Comparison of Automated Vehicle Struck-from-Behind Crash Rates with National Rates Using Naturalistic Data

Noah Goodall
Senior Research Scientist
Virginia Transportation Research Council
Email: noah.goodall@vdot.virginia.gov
ORCiD: 0000-0002-3576-9886

October 6, 2020

Abstract
Automated vehicle developers in California are required to submit records of crashes and distances traveled in autonomous mode for all vehicles in their fleets. Several studies have investigated this database to compare automated vehicle crash rates with national rates. Although automated vehicles are struck from behind in 73% of their autonomous mode crashes, this is the first study to compare automated vehicle struck-from-behind crash rates to national rates using equivalent crash definitions. Rear-end collisions have substantial public health and economic impacts, representing a third of all collisions and $3.9 B in annual economic costs. In this study, automated vehicles were found to be struck from behind while in autonomous mode 17.2 (14.2–20.7, 95% CI) times per million-miles traveled, significantly higher than human-driven vehicles in naturalistic driving studies (3.6, 3.0–4.3, 95% CI). These differences narrow when comparing urban driving and business/industrial driving in the naturalistic driving studies with AV testing in similar environments. Automated vehicles were more likely to be struck when stopped than when moving, suggesting that automated vehicles' decisions about where and when to stop at intersection are more plausible as contributing factors than unexpected rates of deceleration.

Keywords: autonomous vehicle; vehicle automation; rear-end struck; safety

1 Introduction

Vehicles with automated driving features, defined here as combined lateral and longitudinal control, have been tested on public roads in the United States nearly continuously since 2010 (Beiker, 2014). In September 2014, the California Department of Motor Vehicles began requiring companies wishing to test AVs on public roads to obtain permits (California Department of Motor Vehicles, 2018). All permit holders were required to report all crashes using form OL 316 within 10 days of the incident, regardless of severity or whether the vehicle was under human or computer control. Permit holders were also required report all test vehicles, miles driven in autonomous mode, and disengagements of the autonomous driving system by January 1st for the prior period of December to November. The combined public data sets of vehicle crashes and mileages for all autonomous vehicle testing in California proved a valuable resource for researchers, and several studies have shown that automated vehicle (AV) crash rates are lower than general public crash rates when controlling for crash severity (Blanco et al., 2016; Teoh and Kidd, 2017). Studies have also reported that a majority of AV crashes involve the automated vehicle being struck from behind (Leilabadi and Schmidt, 2019). As a proportion of total crashes, these are far higher than those reported by the driving public (Favarò et al., 2017).

Struck-from-behind crashes are a significant economic and public health concern. Rear end collisions account for 32.3% of all crashes in the United States (National Highway Traffic Safety Administration, 2020a, p. 29). Economic losses from whiplash injuries were estimated as \$2.7 B nationally in 2002 dollars (\$3.9 B in 2020) ("Federal Motor Vehicle Safety Standards; Head Restraints," 2010).

Previous studies have investigated the AV crash rates generally, but none have compared AV and human-driven struck-from-behind crash rates. The purposes of this study are to determine whether AVs are struck from behind at higher rates per distance traveled than conventional vehicles, and to investigate potential causes.

2 Literature Review

Several studies have analyzed automated vehicle crash records, differing in the methods and metrics. Table 1 shows an overview of automated vehicle crash studies and comparisons in the literature. Some studies did not calculate crash rates but instead performed exploratory analysis (Das et al., 2020), text mined crash narratives (Alambeigi et al., 2020; Boggs et al., 2020b), or modeled crash severity (Wang and Li, 2019). Other studies calculated automated vehicle crash rates but did not compare them with baseline figures (Leilabadi and Schmidt, 2019).

Schoettle and Sivak (2015) conducted the first study to compare automated vehicle crash rates to conventional vehicle crash rates. The authors found the AV crash rate of 9.1 crashes per million miles to be higher than the conventional vehicle crash rate of 4.1, although 95th percentile confidence intervals overlapped due in part to the small sample size of AV crashes with only 11 crashes over 1.2 million miles. The authors also compared the full set of DMV-reported AV crashes with NHTSA's General Estimates System (GES). This comparison is not equivalent, however, as the AV crash rate includes no-damage crashes while the GES human-driven crash rate is based on estimates of crashes that meet minimum thresholds of damage or injury for police reporting (Blanco et al., 2016; National Highway Traffic Safety Administration, 2020b). Favarò et al. (2017) conducted a similar study comparing AV crashes rates from DMV reports with GES national crash rate estimates, which again suffers from incompatible crash definitions.

Table 1 Automated Vehicle Crash Studies and Comparisons in the Literature

AV Metric	AV Crashes per Million Miles	Baseline Metric	Baseline Crashes per Million Miles	Source
-	-	-	Modeled crash severity.	(Wang and Li, 2019)
-	-	-	Text mined narratives, correlated risk factors.	(Boggs et al., 2020b)
-	-	-	Probabilistic topic modeling of crash narratives.	(Alambeigi et al., 2020)
-	-	-	Exploratory analysis.	(Das et al., 2020)
All crashes	23.4 in 2018	-	-	(Leilabadi and Schmidt, 2019)
All crashes	9.1 (4.5,16.3)	Police-reportable crash estimates	4.1 (3.5, 4.7)	(Schoettle and Sivak, 2015)
All crashes	23.8	Reported crashes	2.0	(Favarò et al., 2017)
All crashes	21.2	Reported by CHP, limited coverage	0.5	(Dixit et al., 2016)
Waymo police-reportable in California	2.19 (0.44, 6.39)	Police-reported in Mountain View	6.06 (5.93, 6.18)	(Teoh and Kidd, 2017)
Google police-reportable	4.57 (2.09, 8.68)	Police-reported	3.59 (2.31, 4.87)	(Teoh and Kidd, 2017)
*All Waymo crashes	9.7 (5.8, 15.1)	SHRP 2 all crashes	27.6 (25.8, 29.5)	(Teoh and Kidd, 2017)
*All Waymo rear-end struck	7.1 (3.9, 11.9)	SHRP 2 rear-end struck	2.7 (2.1, 3.3)	(Teoh and Kidd, 2017)
All Waymo Crashes	8.8 (2.6, 22.8)	All SHRP 2	26.8 (23.9, 30.1)	(Blanco et al., 2016)
*All Waymo Crashes	8.8 (2.6, 22.8)	All SHRP 2, age-adjusted	20.2 (17.7, 23.0)	(Blanco et al., 2016)
Waymo Police-Reportable	3.2 (0.4, 11.4)	SHRP 2 police reported	1.4 (0.9, 2)	(Blanco et al., 2016)
Waymo Police-Reportable	3.2 (0.4, 11.4)	SHRP 2 police reported, age-adjusted	0.9 (0.5, 1.5)	(Blanco et al., 2016)
Waymo Police-Reportable	3.2 (0.4, 11.4)	SHRP 2 police reportable	8.2 (6.9, 9.7)	(Blanco et al., 2016)
*Waymo Police-Reportable	3.2 (0.4, 11.4)	SHRP 2 police reportable, age-adjusted	5.8 (4.7, 7.0)	(Blanco et al., 2016)
*Waymo Police-Reportable	3.2 (0.4, 11.4)	NHTSA police reportable	4.2 (2.8, 9.9)	(Blanco et al., 2016)

* Metrics use dissimilar crash definitions and are directly comparable.

Dixit et al. (2016) studied crashes and disengagements of automated vehicles in California from September 2014 to November 2015. Waymo's vehicles over this time period crashed at a rate of 21.2 crashes per million miles. Dixit et al. compared Waymo's crash rate with the California Highway Patrol's estimated statewide crash rate of 0.5 crashes per million miles, but the two datasets are not comparable. The authors note that California Highway Patrol records only cover State, U.S., and Interstate roads, while much AV testing is performed on local streets with generally higher crash rates. The authors fail to note that although Waymo is required to report all crashes, even those with no damage, California Highway Patrol records would only record crashes that met reporting criteria, were reported to police, and entered into the database. Past national studies estimate that 15% of injury crashes and 24% of property damage-only crashes are never reported to police (M. Davis and Company, Inc., 2015), while an additional 9% of injury crashes and 24% of property damage-only crashes are reported but not entered into databases (Blincoe et al., 2015). Based on these estimates and evidence from the Second Strategic Highway Research Program Naturalistic Driving Study (SHRP 2 NDS), Blanco et al. (2016) estimated national-level crash rates of between 2.75 and 9.87 crashes per million miles, far higher than 0.5 estimated by California Highway Patrol. When including minor crashes that AVs must report to California DMV but that do not meet police-reporting thresholds, Blanco et al. (2016)estimates a crash rate of 20.2 crashes per million miles.

Teoh and Kidd (2017) calculated crash rates for all Google[1] automated vehicles, supplementing the California DMV reports with Google's monthly activity reports describing crashes and mileages outside California. As all of Google's pre-2016 crashes occurred in Mountain View, California, the AV crash rate was compared to general crash rates for Mountain View, surrounding Santa Clara County, and the state of California. While the regional crash rates used police-reported crashes, the Google data was restricted to crashes that met the minimum threshold for police-reporting regardless of specific crashes were actually reported. This distinction would seem to inflate the number of Google crashes, as several of their crashes seemed to meet reporting requirements yet were not reported, while in others the police were called but declined to respond. Teoh and Kidd (2017) further compared all Google crashes with the full SHRP 2 NDS crash rate, although they appear to have used raw NDS data when NDS subject selection was weighted towards young and older drivers who were at higher risk (Antin et al., 2019). They found that drivers in the SHRP 2 NDS crashed at higher rates than Google's AVs (27.6 vs. 9.7 crashes per million miles) and that this difference was statistically significant at 95% confidence intervals. The authors evaluated struck-from-behind crash rates and found that Google's rear-end-struck rate of 7.1 (3.9–11.9, 95% CI) was higher than the SHRP2 NDS unweighted rate of 2.7 (2.1–3.3, 95% CI) crashes per million miles.

Blanco et al. (2016) compared the crash rate of automated vehicles operated by Google in California from May 2010 to October 31, 2015. At that time, Google had driven over 2.3 million miles of which 1,266,611 miles were in autonomous mode. Over the same period, Google's cars had been involved in 16 crashes, of which 11 occurred while the vehicle was operating in autonomous mode. Google's crash rate for automated vehicles was therefore 11 crashes per

[1] The Google Self-Driving Car Project was renamed Waymo in 2016. For consistency in the Literature Review, whichever name used in a reference is used here. Waymo data in the Results section includes data from both Waymo and the Google Self-Driving Car Project.

1,266,611 miles, or 8.7 crashes per million miles. The authors chose to compare crashes that were police-reportable, defined roughly as resulting in more than $1500 in damage, significant impacts (e.g. delta-v > 20 mi/hr or acceleration > 1.3g excluding curb strikes), or contact with a large animal or sign. Seven Google crashes were considered not reportable by these definitions, resulting in four remaining crashes for a crash rate of 3.2 crashes per million miles. This was higher than the National Highway Traffic Safety Administration's (NHTSA) estimate of 1.92 police-reported crashes per million miles. NHTSA's crash rate, however, includes only crashes that were reported to police and excludes those that either were not reported or were reported but never officially filed. The researchers used three sources to estimate the proportion of unreported crashes: NHTSA's two published estimates (Blincoe et al., 2015; M. Davis and Company, Inc., 2015) and the percentage of SHRP2 Naturalistic Driving Study crashes that met reporting standards but were never reported (Blanco et al., 2016). Combining these sources, the total national police-reportable crash rate was estimated as 4.2 per million miles, higher than Google's crash rate of 3.2 per million miles.

Blanco et al. (2016) also compared Google's crash rate across all crashes, even those which did not meet police-reportable thresholds, with all crashes from the SHRP 2 NDS data set. Google's AVs crash rate was 8.8 (2.6–22.8, 95% CI) per million miles, while the SHRP 2 age-adjusted crash rate was 20.2 (17.7–23.0, 95% CI) per million miles. Although Google's crash rate was lower than the SHRP 2 data, the 95% confidence interval overlapped, providing weak evidence that crash rate means were unequal.

Although several studies have compared AV and human-driven crash rates, only two used compatible crash definitions for both AV and human-driven crashes (Blanco et al., 2016; Teoh and Kidd, 2017). Both studies evaluated only Google's vehicles, which represent 63% of all autonomous miles driven in California. Teoh and Kidd (2017) compared struck-from-behind crash rates but used unweighted SHRP 2 NDS data that does not reflect the United States population, and again considered only Google's vehicles.

This study is the first effort to compare crash rates of all AV testing in California regardless of developer, using compatible crash definitions and age-weighted data that reflects the United States driving population. This represents the most accurate and thorough analysis of automated vehicle struck-from-behind crashes in the literature.

3 Materials and Methods

3.1 Automated Vehicle Crash Records

Crash records were obtained from the California Department of Motor Vehicles (California Department of Motor Vehicles, 2020a). All automated vehicle developers wishing to test on public roads in California after May 2014 must obtain a Manufacturer's Testing Permit and submit the OL316 form describing any crash involving one of the test vehicles, regardless of whether the vehicle was operating in autonomous mode at the time (California Department of Motor Vehicles, 2018). Recent reports are available online, while older reports can be requested via email (California Department of Motor Vehicles, 2020a). Each report provides basic information about the crash such as date, time, vehicles involved, whether the AV was in manual or autonomous mode, and whether the AV was moving or stopped in traffic. Testers also provide a brief narrative of the crash which often includes additional details such as behavior of the other vehicle, whether police were contacted, and descriptions of any damage. For this study, 256 OL316 forms were reviewed covering crashes between October 14, 2014 and March 10, 2020 immediately prior to suspension of testing due to COVID-19 travel restrictions. Several attributes were manually collected from crash records, including date, company, vehicle stopped at the time of impact, vehicle struck from behind, “autonomous mode” box checked, and whether police were called or responded. Initially, the severity level was estimated using guidance from the SHRP 2 Naturalistic Driving study as performed in Blanco et al. (2016). This process was later abandoned, as the thresholds between severity levels were sensitive to assumptions—the severity of a small crash resulting in sensor damage depended largely on the cost of the sensor, and crashes resulting in neck pain complaints the following day could move a crash from Level 3 to Level 1 even though there was no damage. Crash locations were obtained from a database shared by the authors of a recent study on AV disengagements (Das et al., 2020).

While the OL316 form uses a checkbox to indicate whether the vehicle was operating in autonomous mode at the time of the crash, analysis of the crash narrative indicates that in 31 of the 88 manual mode crashes, the vehicle had been in autonomous mode immediately prior to the crash. In many instances, the vehicle was stopped the entire duration between transitioning to manual control and collision. In keeping with practices employed in other studies (Blanco et al., 2016; Schoettle and Sivak, 2015), these crashes were classified as occurring in autonomous mode. Of the 122 autonomous mode rear-end-struck crashes obtained from the records, 18 involved vehicles transitioning to manual control immediately prior to collision.

A summary of crash record counts based on inclusion criteria is shown in Figure 1

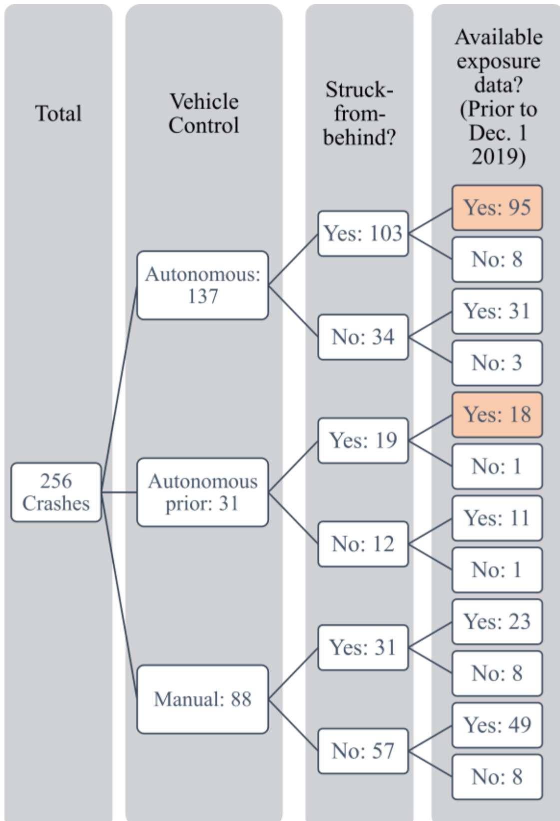

Figure 1 Crash record inclusion criteria and counts.

3.2 Automated Vehicle Mileage

Each year by the first of January, testers must also submit disengagement reports detailing the number and circumstances around each time a vehicle had an unplanned transition from autonomous mode to manual mode (California Department of Motor Vehicles, 2018, p. 13). The disengagement reports also list the total miles traveled in autonomous mode for each vehicle for the prior period of December to November. Vehicle mileages by manufacturer were obtained from these reports as summarized by Boggs et al. (2020a) and supplemented with 2019 data from California Department of Motor Vehicles (2020b).

3.3 Human-Driven Crash Rates

The Second Strategic Highway Research Program Naturalistic Driving Study (SHRP 2 NDS) data was used for a crash rate baseline. From 2012 to 2014, the SHRP 2 NDS collected over 2 petabytes of video, kinematic, and audio data from more than 3,500 drivers via passive data collection systems installed in participants' personal vehicles (Antin et al., 2019). Data was collected during short intervals prior to and following critical events as detected through the vehicles' kinematic sensors or the driver pressing a button in the vehicle. Events are analyzed by trained data reductionists to identify crash attributes and driver risk factors. Data with non-identifying information can be accessed through the InSight data portal ("SHRP2 NDS Data Access," n.d.). The SHRP 2 NDS continues to evolve with changing participant anonymity preferences, and so crash counts may be inconsistent if pulled at different times. All data for this analysis was accessed from InSight version 3.3.0 (Center for Data Reduction and Analysis Support, 2020), between May and June 2020. Raw crash records were queried for Event Type = "Crash" and Incident Type = "Rear end, struck." InSight records up to two events per record, and occasionally the struck-from-behind crash would occur following a primary event such as the subject vehicle rear ending the lead vehicle. Both first and secondary events were queried and added to the database.

The SHRP 2 NDS data was heavily weighted with younger and older drivers, both of whom represent high-risk groups. To ensure the data reflects national crash rates, the crashes and mileages must be categorized by age group and weighted by the U.S. driving population. Mileages and weights were obtained from Blanco et al. (2016) and reproduced in Table 2.

Table 2 Age Group Sample Weights for SHRP 2 Naturalistic Driving Study Data

Age	Weight	Percentage in SHRP 2 NDS	Percentage of US Licensed Drivers	Million miles driven	Weighted million miles driven
16-24	0.32	37	12	12.9	4.1
25-39	1.53	17	26	6.4	9.8
40-54	2.33	12	28	4.6	10.7
55-74	1.35	20	27	6.3	8.5
75+	0.5	14	7	3.4	1.7
Totals	-	100	100	33.6	34.8

3.4 Confidence Intervals

Confidence intervals for crash rates were calculated using a Poisson distribution. Crash counts are well-approximated by a Poisson process, as crashes are discrete, non-negative integers—several studies have modeled general public crashes (Jones et al., 1991; Joshua and Garber, 1990; Kim et al., 2006; Miaou, 1994) and automated vehicle crashes (Blanco et al., 2016) as Poisson processes. Calculations were performed using the statistics package in GNU Octave (Eaton et al., 2019). Low and high crash estimates were divided by vehicle-miles traveled to determine crash rates.

Because they had access to data at the individual driver level, Blanco et al. (2016) used bootstrapping methods to calculate SHRP 2 NDS crash rate confidence intervals. Access to the individual driver records is limited to onsite retrieval at a secure terminal in Blacksburg, Virginia. Due to COVID-19 travel restrictions, access to these data were impractical, and instead a Poisson distribution was used with minimal effect on accuracy. For example, Blanco et al.'s 95% confidence interval for all SHRP 2 NDS crashes was 2.0–3.0 (Blanco et al., 2016), while a Poisson distribution yielded a confidence interval of 2.0–3.1.

4 Results and Discussion

Automated vehicle crash rates per million vehicle-miles traveled were compared with crash rates of human-driven vehicles from the SHRP 2 NDS dataset. Table 3 shows an overview of the crash rate comparisons.

Table 3 AV and SHRP 2 NDS Struck-from-Behind Crash Rates

Vehicles	Source	Struck-from-behind crashes per million vehicle-miles traveled	
		Average	95% CI
AVs	CA DMV Reports	17.2	(14.2, 20.7)
AVs, excluding late handovers	CA DMV Reports	14.5	(11.7, 17.7)
Human-driven vehicles in all environments	SHRP 2 NDS	3.6	(3.0, 4.3)
Human-driven vehicles in urban environments	SHRP 2 NDS	6.6	(2.0, 16.0)
Human-driven vehicles in business/industrial environments	SHRP 2 NDS	7.6	(6.1, 9.4)
Cruise (downtown San Francisco)	CA DMV Reports	43.6	(33.5, 56.0)
Cruise, excluding late handovers	CA DMV Reports	33.1	(24.3, 44.0)
Waymo (Mountain View)	CA DMV Reports	10.4	(7.5, 14.0)
Waymo, excluding late handovers	CA DMV Reports	10.2	(7.3, 13.8)

4.1 General Crash Rates

When considering the entire California DMV dataset, AVs appear to be struck from behind at significantly higher rates (17.2, 14.2–20.7, 95% CI) than the national average of human-driven vehicles (3.6, 3.0–4.3, 95% CI). Eighteen of the AV crashes involved vehicles transitioning to manual control immediately prior to collision. These were classified as autonomous-mode crashes. When these late handovers are excluded from analysis, the struck-from-behind AV crash rate drops to 14.5 (11.7–17.7, 95% CI) crashes per million miles, which remains significantly higher than the crash rate of human-driven vehicles.

4.2 Crash Rates over Time

Automated vehicle technology continues to be refined through ongoing testing, and therefore AVs in more recent years may crash at different rates than AVs in early years. A comparison of struck-from-behind crash rates for all AVs, Waymo, and Cruise are shown in Figure 2. Crash rates do not show a clear trend over time, but instead fluctuate year to year. This fluctuation may be due to struck-from-behind crashes being independent of an AVs driving behavior, or instead that manufacturers are testing in more complex environments, negating any improvements in AV driving abilities. The lack of a clear crash rate trend over time aligns with total AV crash rate trends (Leilabadi and Schmidt, 2019).

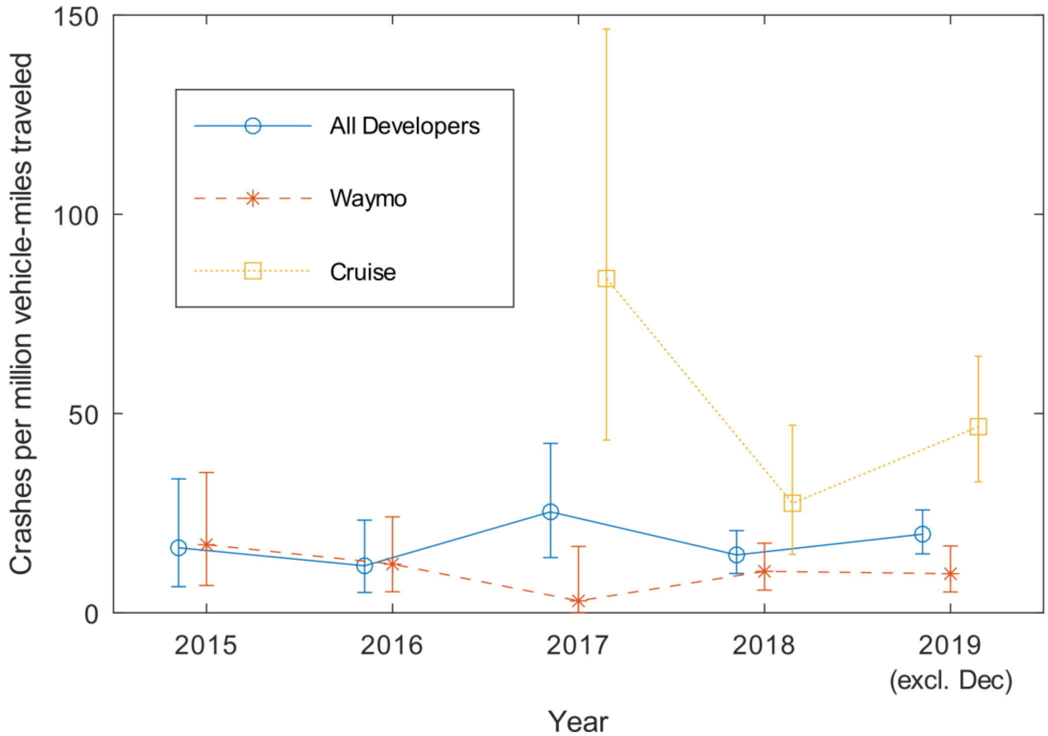

Figure 2 Struck-from-behind crash rates when in autonomous mode by year for all developers, Waymo, and Cruise. Years with no reported crashes were excluded.

4.3 Effect of Urban Driving Environments

One reason for higher AV struck-from-behind crash rates may be the density of traffic in urban and commercial environments where vehicles in California often test. Cruise CEO Kyle Vogt (2017) has noted that their vehicles encounter 39 times more interactions in San Francisco than in suburban Phoenix, Arizona. More interactions with other vehicles could result in more opportunities for struck-from-behind crashes.

There are a few ways to explore this theory. The first is to compare crash rates of companies that test in urban vs. less dense commercial environments. Of the 46 companies that have reported testing AVs in California, only two, Cruise and Waymo, reported more than four struck-from-behind crashes. While neither Cruise nor Waymo reports the general locations of their AV testing, both report crash locations. Figure 3 shows the locations of Cruise and Waymo crashes through March 2020. Nearly all Cruise crashes are in downtown San Francisco, while Waymo's crashes are predominately near suburban Mountain View along commercial corridors. These data are supported by the National Highway Traffic Safety Administration's (2020c) database of AV testing, which lists only one testing site for Cruise in San Francisco and three for Waymo, of which one is in Mountain View, one is on private roads and therefore not reportable to California DMV, and one is for limited heat testing in Death Valley National Park (Waymo, 2017). While it is impossible to determine manufacturer AV testing locations with complete certainty, the evidence suggests that most Cruise testing occurs in urban San Francisco and most Waymo testing occurs in suburban Mountain View along commercial corridors.

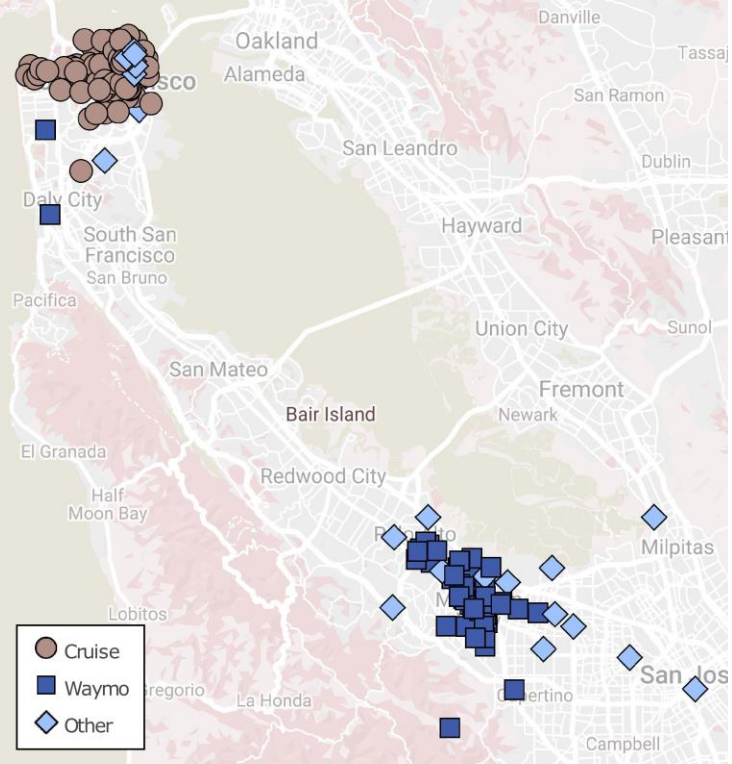

Figure 3 Map of Cruise, Waymo, and other developer AV crashes as of March 2020.

As shown in Table 3, Cruise vehicles in autonomous mode are struck from behind at 3–4 times the rate of Waymo's vehicles. If both manufacturers' vehicles drive identically in traffic (an unsupported assumption), then Cruise's higher crash rate suggests that struck-from-behind crashes may be more prevalent in urban environments.

Another way to test this theory is to compare driving environments from the SHRP 2 NDS data. Samples from the SHRP 2 NDS were categorized by environment, referred to as "localities" in the data set. These were not obtained from GPS traces, but rather from a visual inspection of the environment from the vehicle's outward facing cameras. Analysts were trained to consistently classify these environments.

Table 4 shows the guidance used by data reductionists when classifying events as occurring in urban or business/industrial settings, the two environments closest to Cruise's and Waymo's testing environments. Guidance for classifying all 11 environments can be found in the SHRP 2 NDS researcher dictionary (Virginia Tech Transportation Institute, 2015).

Table 4 SHRP 2 NDS Guidance for Classifying Roadway as Urban or Business/Industrial (Virginia Tech Transportation Institute, 2015)

Locality	Guidance
General	Best description of the surroundings that influence or may influence the flow of traffic at the time of the start of the precipitating event. If there are ANY commercial buildings, indicate as business/industrial or urban area as appropriate (these categories take precedence over others except for church, school, and playground).
Urban	Higher density area where blocks are shorter, streets are a mix of one and two way, and traffic can include buses and trams. (This category takes precedence over others when either businesses and/or residences are present.)
Business/Industrial	Any type of business or industrial structure is present, but is not as dense as an Urban Locality. (If there are also houses visible, this category takes precedence over Open residential and Moderate residential).

Localities were assigned not only to crash events, but also to randomly selected windows of baseline driving. The number of baseline driving samples in a particular environment were used to estimate an environment's total mileage. If, for example, vehicles traveled 10 million total miles, and 20 percent of samples were in rural areas, then the total number of rural miles would be calculated as 10 million miles × 20% = 2 million rural miles.

Table 5 shows the SHRP 2 NDS weighted struck-from-behind crash rates per million vehicle-mile traveled (MVMT) across different environments. Urban and industrial environments exhibit struck-from-behind crash rates that are 182% and 212% of the total crash rate, respectively. These higher crash rates suggest that the inherent dangers of urban driving may contribute to the higher struck-from-behind crash rate experienced by AVs. Waymo's crash rate, for example, is within the 95% confidence interval for human-driven vehicles in business/industrial settings, suggesting that the different crash rates are not statistically significant.

Table 5 SHRP 2 NDS Crash Rates by Observed Driving Environment

Environment	SHRP 2 NDS Weighted Struck-from-Behind Crashes per MVMT	95% CI	% of Total Rate
Open Country	0.0	(0.0, 6.6)	0
Open Residential	0.5	(0.0, 3.0)	14
Moderate Residential	0.6	(0.2, 1.5)	16
Business/Industrial	7.6	(6.1, 9.4)	212
Church	6.1	(2.0, 14.4)	170
Playground	0.0	(0.0, 22.6)	0
School	2.6	(0.8, 6.3)	73
Urban	6.6	(2.0, 16.0)	182
Interstate/Bypass/Divided Highway with no traffic signals	1.5	(0.9, 2.6)	43
Bypass/Divided Highway with traffic signals	4.1	(1.4, 9.5)	114
Other	0.0	(0.0, 79.1)	0
Totals	3.6	(3.0, 4.3)	100

4.4 Crash Rates When Moving vs. When Stopped

Others have suggested that AV behavior may contribute to struck-from-behind crashes. Journalists observing AV demonstrations have described the vehicle’s movements as unsteady (Stewart, 2018). Others point out that AVs strictly adhere to traffic laws, coming to complete stops at stops signs and when turning right at a signalized intersections during a red phase (Beene, 2017; Stewart, 2018). One way to evaluate the influence of vehicle behavior on crash rate is to evaluate struck-from-behind crash rates for moving and stopped vehicles. Struck-from-behind crashes while moving may be due to unexpected decelerations, while crashes while stopped may be due unexpected timing or locations of AV stops.

From an analysis of the AV crash reports entry for “Stopped in Traffic” and the crash narrative, it appears that 30% (20 of 67) of Cruise’s crashes and 79% (37 of 47) of Waymo’s struck-from-behind crashes occurred when the vehicle was stopped. Table 6 shows the struck-from-behind crash rate of both AV developers when the vehicle was both stopped and moving.

Table 6 Comparison of Struck-from-Behind Crash Rates while Stopped and Moving

Stopped	Crashes per MVMT	95% CI	n
Automated Vehicles	8.9	(6.7, 11.4)	58
SHRP 2 NDS Age Weighted	0.6	(0.4, 0.9)	23.3
SHRP 2 Urban	0.0	(0.0, 5.4)	0.0
SHRP 2 Business/Industrial	1.8	(1.1, 2.7)	19.9
SHRP 2 All Other Roads	0.1	(0.0, 0.4)	3.4
Moving			
Automated Vehicles	8.4	(6.3, 10.9)	55
SHRP 2 NDS Age Weighted	3.0	(2.5, 3.6)	104.8
SHRP 2 Urban	6.9	(2.9, 18.3)	4.7
SHRP 2 Business/Industrial	6.5	(6.2, 9.6)	73.4
SHRP 2 All Other Roads	1.2	(0.8, 1.7)	26.7

Differences between AV and human-driven crash rates are not significant when the vehicle is moving in urban or business/industrial settings. In contrast, differences are significant when vehicles are stopped, with AV crash rates of 8.9 (6.7–11.4, 95% CI) crashes per million miles when stopped, compared to 0.0 (0.0–5.4, 95% CI) for urban driving and 1.8 (1.1–2.7 95% CI) for business/industrial driving. These stopped crash rates suggests that any effect of AV behavior on struck-from-behind crashes is probably due to unexpected timing and location of stops and not unexpected rate or method of deceleration. These effects could be further isolated by determining crash rates at stops signs and right-turn-on-red movements. While a large portion of AVs are turning right when struck, there is no baseline data in the SHRP 2 NDS data set to allow a direct comparison of human crashes at stop signs or right-turn-on-red.

5 Conclusions

Automation of the driving will profoundly affect transportation both in terms of mobility and safety. Understanding the performance of automated driving systems, especially early deployments, is of profound importance. While previous studies have found AV crashes to occur at lower rates than those of human-driven vehicles, this is the first study to investigate struck-from-behind crashes which represent 73% of autonomous-mode crashes. While automated vehicles are struck from behind at higher rates than conventional vehicles, these differences are reduced when considering the operating environments of AVs. Vehicles operated by Cruise predominately test in urban San Francisco while Waymo’s vehicles test in suburban Mountain View along business corridors. Human-driven crash rates from SHRP 2 NDS data for urban and business/industrial environments (the two closest environments to Cruise and Waymo’s testing) are higher than human-driven struck-from-behind crash rates generally (6.6 and 7.6 crashes per MVMT, respectively, compared to 3.6 generally). It is possible that the number of interactions captured in SHRP 2 NDS urban driving does not match the number of conflicts in downtown San

Francisco, one of the densest cities in the United States. Without better data on minor crash rates in large cities, it is impossible to rule out that the high struck-from-behind crash rates experienced by Cruise may simply be a factor of environment.

When compared to human-driven vehicles, AVs are more likely to be struck from behind when stopped than when moving. This suggests that, if AV behavior contributes to struck-from-behind crashes as some have suggested, the timing and locations of AV stops rather than deceleration behavior may contribute to crashes. Further research on vehicle position in the intersection, presence of right-turn-on-red maneuvers, pedestrian presence and other contributing factors could further isolate the contributing factors for AV struck-from-behind crashes.

It should be noted that the vast majority of crashes involving automated vehicles occur at low speeds and result in minimal damage. A high crash rate does not necessarily indicate a dangerous vehicle, as many minor crashes may be preferable to a few severe ones.

Researchers, regulators, and industry should continue to assess the safety of automated vehicles. Mandatory reporting of crashes and exposure (in accessible databases) simplifies these efforts. When governments do not mandate reporting, automated vehicle developers can post their own, greatly improving transparency and building trust with regulators and the public.

Funding

This work was sponsored by the Virginia Department of Transportation.

CRediT Authorship Contribution Statement

Noah Goodall: Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization.

Declaration of Competing Interests

The author has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Special thanks to Jeremy Sudweeks for clarifying total mileage figures in the SHRP 2 Naturalistic Driving Study Dr. Michael Fontaine for comments on an earlier draft of this paper, and Dr. Subasish Das for providing a database of automated vehicle crashes in California through March 2020.

References

Alambeigi, H., McDonald, A.D., Tankasala, S.R., 2020. Crash Themes in Automated Vehicles: A Topic Modeling Analysis of the California Department of Motor Vehicles Automated Vehicle Crash Database. ArXiv200111087 Stat.

Antin, J.F., Lee, S., Perez, M.A., Dingus, T.A., Hankey, J.M., Brach, A., 2019. Second strategic highway research program naturalistic driving study methods. Saf. Sci. 119, 2–10. doi:10.1016/j.ssci.2019.01.016

Beene, R., 2017. Self-driving car accidents: Robot drivers are 'odd, and that's why they get hit' [WWW Document]. Seattle Times. URL https://www.seattletimes.com/business/self-driving-car-accidents-robot-drivers-are-odd-and-thats-why-they-get-hit/ (accessed 7.26.20).

Beiker, S., 2014. History and Status of Automated Driving in the United States, in: Meyer, G., Beiker, S. (Eds.), Road Vehicle Automation, Lecture Notes in Mobility. Springer International Publishing, Cham, pp. 61–70. doi:10.1007/978-3-319-05990-7_6

Blanco, M., Atwood, J., Russell, S., Trimble, T., McClafferty, J., Perez, M., 2016. Automated Vehicle Crash Rate Comparison Using Naturalistic Data. Virginia Tech Transportation Institute.

Blincoe, L.J., Miller, T.R., Zalashnja, E., Lawrence, B.A., 2015. The Economic and Societal Impact of Motor Vehicle Crashes, 2010 (Revised) (No. DOT HS 812 013). National Highway Traffic Safety Administration, Washington, DC.

Boggs, A.M., Arvin, R., Khattak, A.J., 2020a. Exploring the who, what, when, where, and why of automated vehicle disengagements. Accid. Anal. Prev. 136, 105406. doi:10.1016/j.aap.2019.105406

Boggs, A.M., Wali, B., Khattak, A.J., 2020b. Exploratory analysis of automated vehicle crashes in California: A text analytics & hierarchical Bayesian heterogeneity-based approach. Accid. Anal. Prev. 135, 105354. doi:10.1016/j.aap.2019.105354

California Department of Motor Vehicles, 2020a. Autonomous Vehicle Collision Reports [WWW Document]. Calif. Dep. Mot. Veh. URL https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/disengagement-reports/

California Department of Motor Vehicles, 2020b. Disengagement Reports [WWW Document]. Calif. Dep. Mot. Veh. URL https://www.dmv.ca.gov/portal/vehicle-industry-services/autonomous-vehicles/disengagement-reports/

California Department of Motor Vehicles, 2018. Title 13, Division 1, Chapter 1, Article 3.7 – Testing of Autonomous Vehicles [WWW Document]. URL https://www.dmv.ca.gov/portal/uploads/2020/06/Adopted-Regulatory-Text-2019.pdf (accessed 5.15.19).

Center for Data Reduction and Analysis Support, 2020. Release May 2020 SHRP2 Phase I Error Correction - Change Log [WWW Document]. SHRP 2 NDS. URL https://insight.shrp2nds.us/documents/CFDRAS/error_correction_7_changelog.html (accessed 7.15.20).

Das, S., Dutta, A., Tsapakis, I., 2020. Automated vehicle collisions in California: Applying Bayesian latent class model. IATSS Res. doi:10.1016/j.iatssr.2020.03.001

Dixit, V.V., Chand, S., Nair, D.J., 2016. Autonomous Vehicles: Disengagements, Accidents and Reaction Times. PLOS ONE 11 12 , e0168054. doi:10.1371/journal.pone.0168054

Eaton, J.W., Bateman, D., Hauberg, S., Wehbring, R., 2019. GNU Octave version 5.1.0 manual: a high-level interactive language for numerical computations. [WWW Document]. URL https://www.gnu.org/software/octave/doc/v5.1.0/ (accessed 7.2.19).

Favarò, F.M., Nader, N., Eurich, S.O., Tripp, M., Varadaraju, N., 2017. Examining accident reports involving autonomous vehicles in California. PLOS ONE 12 9 , e0184952. doi:10.1371/journal.pone.0184952

Federal Motor Vehicle Safety Standards; Head Restraints [WWW Document], 2010. . Fed. Regist. URL https://www.federalregister.gov/documents/2010/11/02/2010-27669/federal-motor-vehicle-safety-standards-head-restraints (accessed 7.19.20).

Jones, B., Janssen, L., Mannering, F., 1991. Analysis of the frequency and duration of freeway accidents in Seattle. Accid. Anal. Prev. 23 4 , 239–255. doi:10.1016/0001-4575(91)90003-N

Joshua, S.C., Garber, N.J., 1990. Estimating truck accident rate and involvements using linear and Poisson regression models. Transp. Plan. Technol. 15 1 , 41–58. doi:10.1080/03081069008717439

Kim, D.-G., Washington, S., Oh, J., 2006. Modeling Crash Types: New Insights into the Effects of Covariates on Crashes at Rural Intersections. J. Transp. Eng. 132 4 , 282–292. doi:10.1061/(ASCE)0733-947X(2006)132:4(282)

Leilabadi, S.H., Schmidt, S., 2019. In-depth Analysis of Autonomous Vehicle Collisions in California, in: 2019 IEEE Intelligent Transportation Systems Conference (ITSC). Presented at the 2019 IEEE Intelligent Transportation Systems Conference - ITSC, IEEE, Auckland, New Zealand, pp. 889–893. doi:10.1109/ITSC.2019.8916775

M. Davis and Company, Inc., 2015. National Telephone Survey of Reported and Unreported Motor Vehicle Crashes (No. DOT HS 812 183). National Highway Traffic Safety Administration, Washington, DC.

Miaou, S.-P., 1994. The relationship between truck accidents and geometric design of road sections: Poisson versus negative binomial regressions. Accid. Anal. Prev. 26 4 , 471–482. doi:10.1016/0001-4575(94)90038-8

National Highway Traffic Safety Administration, 2020a. Table 29: Crashes, by First Harmful Event, Manner of Collision, and Crash Severity, 2018 [WWW Document]. Traffic Saf. Facts Annu. Rep. Tables. URL https://cdan.nhtsa.gov/tsftables/tsfar.htm# (accessed 7.19.20).

National Highway Traffic Safety Administration, 2020b. Traffic Safety Facts Annual Report Tables [WWW Document]. Natl. Highw. Traffic Saf. Adm. URL https://cdan.nhtsa.gov/tsftables/tsfar.htm (accessed 7.13.20).

National Highway Traffic Safety Administration, 2020c. Automated Vehicle Test Tracking Tool [WWW Document]. NHTSA. URL https://www.nhtsa.gov/automated-vehicles-safety/av-test-initiative-tracking-tool (accessed 10.6.20).

Schoettle, B., Sivak, M., 2015. A Preliminary Analysis of Real-World Crashes Involving Self-Driving Vehicles (No. UMTRI-2015-34). University of Michigan Transportation Research Institute, Ann Arbor, MI.

SHRP2 NDS Data Access [WWW Document], n.d. URL https://insight.shrp2nds.us/ (accessed 7.15.20).

Stewart, J., 2018. Why People Keep Rear-Ending Self-Driving Cars [WWW Document]. Wired. URL https://www.wired.com/story/self-driving-car-crashes-rear-endings-why-charts-statistics/ (accessed 10.19.18).

Teoh, E.R., Kidd, D.G., 2017. Rage against the machine? Google's self-driving cars versus human drivers. J. Safety Res. 63, 57–60. doi:10.1016/j.jsr.2017.08.008

Virginia Tech Transportation Institute, 2015. SHRP2 Researcher Dictionary for Video Reduction Data Version 3.4. Virginia Tech Transportation Institute, Blacksburg, Virginia.

Vogt, K., 2017. Why testing self-driving cars in SF is challenging but necessary [WWW Document]. Medium. URL https://medium.com/cruise/why-testing-self-driving-cars-in-sf-is-challenging-but-necessary-77dbe8345927 (accessed 7.26.20).

Wang, S., Li, Z., 2019. Exploring the mechanism of crashes with automated vehicles using statistical modeling approaches. PLoS ONE 14 3 . doi:10.1371/journal.pone.0214550

Waymo, 2017. Beating the Heat: Thermal Testing in Death Valley [WWW Document]. Medium. URL https://medium.com/waymo/beating-the-heat-thermal-testing-in-death-valley-83b881352216 (accessed 10.6.20).