FARS case, the crash had to involve a motor vehicle traveling on a trafficway customarily open to the public and must have resulted in the death of a motorist or a non-motorist within 30 days of the crash [8].

PARTS Overview

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

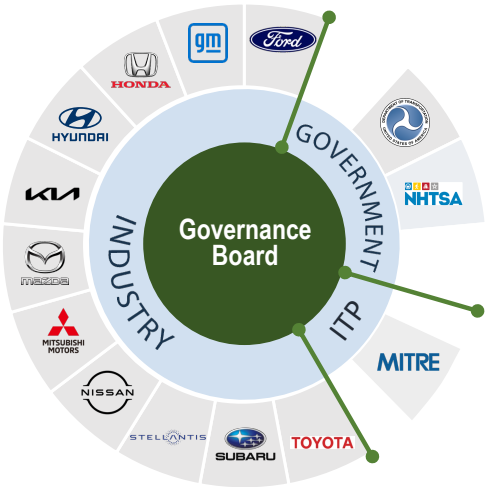


Figure 1. PARTS participation.

Of the 11 OEMs participating in PARTS (see Figure 1), nine provided vehicle data for this study. These 9 participating OEMs accounted for more than 80% of 2024 United States (U.S.) passenger car and light truck market sales [9].

Study Goal

This study intended to investigate methods for estimating the effectiveness of LKA features in preventing or mitigating fatal system-relevant crashes using the FARS dataset. The large PARTS dataset has previously supported estimation of the differential outcome of crash rates based on equipage of features that are generally vehicle enabled such as Automatic Emergency Braking (AEB) and Pedestrian Automatic Emergency Braking (PAEB), as well as for typically customer selectable features such as Lane Departure Warning (LDW), LKA, and LCA. Prior PARTS studies have evaluated all crashes and injury crashes, including focused analyses on the most severe crashes involving police reported fatality or serious injury [10]. However, analysis of police reported fatal injury crashes using the previous PARTS dataset did not provide interpretable results due to low sample sizes and resulting model instability.

A key challenge in using FARS to estimate the changes in fatal crash rates associated with LKA equipage is the need to apply driving exposure accurately across different vehicle populations and explanatory factors. In this context, risk is framed as an event rate based on the number of fatal system-relevant crashes per unit of exposure. In traffic safety, exposure can be defined in several ways, such as “per year,” “per licensed driver,” “per vehicle,” or “per vehicle miles traveled.” Because perfectly accurate on-road exposure measures were not available for this study, alternative approaches were considered. In its assessment of ADAS effectiveness, IIHS used insured vehicle days as the exposure measure [4]. However, a more common approach for police reported crash data, used by PARTS and Leslie et al. [2] [3], is called Quasi-induced Exposure (QIE), which derives a proxy for miles driven from the crash data itself. QIE uses a crash type that is assumed to be unaffected by the system under study to estimate driving exposure. This crash type is argued to occur largely in proportion to how often a driver is on the road rather than their risk level relative to other drivers. The most commonly used QIE control crash type is rear-end struck, which has been examined in several studies. Keall and Newstead [11] identified rear-end struck as a representative exposure proxy after comparing candidate crash types. Both PARTS [12] and IIHS [13] adopted rear-end struck to better account for exposure to covariates important to system-relevant crashes.

For this study, the objective was to compare methods for estimating LKA effectiveness on run-off-road crashes using two exposure methods: estimated mileage and QIE-based exposure. A recent PARTS study [14] demonstrated that the estimated effectiveness of lane assistance features in preventing single vehicle road departures is nearly the same as using QIE versus vehicle reported mileage, providing the most direct and convincing validation that police-reported rear-end struck crashes can be used as a proxy for miles driven. The current study did not have access to either vehicle reported mileage or police reported rear-end struck crashes for the complete locality and population covered by FARS, so we applied similar methods using available data and compared our findings to prior research.

A recent FARS-based analysis conducted by NHTSA [15] using QIE estimated a 26% (4%, 43%) reduction in fatal single vehicle road departure crashes for vehicles equipped with LKA with posted speed limits ≥ 40 mph. In contrast, this study did not restrict by posted speed limit and used Volpe pre-crash mappings to more strictly define single-vehicle road departures. This study also used a larger sample that included vehicle models with optional LKA feature content, leveraging PARTS detailed information on the specific technology present on each vehicle. In addition, we conducted a separate analysis using estimated mileage data to account for differences in exposure to certain key context variables for those who drive equipped and unequipped vehicles. Based on the results, we evaluate the relative success of the two exposure methods compared to related prior research and examine how each method handles driving exposure. We also discuss potential bias in the resulting estimates of LKA effectiveness on fatal crashes.

METHODS

Vehicle Equipment Data

The study used OEM partner provided data on 98 million passenger vehicles sold in the U.S., encompassing 168 vehicle models from model years 2015–2023 across 10 vehicle segments (Figure 2). This same dataset supported previous ADAS effectiveness studies [2]. Vehicle equipment data describes ADAS features installed at the time of manufacture. ADAS features were individually defined, and VIN level content was assigned by feature. While most vehicles include significant content and hardware overlap, due to variability in implementations and operational domains over time and across manufacturers and models, the study focused on LKA and did not consider feature interactions. LKA was defined as a feature that provides momentary steering support to help keep the vehicle in the lane when the vehicle approaches or crosses a lane line or road edge. The availability or activation of ADAS features at the time of crash was not available for consideration in this study.

As detailed in the PARTS 2025 study [2], OEM-supplied 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 – includes the Ford and Lincoln brands
- General Motors LLC – includes the Buick, Cadillac, Chevrolet, and GMC brands
- Hyundai Motor Company – includes the Hyundai and Genesis brands
- Mazda North American Operations
- Mitsubishi Motors R&D of America
- Stellantis (Fiat Chrysler Automobiles U.S. LLC) – includes the Alfa Romeo, Chrysler, Dodge, Fiat, Jeep, and Ram brands
- Subaru Corporation
- Toyota Motor North America – includes the Toyota and Lexus brands

Vehicles were categorized into 10 segments based on their size and intended use, as shown in Figure 2. PARTS determined these vehicle segments using the IIHS vehicle segment definitions [16], with some modifications.[1]

Vehicle models selected for inclusion are based on the following guidelines:

- Sufficient Sample Size: A minimum sales threshold of 5,000 units per model per year helped ensure a sufficient sample size for analysis.
- ADAS Feature Equipage: At least one model year for each model was required to have at least one ADAS feature as optional equipment to be considered in scope for the analysis.
- Passenger Vehicle Study Scope: Gross Vehicle Weight Rating (GVWR) was limited to less than 10,000 pounds to target passenger vehicle populations.
- Non-attribution: Among other data protection measures, PARTS required vehicle models from at least three OEMs in a vehicle segment to maintain anonymity of the results.

[1] 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 Sport Utility Vehicle (SUV) criteria, which had the effect of moving some three-row SUVs from the small SUV to the midsize SUV segment.

The resulting dataset included 98 million vehicles from 168 models, covering model years 2015–2023, manufactured on or before July 31, 2023.



Figure 2. Vehicle data - mapping models to segments.

Crash Data

Crash involved fatality data used in this study came from FARS crash years 2019-2023. The first event in the crash sequence of events was identified and only the 2 vehicles (or 1 vehicle for single vehicle road departures) involved in the first event were included in the study. A second filter was applied to limit the study data to cases where the fatality was identified as occurring in the first crash event. This combination of filters worked to exclude complex sequence of event situations where the only fatalities resulted from secondary impacts and beyond as these types of crash scenarios are outside the intended design function of the lane assistance features under study. The data was then filtered to system relevant pre-crash scenarios.

System-relevant crash definition

The LKA feature was mapped to system-relevant crash types, as defined in Table 1 resulting in 55,071 vehicles-in-transport. Pre-crash scenarios were defined based on work conducted by the John A. Volpe National Transportation Research [6]. These defined scenarios were mapped to LKA based on operational design domain and expert opinions from the partnership. Additional filtering was applied to focus on the initial event in the crash sequence and align to LKA intended functionality. Due to variation in feature executions and lack of vehicle speed data at time of lane crossing, no filter was applied for speed. Relevant crash, vehicle, and occupant data were merged from FARS data tables to support further analysis.

Table 1.
LKA feature system-relevant crash type definitions

System	System-Relevant Crash Type	Definition
Lane Keeping Assistance	Single-vehicle Road Departure Maneuver Single-vehicle Road Departure No Maneuver Drifting Same Direction Opposite Direction Maneuver Opposite Direction No Maneuver	Crash Event = 1 AND Fatal occurred in Crash Event = 1 AND Pre-crash scenario IN [Road edge departure / maneuver, Road edge departure / no maneuver, Drifting / same direction, Opposite direction / maneuver, Opposite direction / no maneuver] AND Single-vehicle crashes only for Road edge departure scenarios (accident.ve_total = 1) AND Exclude vehicles driving wrong direction (for 2019 FARS vehicle.dr_sf1 - dr_sf4 NOT IN [50, 51], for 2020-2023 FARS driverrf.driverrf NOT IN [50, 51])

Data Preparation and Linkage

Partner OEM supplied vehicle equipment data was standardized across LKA implementations by working directly with OEMs to map their VIN-level records to a common feature definition. Vehicles equipped with LKA or LDW and LKA were considered. Vehicles equipped with LCA or a combination of LKA and LCA were excluded from the LKA analysis. Vehicles requiring the engagement of additional ADAS features such as ACC to enable LKA were excluded. The standardized dataset was then linked to the system-relevant FARS case vehicles using masked 17-digit VIN. The subset of system-relevant crashes involving a partner OEM vehicle as one of the first-event vehicles was isolated for further study. The resulting dataset included 7,565 linked partner OEM vehicles.

Vehicle segments aligned to manufacturer (Figure 2) were then aligned to NHTSA Corporate Average Fuel Economy (CAFE) defined segments [7] based on input from partnership experts (Table 2). These CAFE segments with associated annual vehicle mileage estimates by vehicle age include passenger cars, vans and SUVs, pickup trucks, and heavy-duty pickup trucks and vans (HDPUV). This allowed for the attribution of estimated miles to support the Poisson regression analysis. A summary of lane assistance content by crash scenario and system-relevant filtered fatal crash counts for the FARS linked dataset are shown in Table 3.

Table 2.
CAFE body style vehicle segment alignment to PARTS dataset

	CAFE Body Styles			
	Car	Van/SUV	Pickup	HDPUV
OEM Vehicle Segments	Small Car Midsize Car Large Car	Small SUV Midsize SUV Large SUV Minivan	Light Duty Pickup Medium Pickup	Heavy Duty Pickup

Table 3.
Vehicle LKA populations by crash type – FARS linked

System	Scenario	Fatal Crash Count	LKA Equipped Count (%)
Lane Keeping Assistance	Single-vehicle Road Departure, No Maneuver	4,611	745 (16.2%)
	Single-vehicle Road Departure, Maneuver	211	33 (15.6%)
	Drifting Same Direction	113	17 (15.0%)
	Opposite Direction, Maneuver	304	46 (15.1%)
	Opposite Direction, No Maneuver	2,326	361 (15.5%)
Control	Rear-end Struck	1,591	274 (17.2%)

Statistical Approach

This study used two statistical approaches to evaluate the effectiveness of ADAS systems on fatal crashes. While model efforts were undertaken for AEB, PAEB, LDW, LKA, and LCA, this report focuses on the LKA results as an exemplar of the patterns observed. LKA was selected for this role due to the large scope of crash types covered and the availability of other work estimating the impact of LKA on fatal crashes [15]. All modeling was performed using R (v4.5.2).

Approach 1 estimated adjusted national average VMT using a two-step approach. First, the PARTS partner vehicle dataset was aggregated by vehicle segment, model year, calendar year, vehicle age, and feature equipage. Each aggregated row was then assigned a per-vehicle estimate of annual VMT based on the vehicle age and segment using the Corporate Average Fuel Economy (CAFE) report [7]. Table 4-12 of that report lists estimated annual VMT by vehicle segment and vehicle age. The total VMT estimate for each row of the aggregated data was calculated by multiplying the vehicle count of the row by the assigned per-vehicle VMT.

To account for the decrease in vehicle travel during the COVID-19 pandemic, the final VMT estimates for 2020 and 2021 were scaled down. Based on estimates developed using Federal Highway Administration data [17], the calendar year 2020 estimates were reduced by 11% and the calendar year 2021 estimates were decreased by 3.7%. Since the specific driving locations of partner vehicles was unknown, these corrections were made nationally and do not reflect regional differences in traffic patterns. This produced estimated VMT for the partner vehicle fleet allocated across the five VMT-linked variables: vehicle segment, model year, calendar year, vehicle age, and equipment status. Later, due to the high correlation between model year and vehicle age, only model year was retained for the final modeling efforts.

In the second step, we allocated the VMT in each row to equipped and unequipped vehicles. As discussed in PARTS 2025 [14] and mentioned earlier, VMT cannot be assigned to specific environmental conditions or driver demographics. However, since older drivers, especially those above 65 years of age, are 1) more likely to drive equipped vehicles [18], 2) likely to drive less than younger drivers, and 3) more likely to be injured in crashes, additional efforts were taken to more accurately reflect the VMT differences across driver age and other covariates using police reported data from a prior PARTS study.

The potential age-related factors described above were analyzed and as expected, young drivers were found substantially less likely to drive equipped vehicles, and older drivers are more likely to do so. Given the magnitude of the differences (a 29.5% increase from the lowest age bin to the highest), inclusion of driver age was determined to be important to accurately estimate the relevant exposure for the fatality analysis. The analysis was performed using the rear-end struck crashes from the Consolidated State Crash (CSC) database containing police reported

crashes as explained in previous PARTS studies [2] [12] as a surrogate for driving exposure, a series of logistic regression models were fit to evaluate the importance of additional covariates. The starting model predicted the probability of being equipped with AEB in rear-end struck crashes based on vehicle segment and model year. A second model then was fit including driver age as an additional predictor while holding the fitted values of the starting model constant. This evaluated whether driver age provided a significant benefit in allocating exposure above and beyond the existing VMT-linked variables. The results of these models are shown in Table 4. Even after accounting for the VMT-linked variables, driver age has a substantial impact on exposure, with the proportion of equipped vehicles ranging from 42% to 57% across the age ranges.

Table 4.
Results of CSC-based evaluation of driver age effect on exposure

Driver Age	25 or less	26 to 64	65 to 74	75 or more	Unknown
Probability of being AEB equipped	0.437	0.500	0.560	0.569	0.418
Percent increase over lowest age bin	+0.0%	+13.6 %	+27.3%	+29.5%	-4.6%

Similar efforts were made to evaluate the benefit of road alignment, rural vs. urban roadway, presence of unbelted occupants, crash located at intersection, driver sex, weather condition, light condition, posted speed limit, crash year, presence of occupants over 65 years old, and road surface condition. After accounting for driver age, none of the factors considered produced magnitudes of effect comparable to driver age. As such, in order to control complexity only the driver age patterns were used to adjust VMT.

To incorporate the driver age effect, driver age bins were added to each row in the aggregated table from Step 1. Next, the VMT in that row was allocated to those age bins based on whether the row represented equipped or unequipped vehicles. The allocations were calculated using the proportion of vehicles driven by drivers of the relevant age (a_i) and the probability of being equipped for that age group (e_i). For the equipped vehicles the proportion of VMT allocated to an age group was:

$$\propto_{VMTequip} = a_i * \frac{e_i}{1 - e_i} \quad \text{Equation (1)}$$

and for unequipped vehicles it was:

$$\propto_{VMTunequip} = a_i * \frac{1 - e_i}{e_i} \quad \text{Equation (2)}$$

For example, in the CSC data, 11.6% of vehicles had a driver of age 25 or less and the probability of being equipped with AEB was 0.437 for drivers of that age. The proportion of VMT allocated to drivers of age 25 or less for equipped vehicles was thus:

$$0.116 * \frac{0.437}{0.563} = 0.090 \quad \text{Equation (3)}$$

The final CSC-based VMT adjustments are shown in Table 5.

Table 5.
Driver age VMT allocation based on CSC rear-end struck crashes

Driver Age	25 or less	26 to 64	65 to 74	75 or more	Unknown
Unequipped VMT Proportion	0.150	0.763	0.065	0.023	0.008

Poisson Rate Modeling was the core approach assessing crashes per VMT similar to the approach described in the PARTS [14] report. As in that study, a dispersion parameter was included in the Poisson regression to address overdispersion. A total of six models were constructed, with each using a different crash type as the outcome. Crash types of interest were defined primarily using the Volpe pre-crash typology [6] with secondary filters applied to refine the crash scenario. To be included, the partner vehicle must have participated in the first event of the crash and satisfied one of the following definitions:

1. Single-Vehicle Road Departure, No Maneuver
    a. Pre-crash type: road edge departure/no maneuver (5)
    b. Single vehicle crash
2. Single-Vehicle Road Departure, Maneuver
    a. Pre-crash type: road edge departure/maneuver (4)
    b. Single vehicle crash
3. Same Direction Drifting
    a. Pre-crash type: drifting/same direction (17)
    b. Host vehicle departed lane[2]
    c. Neither vehicle had a critical pre-crash event of over the road edge or conflict with an in path stopped vehicle
4. Opposite Direction, No Maneuver
    a. Pre-crash type: opposite direction/no maneuver (19)
    b. Host vehicle departed lane[3]
5. Opposite Direction, Maneuver
    a. Pre-crash type: opposite direction/ maneuver (18)
    b. Host vehicle departed lane
6. Rear-end Struck (for control group)
    a. Pre-crash type: rear-end/striking maneuver (20), rear-end/lead vehicle accelerating (21), rear-end/lead vehicle moving (22), rear-end/lead vehicle decelerating (23), rear-end/lead vehicle stopped (24)
    b. Initial point of contact: 11 o'clock, 12 o'clock, 1 o'clock
    c. Manner of collision: front-to-rear

The models predicted the rate of fatal crashes per million VMT for partner vehicles based on:

- Equipment Status
- Vehicle Model Year: 2015-2023
- Calendar Year: 2019-2023
- CAFE Vehicle Segment: Car, Van/SUV, Pickup, Heavy Duty Pickup
- Driver Age: 25 or less, 26-64, 65-74, 75 or older, Unknown

Approach 2 used QIE modeling to evaluate the effect of LKA on fatal single-vehicle road departure crashes. Since this effort was intended to be compared to the VMT-based approach, it used the crash types listed above, with the two single-vehicle road departure crashes being system-relevant and rear-end struck serving as the control. It also used the same set of predictor variables as the Poisson models. Other than this, the models followed the same approach as described in previous PARTS publications [2] [12].

[2] Host Critical Pre-crash – Event was "over the lane line on left side of travel lane" or "over the lane line on right side of travel lane" or was Vehicle 1 when neither vehicle had those pre-crash events.
[3] Host Critical Pre-crash – Event was "over the lane line on left side of travel lane," "over the lane line on right side of travel lane," "off the edge of the road on the left side," or "off the edge of the road on the right side" or was Vehicle 1 when neither vehicle had those pre-crash events.

RESULTS

Poisson Rate Modeling

Estimated effectiveness values for LKA are shown in Table 6. The estimates of system-relevant fatal crash reductions range from 32.7% to 45.4%. For fatal rear-end struck crashes (not system-relevant), there was a significant 27.2% reduction for LKA-equipped vehicles.

The Swanson et al [6] pre-crash typology also identifies “maneuver” crashes which involve active steering actions by the driver (e.g., turns and lane changes). Since the studied LKA systems do not command sufficient steering authority to override driver maneuvers some implementations disable LKA when turn-signals are activated, these are also considered to be not system-relevant. While some implementations of LKA are disabled when braking is applied, information related to the application of braking prior to the lane departure was not available for this study. As seen in Table 6, while the maneuver crash types have wider confidence intervals, the point estimates are close to their no maneuver equivalents (-2% for single-vehicle road departure and +0.3% for opposite direction). While this could reflect unreliability in the maneuver coding, it would be expected that LKA systems would demonstrate less effectiveness in crashes that a driver engages in a maneuver that would likely prevent the system from intervening.

Table 6.
Poisson VMT-based LKA effectiveness estimates

Crash Type	Source	Target Crash Population	Estimated Crash Reduction (%)	Confidence Interval
Single-vehicle Road Departure	PARTS [14]	All Crashes (KABCO)	13	(-25,40)
Rear-end Struck	PARTS [14]	All Crashes (KABCO)	6	(1,10)
Single-vehicle Road Departure	Current Study	Fatal No Maneuver Crashes	35	(28,41)
Single-vehicle Road Departure	Current Study	Fatal Maneuver Crashes	33	(6,52)
Same Direction Drifting	Current Study	Fatal Crashes	45	(3,69)
Opposite Direction	Current Study	Fatal No Maneuver Crashes	37	(29,45)
Opposite Direction	Current Study	Fatal Maneuver Crashes	37	(12,55)
Rear-end Struck	Current Study	Fatal Crashes	27	(16,37)

Quasi-induced Exposure Modeling

The QIE results for the same set of partner vehicles are presented in Table 7. The results were non-significant, but the point estimates are similar to PARTS injury-crash (KAB) results [10].

Table 7.
QIE-based LKA effectiveness estimates in single-vehicle road departure crashes

Crash Type	Source	Target Crash Population	Estimated Crash Reduction (%)	Confidence Interval
Single-vehicle Road Departure	NHTSA [15]	Fatal Crashes, with conditions[4]	26	(4,43)
Single-vehicle Road Departure	Leslie et al. [3]	All Crashes (KABCO), speed limit ≥ 30	9	(2,16)
Single-vehicle Road Departure	Leslie et al. [3]	Injury Crashes (KAB), speed limit ≥ 30	8	(-6,20)
Single-vehicle Road Departure	PARTS [2]	All Crashes (KABCO)	5	(3,7)
Single-vehicle Road Departure	PARTS [10]	Injury Crashes (KAB)	9	(5,13)
Single-vehicle Road Departure	PARTS [10]	Fatal and Serious Injury Crashes (KA)	6	(-2,13)
Single-vehicle Road Departure	Current Study	Fatal No Maneuver Crashes	10	(-7,24)
Single-vehicle Road Departure	Current Study	Fatal Maneuver Crashes	4	(-51,39)

Synthesis of Results

The LKA results from QIE described in Table 7 above are broadly consistent with previous observations. Since the Poisson rate study could not address unobserved confounding factors, leading to unexpectedly high effectiveness estimates, it is reasonable to examine the effect of adjusting the VMT-based estimates based on the observed rear-end struck patterns. This represents an approximated adjustment aggregating the error and potential confounding factors into a single adjustment term. It is not clear how to assess statistical significance, and the results are used for approximation and discussion only.

To do this, assume that the LKA reduction for system-irrelevant rear-end struck crashes reflects the observed reduction in crash risk due to factors other than the system. With this interpretation, the risk ratio for control crashes, r_c, estimates the baseline risk ratio for equipped vehicles. If the same factors apply, portion of the risk ratio for a system-relevant crash, r_s, that is attributable to the system could be estimated as:

$$\tilde{r}_s = \frac{r_s}{r_c} \quad \text{Equation (4)}$$

with the estimated crash reduction being:

$$\tilde{R} = 1 - \tilde{r}_s \quad \text{Equation (5)}$$

For the estimated effectiveness value from the Poisson analyses above, this approach would produce the adjusted effectiveness values in Table 8.

[4] ≥40 mph speed limit zones, standard equipage vehicles only

Table 8.
Adjusted effectiveness values for VMT-based estimates

Crash Type	Raw Risk Ratio	Adjusted Risk Ratio	Adjusted Crash Reduction
Single-vehicle road Departure, No Maneuver	0.653	0.897	10
Single-vehicle road Departure, Maneuver	0.673	0.924	8
Same Direction Drifting	0.546	0.750	25
Opposite Direction, No Maneuver	0.629	0.864	14
Opposite Direction, Maneuver	0.626	0.860	14

While the adjusted effectiveness values in Table 8 more closely align with prior research for single-vehicle road departure crashes, they continue to reflect unlikely crash reduction values for maneuver scenarios under which lane keeping systems should have been overridden by driver action. An improved method or data are likely required to accurately represent estimated effectiveness and statistical confidence.

DISCUSSION

As the analysis has shown, the approaches used in this study could not address unobserved and uncontrolled factors and isolate the performance of LKA leading to likely unrealistic overestimation of effectiveness in fatal crashes. These factors could include differences in exposure or driving behaviors in equipped vehicles that changed their risk of fatal crash. Prior research suggests crash reductions and injury crash reductions of less than 10% [2] [10] [12], and system functionality and capability does not suggest markedly increased effectiveness should be uniquely expected for fatal crashes. Studies have also found that customer selected usage of LKA varies widely (35% to 97%) over time and across different implementations [19] [20] which could make the Poisson based effectiveness estimates implausible (e.g., up to ~70% for fatal road departures). Additionally, the large and statistically significant estimated reduction for rear-end struck crashes associated with LKA equipage, suggests that there are additional factors influencing the estimates, as rear-end struck crash rates should not be influenced by the presence of LKA. Finally, while there may be issues with the coding of maneuver on the crash reports, the fact that the estimated effectiveness does not change in the presence of maneuvers is suspect since LKA should not be active during active steering by the driver.

While fatal crashes are critical to traffic safety, they make up a small and unique portion of the US crash population. Crashes resulting in a fatality often involve confounding circumstances such as unbelted occupants, impaired drivers, speeding, and occupant co-morbidities. This poses a problem when using VMT both because these behavioral and occupant factors cannot be readily mapped to VMT and because the demographic differences in the riskiness of driven miles can impact the fatality rate. For analyses that compare demographically different populations, like this one, this may make the feasibility of VMT-based analyses questionable.

Adjusting crash reduction estimates based on non-system relevant control crash effectiveness estimates may address some of the confounding, however calculating appropriate confidence intervals is not feasible and it is unclear whether additional unexplained factors may still be present. Additional explanatory variables may be necessary as well as improved exposure assignment to accurately estimate the effectiveness of these systems but doing so is difficult within the VMT-based modeling structure.

QIE, which uses rear-end struck crashes to estimate exposure to risk, can account for additional factors. The close correspondence between the QIE effectiveness estimates for fatal single-vehicle road departures and previous estimates by PARTS [2][10] suggest that QIE may be less influenced by the confounding factors as well. However,

as shown by the NHTSA LKA analysis [15] the method can produce substantially different estimates when the vehicle population is changed.

LIMITATIONS

Vehicle data in this study are limited to the lane assistance equipage at the time of manufacture. No data on feature usage or availability was provided for this study, so analyses do not comprehend errors associated with features that have been turned off or are otherwise not functional at the time of crash.

Variability in LKA implementations is not captured in the data nor accounted for in the analysis. Differences related to operation, feature technology integration, or software are not comprehended. Similarly, the study does not consider the operational design domain for a given LKA feature that defines the functional capability of the feature to operate.

The study includes vehicle model years 2015 – 2023 across many manufacturers and vehicle segments. Changes in vehicle design, technology, and execution related to a given vehicle model lifecycle are not directly captured in this study. Vehicle performance differences related to advances in materials, sensors, computing capability, and manufacturing are not considered.

FARS crash data are based on police reports and have known limitations. Data does not capture detailed crash dynamics (e.g., travel speed or delta-V), occupant injury details or co-morbidities. Many factors that have been previously shown to influence crash rates, such as driver gender, roadway alignment, road surface condition, weather, and light condition, could not be associated with VMT. This analysis was unable to control for these covariates, which may have contributed to the confounding challenges.

VMT was estimated using national FHWA CAFE modeling by vehicle age and segment with uniform adjustments made for COVID-19 years 2020 and 2021 that do not reflect variability in state shutdowns or changes in driver behavior or demographics that may have been uniquely present during this time. Potential bias in the CSC-based mileage adjustments to driver age could be present as the CSC data only represented a subset of 16 reporting states. This may have changed the calculated magnitude of effects seen with the other covariates assessed for mileage adjustment. Furthermore, VMT was assigned only by vehicle segment, vehicle age/model year, calendar year, and driver age without incorporating roadway, environmental, or many driver behavior factors documented in FARS, so systematic differences in where and how LKA-equipped vehicles are driven may not be fully captured. As a result, unmeasured exposure differences between equipped and unequipped vehicles can appear as spurious crash rate reductions in both system-relevant and system-irrelevant crash types, including rear-end struck crashes.

CONCLUSIONS

In summary, FARS and OEM provided content data were linked and integrated with exposure estimated using NHTSA CAFE VMT and QIE with rear-end struck as a control. System-relevant crashes were defined using pre-crash mapping scenarios aligned to LKA operational design capabilities. Multiple modeling approaches were evaluated to compare their estimates of LKA effectiveness in preventing or mitigating system-relevant fatal crashes.

The effectiveness estimates were substantially higher than prior research or engineering performance expectations and assessments of system-irrelevant crash scenarios resulted in positive effectiveness estimates suggesting unexplained confounding within the available data. Attempts to address this confounding were unsuccessful, indicating that the current data and methods are insufficient to isolate the specific contribution of LKA to fatal crash reductions.

Future research to better understand the complex nature of fatal crashes and the unique contributors to these crashes is warranted. Improvements in exposure data and methodology are needed to obtain unbiased estimates of ADAS effectiveness in reducing system-relevant fatal crashes.

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