# Comparison of Waymo Rider-Only Crash Data to Human Benchmarks at 7.1 Million Miles

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ABSTRACT

This paper examines the safety performance of the Waymo Driver, an SAE level 4 automated driving system (ADS) used in a rider-only (RO) ride-hailing application without a human driver, either in the vehicle or remotely. ADS crash data was derived from NHTSA's Standing General Order (SGO) reporting over 7.14 million RO miles through the end of October 2023 in Phoenix, AZ, San Francisco, CA, and Los Angeles, CA. This study is one of the first to compare overall crashed vehicle rates using only RO data (as opposed to ADS testing with a human behind the wheel) to a human benchmark that also corrects for biases caused by underreporting and unequal reporting thresholds reported in the literature. When considering all locations together, the *any-injury-reported* crashed vehicle rate was 0.41 incidents per million miles (IPMM) for the ADS vs 2.78 IPMM for the human benchmark, an 85% reduction or a 6.8 times lower rate. *Police-reported* crashed vehicle rates for all locations together were 2.1 IPMM for the ADS vs. 4.85 IPMM for the human benchmark, a 57% reduction or 2.3 times lower rate. *Police-reported* and *any-injury-reported* crashed vehicle rate reductions for the ADS were statistically significant when compared in San Francisco and Phoenix as well as combined across all locations. The comparison in Los Angeles, which to date has low mileage and no reported events, was not statistically significant. In general, the Waymo ADS had a lower *any property damage or injury* rate than the human benchmarks. Given imprecision in the benchmark estimate and multiple potential sources of underreporting biasing the benchmarks, caution should be taken when interpreting the results of the *any property damage or injury comparison*. Together, these crash-rate results should be interpreted as a directional and continuous confidence growth indicator, together with other methodologies, in a safety case approach.

## 1. Introduction

The safety of automated vehicles is a complex and evolving topic. The growing consensus, based on decades of experience in related safety-critical fields, is that a safety case approach is a suitable and structured method to demonstrate safety of an automated driving system (ADS), like the Waymo Driver (Favaro et al., 2023a). The safety case approach described in Favaro et al. (2023a) describes three complementary views on safety determination: a layered approach, a credible approach, and a dynamic approach to safety. The layered approach comprises a goal of demonstrating absence of unreasonable risk, where risks are decomposed into architectural, behavioral, and operational layers and appropriate acceptance criteria are set. The credible approach describes a case credibility assessment (CCA), where the credibility of the argument and evidence in the safety case can be evaluated. Finally, the dynamic approach describes the safety determination lifecycle where safety is assessed as an emergent property, predictions,

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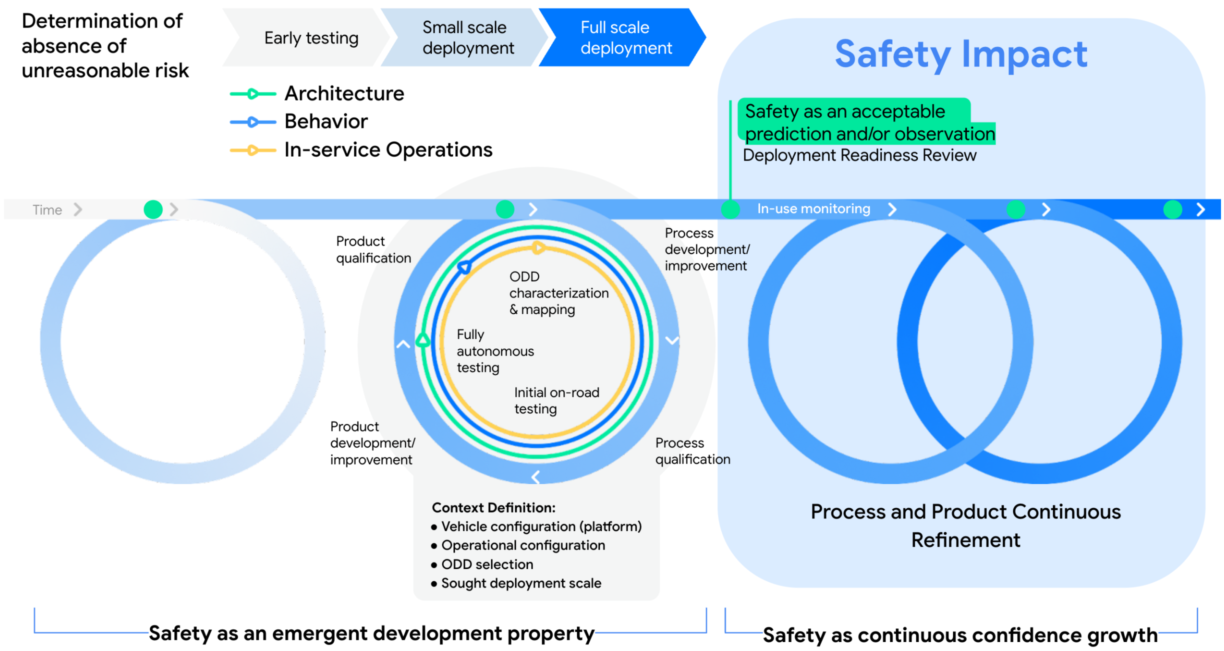


**Figure 1:** Visualization of Waymo's Safety Determination Life Cycle (adapted from Figure 6, Favaro et al. (2023a))

and confidence growth over time. The safety methodologies described in Webb et al. (2020) can be seen as a "collective set of evidence used to populate the safety case" (Favaro et al., 2023a).

This paper describes crash results from an in-field deployment of a Rider-Only (RO) ADS ride-hailing service as part of the safety determination lifecycle. The in-field crash results may serve as one important factor in confirming design elements and predictions done in earlier iterations of this safety determination lifecycle, as shown in Figure 1 (Favaro et al., 2023a). While a system is being developed and before starting RO operations or when considering an update to an existing RO deployment, only prospective methods which predict expected performance can be applied. In a prospective method, for example in simulated deployments (Webb et al., 2020) or as described in Favaro et al. (2023b), simulation is used to predict an ADS crash rate and compare that rate to a benchmark. In this approach, benchmarks can be set for different severity levels that are determined based on a crash severity model, as outcomes such as injury are not available from simulation. Retrospective analyses based on crash outcomes like presented in this paper can be used to complement and/or confirm these prospective methods that are used in an ADS readiness determination (Webb et al., 2020).

Retrospective examination of crash performance against a human benchmark is one of many safety determination activities that comprise an ADS safety case. It is well understood, however, that the human driving population engages in behaviors that increase risk of crashes, such as driving while intoxicated, distracted, or drowsy. Therefore, an ADS with a crash involvement rate lower than the general driving population does not by itself allow for a determination that the ADS has an absence of unreasonable risk. Assessment methodologies that use other benchmarks are important in addition to retrospective crash involvement. One example is the Collision Avoidance Testing (CAT) program that uses virtual simulation to compare the ADS crash performance in nominal (i.e., not degraded) responder role conditions to a Non-Impaired Eyes On Conflict (NIEON) (Kusano et al., 2022). The NIEON model is fit to human near-crash data where the driver had their eyes on the conflict and is not an achievable state for real human drivers, who will always have some level of not looking at the road. The broader safety case approach, with its goal to demonstrate an absence of unreasonable risk, considers a broad range of potential issues that can come from the ADS ride-hailing operations, including measures of the ADS's drivership, the realization of expected driving behaviors that position the ADS as a good citizen of the road. Evaluation of drivership can extend beyond crash risk.

For over 50 years, the study of motor vehicle safety has relied on crash reporting databases to understand trends and develop countermeasures to improve traffic safety. Examples of these databases in the United States are the Fatal Analysis Reporting System (FARS), the Crash Report Sampling Systems (CRSS), and the Crash Investigation Sampling System (CISS). Each of these data sources are maintained by the National Highway Traffic Safety Administration (NHTSA). Estimates of Vehicle Miles Traveled (VMT) are also maintained by federal and local transportation agencies, such as the Federal Highway Administration's "Highway Statistics" annual reporting (Federal Highway Administration, 2023). Putting these types of crash reporting and VMT estimates together, public agencies such as NHTSA often examine the trends in the rate of different severities of crashes. For example, in 2021 (the most recent year that complete data is available and analyzed), the rate of fatalities per 100 million VMT was 1.37 and the rate of injuries per 100 million VMT was 80 (Stewart, 2023). Analyzing the trends in crash rates over time and in different conditions (e.g., urban vs rural areas) is possible because there is a consistent reporting standard that changes little from year-to-year.

ADS manufacturers have also been required to report crashes for some time, albeit with a different reporting standard than in police-reported crash databases. The California Department of Motor Vehicles was one of the first agencies to collect and publish data on crashes involving ADS-equipped vehicles, in their case those operating in California. More recently, the NHTSA Standing General Order (SGO) 2021-01 has required ADS developers to report all crashes meeting certain criteria, which are then published publicly since July 2021 (National Highway Traffic Safety Administration, 2023). Because ADS are emerging technologies and are currently deployed in small numbers compared to human-operated vehicles, the reporting requirements for ADS manufacturers is to report any crashes that the manufacturer knows to have occurred or that are alleged and that result in "any property damage, injury, or fatality", occur on a public road, and in which the ADS was engaged at any time during the 30 seconds immediately prior to the crash through the conclusion of the crash (National Highway Traffic Safety Administration, 2023).

The observed crash and injury reduction following the introduction of ADS technology is referred to as retrospective safety impact. A valid retrospective safety impact assessment requires accurate calibration of benchmark human and ADS crash and VMT data sources to make a valid comparison. Different approaches are needed depending on the nature of the human benchmark and ADS data sources. For example, in a reported crash database, such as data derived from police reports, there is a need to apply some underreporting adjustment[1] if the ADS data includes any property damage. This underreporting adjustment to police-reported crashes is the approach Scanlon et al. (2023) took to estimate crash rates for any property damage. Another human data source used for generating a benchmark is Naturalistic Driving Study (NDS) databases, which equip vehicles with sensors such as accelerometers and cameras to record driving. Using a combination of algorithmic triggers (e.g., hard braking or swerving) plus manual review to find true positive crashes based on the video data, an observed crash rate can be found. NDS generally have less advanced sensors than those that are equipped on a SAE level 4 ADS vehicle, which may induce, for example, blind spots in the camera or sensor views. Other NDS data sources may have even less data recorded, such as those from dash cameras that may only have a front camera view. The less advanced sensors also necessitate the approach of using kinematic triggers followed by manual review of the video data. This approach may lead to missing property damage crashes that do not meet the kinematic triggers (e.g., low speed contacts while the ego vehicle is stationary). To adjust for potential missed crashes, Flannagan et al. (2023) used a mixture of insurance, telematics, and NDS data to estimate any property damage crash rate.

Given public accessibility of both human and ADS crash and VMT data, researchers have the opportunity to begin evaluating ADS's safety performance. Working with these public crash and VMT data sources, however, has certain challenges. Several reviews of the literature have found that many of the early studies comparing ADS and human benchmarks introduced biases (Young, 2021; Scanlon et al., 2023). Scanlon et al. (2023) describes errors and biases that should be accounted for when attempting to compare human and ADS crash rates: (1) information biases (surveillance bias caused by reporting thresholds, reporting bias caused by underreporting), and (2) biases from analytical choices (selection bias caused by lack of operational design domain, ODD, matching). A large number of human crashes are not reported to police or are reported but no police report is filed (reporting bias). NHTSA estimates that 60%

[1] For ease of writing, we will refer to "underreporting" in reported crash data to include both crashes that meet the reporting threshold but were not reported and crashes that do not meet the reporting threshold. See the discussion in Scanlon et al. (2023) for a more thorough discusion of these topics, and how the Blincoe et al. (2022) and Blanco et al. (2016) underreporting adjustments differed in regards to these two dimensions.

of property-damage-only and 32% of injury crashes are not reported to police (Blincoe et al., 2022). The reporting requirement of "any property damage", without any lower limit for property damage for ADS crash data, is a lower threshold than human crash data sources such as CRSS or state police report data that require a police report to be filed in order to appear in these data sources (surveillance bias). In contrast, ADS fleet operators are required to report almost every crash and the large number of sensors combined with operational procedures result in almost all contacts being discovered and reported. Finally, the driving environment and/or vehicle characteristics of a datasource can impact the crash rate (selection bias). Factors such as population density (rural vs. urban), roadway type (surface street vs freeway), and vehicle use type (commercial heavy vehicles, passenger vehicles, ride hail vehicle) can all affect crash rates.

Generating a valid comparison of human and ADS crash rates that adjusts for the above mentioned biases is of great importance at this point in time. Larger ADS deployments in recent years have led to inquiries from the general public, public officials, and researchers about the safety of current ADS fleets. Improving traffic safety is a goal held by many ADS stakeholders. All stakeholders have an interest in understanding the current state of ADS safety performance through as many objective measures as are available, which include retrospective crash rates. If biases are present in the data that either inflate or deflate the ADS or benchmark crash rates, the conclusions may lead to incorrect public perceptions of ADS safety and questionable policy recommendations or decisions. As pointed out in Scanlon et al. (2023, Table 1) and Young (2021), past studies have varying degrees of biases in their analyses. In addition, non-academic studies, either in the popular press or done by government agencies, are being done. All data sources, both from human and ADS sources, have limitations in the data available. Therefore, generating sets of crashes that are comparable between human benchmarks and ADS sources is complex and requires judgment based on recognized best practices. The analysis in this paper serves to present an analysis that uses publicly available ADS and benchmark data in order to advance the understanding of ADS safety so that stakeholders can make informed decisions. This analysis is also a step toward further harmonization and standardization of retrospective safety impact analysis for ADS fleets.

The purpose of this paper is to present Waymo ADS crash rates from data reported according to NHTSA's Standing General Order (SGO) and compare to benchmark rates that are as accurate as possible as derived from comparable human benchmark sources published in the literature.

The NHTSA SGO requires reporting of all crashes involving or alleged to have involved the ADS vehicle resulting in any amount of property damage, injury, or fatalities if the crashes occur on public roads and the ADS was engaged at any time during the 30 seconds immediately prior to the crash through the conclusion of the crash (National Highway Traffic Safety Administration, 2023). The SGO reporting is required in all states, and thus is the most complete crash reporting required for an ADS fleet operator. Comparisons were made for crashes involving *any property damage or injury*, *police-reported*, and *any-injury-reported* outcomes. As the SGO data is publically available, the analyses provided herein can be readily reproduced and developed by other researchers.

## 2. Methods

### 2.1. Selection of Waymo ADS Incidents

The Waymo RO ride-hailing service in Phoenix, San Francisco, and Los Angeles operates in fixed geographic areas in these cities operating 24 hours a day and 7 days a week. The ODD includes non-limited access roads with speed limits up to 50 mph and parking lots without restrictions on maneuvers. The ODD does not include severe weather conditions, such as thick fog, heavy rain, or blowing sand but does include light rain or light fog. The ODD for the Waymo RO service has changed slightly over the years as the service expanded. The ODD features have been relatively unchanged in the past year, which also corresponds to the majority of the RO miles accumulated to date. Therefore, the Waymo RO crashes described in this section were compared to crashes that occurred in the same geographical areas. The selection of human benchmarks is discussed in detail in the following section.

As NHTSA SGO ADS crashes are a mandated and publicly available data source, Waymo's NHTSA SGO reportable crashes became the basis for the incidents examined in this study[2]. The NHTSA SGO requires reporting crashes where the ADS was engaged at any time (not throughout) the 30-second pre-crash and crash period, regardless of whether a human driver operated the vehicle during that period or whether the ADS was operating the vehicle in RO mode during some or all of that period. For this analysis, only Waymo SGO-reported crashes where the ADS was operating in RO mode were included for analysis. In the SGO data, collisions reported by Waymo were identified using the "Reporting Entity" field having the value "Waymo LLC". The field "Driver / Operator Type" was set to "None" for RO operations, and set to "In-Vehicle (Commercial / Test)" when an autonomous specialist is monitoring the ADS behind the steering wheel. In those ADS crashes with an autonomous specialist present, it is difficult to disambiguate the contribution of the ADS driver and the autonomous specialist. Therefore, this analysis excluded those crashes with an autonomous specialist present behind the wheel, as RO crashes are most representative of the intended autonomous ride-hailing service.

Not-in-transport vehicles are excluded in the crashed vehicle count from the police-reported database human driver benchmarks used in this study. Any SGO-reported crash where the Waymo ADS vehicle was a vehicle not-in-transport were identified to better compare the ADS crashes to police crash report benchmarks. An "in-transport" vehicle is one that is traveling (moving or stopped) in the roadway. "Not-in-transport" vehicles are those that are parked in a designated parking spot out of the roadway. Therefore, including ADS vehicle crashes where the ADS vehicle is a not in-transport vehicle would inflate the ADS crash count relative to the benchmark. The ADS vehicle was considered not in-transport if the ADS vehicle was in the "park" gear and the ADS vehicle was in a designated parking area. This not in-transport status can happen when the ADS vehicle is parked awaiting its next trip instructions. Because the ADS software is running and in control of the vehicle, contacts while the ADS vehicle is not in-transport are reported as part of the NHTSA SGO reporting requirements. If the parking spot was on-street parking parallel to the traffic flow, the ADS vehicle must have been within 18 inches from the curb of the road as measured by the measured sensor data and curb location in the ADS map to be considered not-in-transport. Instances where the ADS vehicle was in "park" gear, but not near the curb were included as in-transport vehicles. The alternative, to include "not-in-transport" vehicle ADS crashes, would require also including "not-in-transport" vehicles in the benchmark, which are included in separate counts from in-transport vehicles in most police report databases, if at all. Additionally, it is unclear how a rate of crashed vehicles per VMT should be interpreted for not-in-transport vehicles, as parked vehicle crash risk is likely more related to amount of time parked rather than VMT. Underreporting for not-in-transport vehicles may also differ from in-transport vehicles, which was not accounted for the underreporting adjustments used in the benchmarks (Scanlon et al., 2023; Blincoe et al., 2022).

Additionally, the NHTSA SGO requires ADS fleet operators to report crashes where the ADS vehicle contributed or is alleged to have contributed (by steering, braking, acceleration, or other operational performance) to another vehicle's physical impact with another road user or property involved in a reportable crash even if the ADS vehicle was not involved in the physical impact. One NHTSA SGO-reported crash (30270-6542) involved two human-driven vehicles that made contact while following behind a Waymo ADS vehicle. The Waymo vehicle was not contacted or damaged. Because the purpose of this paper is to compare crashed vehicle rates between ADS and human benchmarks, we excluded this crash from the NHTSA SGO in-transport vehicle category and subsequent categories. This single event was included in the SGO-reported count. The reason to exclude this type of crash where the ADS vehicle does not impact another vehicle is because vehicles that are not involved in an impact are not included in the crashed vehicle counts in the benchmark crash sources discussed in the following section. Therefore, including SGO-reported events where the ADS did not impact another vehicle or object would inflate the ADS rate compared to the benchmark.

In addition to examining all NHTSA SGO-reported crashes, results were also reported for a dataset that excluded minor crashes, which we will refer to as "SGO Crash Excluding Low Delta-V." Although the benchmark data used in this study and described in detail in the next section was either adjusted for underreporting or used NDS data designed to find most contacts, there is still uncertainty in the benchmark data about the lower reporting threshold for a crash. This result of excluding low delta-V ADS crashes was presented alongside the larger all SGO-reported crashes group to be able to investigate the sensitivity of lower reporting threshold on the comparison to the benchmark. We defined these minor contacts as those where a crash reconstruction model found that both vehicles had a change in velocity

[2]Data is available for download at https://www.nhtsa.gov/laws-regulations/standing-general-order-crash-reporting

(i.e., a delta-V) of less than 1.0 mph. The collision model used was an impulse-momentum model using the inertial properties of the ADS equipped vehicle and estimated inertial properties of the crash partner, as described in Scanlon et al. (2021). Each of the 7 crashes with fixed or non-fixed objects was examined individually to estimate a delta-V, discussed in more detail in the appendix. Of the 7 crashes with fixed or non-fixed objects, 5 were excluded for having a low delta-V. Crashes where the ADS was not-in-transport were also excluded from this group. The single crash involving a cyclist (30270-5456) was included in this group.

Next, police-reported and alleged-injury crashes were identified from the SGO-reported crashes. *Police-reported* crashes were identified using the "Law Enforcement Investigating?" field in the SGO report data. Any SGO-reported crashes that had "Yes" was considered police-reported. For any SGO-reported crashes with "Unknown" in the "Law Enforcement Investigating?" field, Waymo used internal records (e.g., field incident response communication, insurance claims information) to determine if a police report was filed. To determine any injury crashes, the "Highest Injury Severity Alleged" SGO field was used. Any crash that did not have "No Injuries Reported" was considered an *any-injury-reported* crash. In this dataset, there were 3 crashes with "Minor" injuries reported. Crashes where the ADS was not-in-transport were also excluded from *police-reported* and alleged *any-injury-reported* crashes.

A list of all crash incidents included for analysis in this paper is included in the Appendix. Each NHTSA SGO-reported RO crash is listed along with whether the crash was included in the in-transport vehicle, low delta-V, *police-reported*, or *any-injury-reported* outcome groups. Detailed narratives or other data is not included in this paper, as this information can be obtained from the NHTSA SGO reporting website.

## 2.2. Human Benchmarks

Table 1 lists the human benchmarks used to compare to the ADS crashes in this study. The ADS data is derived from the NHTSA SGO-reported crash data. Human crashed vehicle rates derived from all police-reported crashes with two different underreporting adjustments were reported in Scanlon et al. (2023). The Blincoe-adjusted estimate was derived from a combination of a national phone survey and comparing insurance and crash record data as reported in Blincoe et al. (2022). The Blanco-adjusted estimate used the proportion of unreported to police-reported crashes from the Strategic Highway Research Program 2 (SHRP-2) NDS reported in Blanco et al. (2016). Two other property damage benchmarks were considered. First, a benchmark derived from NDS from a population of ride-hailing drivers in San Francisco was described by Flannagan et al. (2023). Second, the overall crashed vehicle rate (excluding tire strikes) from the SHRP-2 NDS was reported in Blanco et al. (2016). The SHRP-2 NDS was conducted in multiple urban and rural areas of the country, so it is most appropriate to compare this benchmark to the aggregate ADS crashes. The two NDS-derived benchmarks both had a higher rate (by a factor of between 1.7 and 8 times) than the Blincoe-adjusted crashed vehicle rates reported in Scanlon et al. (2023). This large discrepancy between the Blincoe-adjusted and NDS rates suggests the Blincoe et al. (2022) property damage adjusted may not represent an any property damage reporting threshold. The Blanco et al. (2016) adjustment for property damage only is derived from NDS data, which as discussed above, is based on recorded events and not self-reported survey data as was used in the Blincoe et al. (2022) adjustment. We therefore used the Blanco et al. (2016) adjustment estimate as the primary comparison to the ADS crashes in this study. The human crash benchmarks reported in Scanlon et al. (2023) in Phoenix, San Francisco, and Los Angeles were combined proportional to the miles driven in the Waymo RO service and are shown in Table 2 as the "mileage blended average." This mileage blended average was compared to the crashed vehicle rate aggregated in the three locations.

As noted in Scanlon et al. (2023), the crashed vehicle count from the police reported data only included in-transport vehicles. Therefore, the "all property damage" crashes from Scanlon et al. (2023) were compared with all SGO-reported ADS crashes, excluding those where the ADS vehicle was not-in-transport as described in the previous section. Because the NDS data sources described in Flannagan et al. (2023) and Blanco et al. (2016) did not specify if not in-transport NDS vehicles were excluded, we compared these NDS data to all reported SGO ADS crashes.

The second comparison made in this study was between ADS NHTSA SGO crashes with a police report filed and the observed human police-reported rate. Third, ADS NHTSA SGO crashes where any injuries were reported were compared to the human injury benchmark, adjusted for underreporting. Because *police-reported* and *any-injury-reported* crashes are relatively rare, most human NDS-based benchmarks have few of these crashes and do not attempt to estimate rates. Police-reported crash databases, on the other hand, aggregate large numbers of crashes over the entire driving fleet. Therefore, the only comparable benchmark data sources available were the police reported and any injury reported (adjusted for underreporting) rate estimates presented in Scanlon et al. (2023).

Table 1 shows the most valid comparisons between the ADS and human benchmark data sources. Table 2 lists all the human benchmark crashed vehicle rates and the underlying VMT the rates are based on.

**Table 1**
Description of Comparable ADS and Human Benchmarks Data Sources.

| Outcome Group | Waymo ADS Data | Human Benchmark Source |
|---|---|---|
| *Any Property Damage or Injury* | All NHTSA SGO Crash - In-Transport Vehicles | Scanlon et al. (2023) Any Property Damage or Injury Blanco Adjusted |
| | All NHTSA SGO Crashes in San Francisco | Flannagan et al. (2023) |
| | All NHTSA SGO Crash in all Locations | Blanco et al. (2016) |
| *Police-Reported* | All NHTSA SGO Crash - In-Transport Vehicles with Police Report | Scanlon et al. (2023) Police-reported Unadjusted |
| *Any-injury-reported* | All NHTSA SGO Crash - In-Transport Vehicles with Reported Injury | Scanlon et al. (2023) Any Injury Blincoe-Adjusted |

**Table 2**
Crashed Vehicle Rates and VMT for Human Benchmarks.

| | | Human Benchmark IPMM and VMT (Millions) | | | |
|---|---|---|---|---|---|
| **Outcome Group** | **Human Benchmark Source** | **National** | **Phoenix** | **San Francisco** | **Los Angeles** |
| *Any Property Damage or Injury* | Scanlon et al. (2023) *Any Property Damage or Injury* Blanco-Adjusted | 21.0<br>2,109,149 | 22.3<br>24,224 | 17.9<br>927 | 15.3<br>28,445 |
| | Mileage Blended | N/A | 21.2<br>18,530 | | |
| | Flannagan et al. (2023) | N/A | N/A | 64.9<br>5.612 | N/A |
| | Blanco et al. (2016) | 20.2<br>34 | N/A | N/A | N/A |
| *Police-Reported* | Scanlon et al. (2023) *Police-Reported* Unadjusted | 4.31<br>2,109,149 | 4.55<br>24,224 | 5.77<br>927 | 3.71<br>28,445 |
| | Mileage Blended | N/A | 4.84<br>18,530 | | |
| *Any-Injury-Reported* | Scanlon et al. (2023) *Any-Injury-Reported* Unadjusted | 1.22<br>2,109,149 | 1.29<br>24,224 | 3.79<br>927 | 1.65<br>28,445 |
| | Mileage Blended | N/A | 1.91<br>18,530 | | |
| | Scanlon et al. (2023) *Any-Injury-Reported* Blincoe-Adjusted | 1.78<br>2,109,149 | 1.88<br>24,224 | 5.55<br>927 | 2.41<br>28,445 |
| | Mileage Blended | N/A | 2.78<br>18,530 | | |

All of the crash rate benchmarks presented in this study are at the vehicle-level (or driver-level crash rates), and are described as a crashed vehicle rate. Crashed vehicle rates represent the rate at which drivers (or a driver) crash(es) per VMT. The physical representation of a vehicle-level crash rate is equivalent to how ADS crash rates are presented - the rate at which the ADS crashes per VMT. It is notable that a common mathematical error is pervasive in the ADS benchmark literature that incorrectly compares a crash-level crash rate from the human benchmarks to a vehicle-level crash rate from the ADS data (Scanlon et al., 2023). As a simple illustration, consider two drivers (driver 1 and 2) that each travels 100 miles and collides. The crash rate in this population is 0.5 crashes per 100 miles (1 crash / 200 miles) and the crashed vehicle rate is 1 crashed vehicle per 100 miles (2 crashed vehicles / 200 miles traveled). Now consider a hypothetical ADS (driver 3) that travels 100 miles and crashes into another vehicle (driver 4), for which the miles traveled is known. This crashed ADS vehicle rate of 1 crashed vehicle per 100 miles is comparable to the benchmark crashed vehicle rate of driver 1 and 2 of 1 crashed vehicle per 100 miles. By contrast, comparing the ADS crashed vehicle rate of 1 crashed vehicle per 100 miles to the human-driven crash rate of 0.5 crashes per 100 miles would produce a faulty comparison that ignores the number of vehicles involved in the calculation of the crash rate.

### 2.3. Confidence Intervals

Two types of confidence intervals are presented in this paper. First, confidence intervals are estimated for Incidents per Million Miles (IPMM) using a Poisson exact model. The confidence interval, IPM, can be computed as

$$IPM \in [qgamma(\alpha/2, n, 1)/m, qgamma(1 - \alpha/2, n + 1, 1)/m] \tag{1}$$

where *qgamma* is the quantile function of the gamma distribution (i.e., inverse cumulative distribution function), $\alpha$ is the significance level (e.g., 0.05), $n$ is the event count, and $m$ number of miles driven. Second, confidence intervals for the ratio between the ADS crash rate of $Y$ events over $t$ miles and the benchmark crash rate of $X$ events over $s$ miles were calculated using the method described in Nelson (1970) as

$$\rho \in [s/t * qbetaprime(\alpha/2, Y, X + 1), s/t * qbetaprime(1 - \alpha/2, Y + 1, X)] \tag{2}$$

where *qbetaprime* is the quantile function of the beta prime distribution (i.e., inverse cumulative distribution function). This formulation of the confidence intervals can be computed in the event of zero event counts in the ADS data (i.e., $Y = 0$), but as a result may be more conservative (i.e., wider confidence intervals) in the case of non-zero ADS events counts compared to the Poisson exact model.

Another interpretation of the ratio between ADS rate ($\mu = Y/t$) and benchmark rate ($\lambda = X/s$) is as a relative difference in the rate, $\delta$,

$$\delta = (\mu - \lambda)/\lambda = \mu/\lambda - 1. \tag{3}$$

Because this percent change in the rate is a direct product of the ratio, the same confidence intervals described in Equation 2 can be used to generate confidence intervals in the relative difference.

## 3. Results

In total, this study considered the first 7.14 million miles of driving by the Waymo RO service, which drove 5.34 million miles in Phoenix, 1.76 million miles in San Francisco, and 0.0467 million (46k) miles in Los Angeles. Table 3 shows the number, IPMM, and 95% confidence intervals for the different event measures examined in this study. In Los Angeles, there was a single event that was an SGO-Reported crash that also met the in-transport and exclude low delta-V inclusion criteria resulting in an IPMM of 21.4 with 95th percentile confidence intervals of (0.5, 119) IPMM. There were no (zero) *police-reported* and *any-injury-reported* crashes in Los Angeles, resulting in a 0 IPMM with 95th percentile confidence intervals of (0, 64.1) IPMM.

Table 4 reports the rate ratio of ADS to Human crashed vehicle rates and their 95th percentile confidence intervals for property damage crashes. Results with bold print and an asterisk indicate statistical significance (i.e., the 95th percentile confidence intervals do not cross a 1.0 rate ratio). Compared to the benchmarks derived from human crash reports adjusted for underreporting, the ADS crashed vehicle rate is lower in Phoenix, San Francisco, and when considering all locations together, while higher in Los Angeles. Only the Phoenix and aggregate comparisons are

**Table 3**
Number and Incidents per Million Miles (IPMM) of Crashed Vehicles for Waymo NHTSA SGO-Reported Crashes with 95% confidence intervals in Phoenix and San Francisco.

| | Phoenix | | | San Francisco | | |
|---|---|---|---|---|---|---|
| **Measure** | **n** | **IPM** | **CI** | **n** | **IPM** | **CI** |
| RO Miles (millions) | 5.33 | - | - | 1.75 | - | - |
| SGO-Reported | 38 | 7.1 | (5.0, 9.8) | 33 | 18.9 | (12.9, 26.4) |
| SGO-Reported in Transport | 33 | 6.2 | (4.3, 8.7) | 29 | 16.6 | (11.1, 23.7) |
| SGO-Reported Exclude Low Delta-V | 18 | 3.4 | (2.0, 5.3) | 14 | 8.0 | (4.4, 13.4) |
| SGO Police-Reported | 12 | 2.2 | (1.2,3.9) | 3 | 1.7 | (0.4,0.5) |
| SGO *any-injury-reported* | 2 | 0.4 | (<0.1, 1.4) | 1 | 0.6 | (<0.1, 3.2) |

statistically significant to a 95% level for both the all NHTSA SGO-Reported and SGO-Reported Excluding Low Delta-V ADS outcome groups.

The result was statistically significant in San Francisco for the SGO-Reported Excluding Low Delta-V group only. Compared to the NDS benchmarks, the ADS also has a lower rate compared to humans, which was statistically significant. The magnitude of the difference between the ADS and the human benchmarks varies depending on the estimate type (underreporting adjusted or observed) and with the exclusion of low delta-V events in the ADS data. As stated above, there was 1 crash in Los Angeles which met both the SGO and low delta-V thresholds. Compared to the Blanco-adjusted benchmark, the rate ratio was 1.40 with confidence intervals of (0.02, 8.92), which indicates the result is not statistically significant. As discussed in the methods section, the large discrepancy between the NDS studies and adjusted *any property damage or injury* crashed vehicle rates suggest that there is systematic uncertainty in the data, which makes interpreting the effect of the ADS on *any property damage or injury* outcomes difficult.

**Table 4**
Comparison of Waymo ADS and Human Benchmark Crashed Vehicle Rate for Crashes with Any Property Damage or Injury.

| | | | All NHTSA SGO-Reported | | | | SGO-Reported Excluding Low Delta-V (<1 mph) | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Human Benchmark** | **Location** | **Human IPMM** | **ADS IPMM** | **ADS to Human Rate Ratio** | **95th Percentile Confidence Intervals** | | **ADS IPMM** | **ADS to Human Rate Ratio** | **95th Percentile Confidence Intervals** | |
| Any Property Damage or Injury Crashes-Blanco Adjustment (Scanlon et al., 2023) | Phoenix | 22.3 | 6.2 | **0.28*** | **0.18** | **0.41** | 3.4 | **0.15*** | **0.08** | **0.25** |
| | San Francisco | 17.9 | 16.5 | 0.92 | 0.58 | 1.39 | 8.0 | **0.45*** | **0.22** | **0.80** |
| | Total - Mile Blend | 21.2 | 8.8 | **0.42*** | **0.31** | **0.55** | 4.5 | **0.21*** | **0.14** | **0.31** |
| | Total - National Average | 21.0 | 8.8 | **0.42*** | **0.31** | **0.55** | 4.5 | **0.21*** | **0.14** | **0.32** |
| UMTRI/VTTI Ride-Hailing (Flannagan et al., 2023) | San Francisco | 64.9 | 18.8 | **0.29*** | **0.19** | **0.43** | 8.0 | **0.12*** | **0.06** | **0.22** |
| SHRP-2 NDS (Blanco et al., 2016) | All Locations | 20.1 | 10.1 | **0.50*** | **0.37** | **0.66** | 4.5 | **0.22*** | **0.14** | **0.33** |

Table 5 shows the ADS to Human rate ratio and their 95th percentile confidence intervals for *police-reported* and *any-injury-reported* crashed vehicle rates. The ADS had a lower *police-reported* and *any-injury-reported* crashed vehicle rate that was statistically significant in Phoenix, San Francisco, and when considered in aggregate. There were no observed *police-reported* or *any-injury-reported* crashes in Los Angeles resulting in an rate ratio of 0. The result in Los Angeles was not statistically significant due to low mileage (confidence intervals of [0, 21.3] for *police-reported* and [0, 32.8] for *any-injury-reported*). Inverting the rate ratios in Table 5, humans have between 2.0 and 3.3 times the rate of *police-reported* crashes and between 4.2 and 10 times the rate of *any-injury-reported* crashes than the Waymo ADS. When considering all locations together compared to the mileage blended benchmark, the *any-injury-reported* crashed vehicle rate was 0.41 incidents per million miles (IPMM) for the ADS vs 2.78 IPMM for the human benchmark, an 85% reduction or a 6.8 times lower rate. *Police-reported* crashed vehicle rates for all locations together were 2.1 IPMM for the ADS vs. 4.85 IPMM for the human benchmark, a 57% reduction or 2.3 times lower rate.

**Table 5**
Comparison of ADS and Human Benchmark Crashed Vehicle Rate for Police Reported and Any Injury Crashes.

| **ADS Events** | **Human Benchmark** | **Location** | **Benchmark IPMM** | **ADS IPMM** | **ADS to Human Rate Ratio** | **95th Percentile Confidence Intervals** | |
|---|---|---|---|---|---|---|---|
| *Police-Reported* | Observed police reported (Scanlon et al., 2023) | Phoenix | 4.55 | 2.2 | **0.49*** | **0.23** | **0.92** |
| | | San Francisco | 5.77 | 1.7 | **0.30*** | **0.05** | **0.96** |
| | | Total Mileage Blended | 4.85 | 2.1 | **0.43*** | **0.22** | **0.76** |
| | | Total National Average | 4.31 | 2.1 | **0.49*** | **0.25** | **0.85** |
| *Any Injury-Reported* | Any Injury (with underreport adjustment) (Scanlon et al., 2023) | Phoenix | 1.88 | 0.4 | **0.19*** | **0.02** | **0.81** |
| | | San Francisco | 5.55 | 0.6 | **0.10*** | **0.001** | **0.66** |
| | | Total Mileage Blended | 2.78 | 0.4 | **0.15*** | **0.02** | **0.49** |
| | | Total National Average | 1.78 | 0.4 | **0.24*** | **0.04** | **0.77** |

* and **bold text** indicates statistically significant at 95% confidence.

Figure 2 shows the percent reduction of the ADS for *police-reported* and *any-injury-reported* crashed vehicle rates and their 95th percentile confidence intervals relative to the human benchmarks from Scanlon et al. (2023). The ADS reduced *police-reported* crashes between 51% and 70% and *any-injury-reported* crashes (adjusted for underreporting) between 76% and 90%. A comparison to the observed *any-injury-reported* rates from Scanlon et al. (2023) are shown in Figure 2 as a demonstration of the sensitivity of the underreporting adjustment to the results. As mentioned in the methods section, an underreporting adjusted *any-injury-reported* rate is the most valid comparison to ADS crashes due to known underreporting of injuries in human crash data, while there is low likelihood of injury underreporting in ADS data. In general, the same conclusions are drawn by comparing the ADS observed and adjusted *any-injury-reported* rates, except for in Phoenix and when compared to a national benchmark where the confidence intervals overlap 0%. Although the point estimates are still lower, because the benchmark rate and observed ADS crash count is small, a small decrease in the benchmark rate greatly increases the confidence intervals.

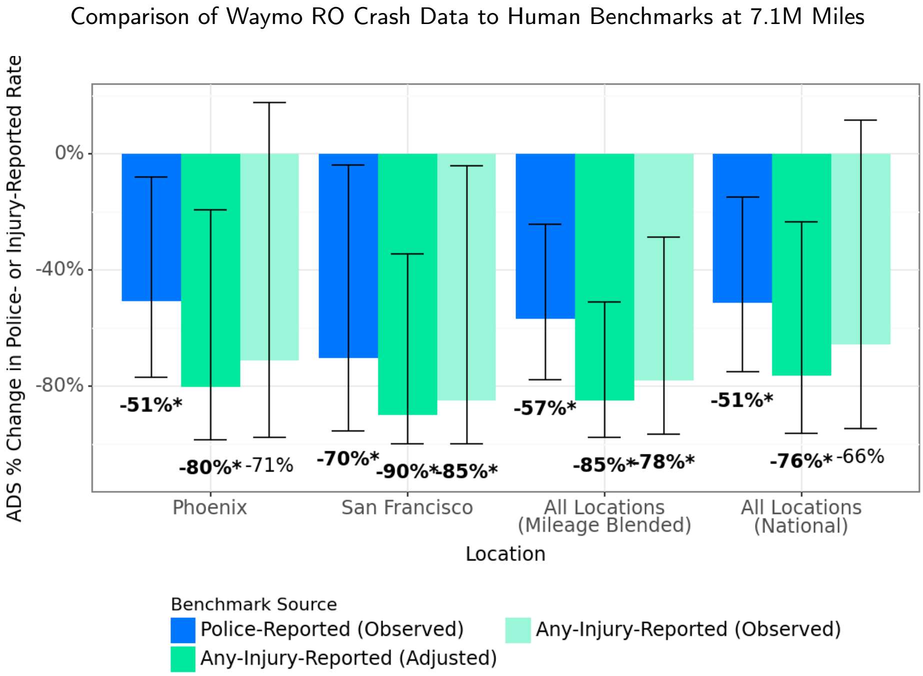


**Figure 2:** Percent Reduction for the Waymo ADS in *Police-Reported* and *Any-Injury-Reported* Crashes Compared to a Human Benchmark from Scanlon et al. (2023) in Phoenix, San Francisco, and All Locations. Note that Los Angeles data is not plotted because of large error bars. See the results in Table 5

# 4. Discussion

## 4.1. Interpretations of Results

### *4.1.1. Any Property Damage or Injury*

The available benchmark crashed vehicle rates for *any property damage or injury* crashes vary greatly depending on the method of estimation (i.e., underreporting adjustment of crash data vs. observations in NDS) and the driving environment (e.g., SF ride-hailing NDS vs. national average NDS). These observed discrepancies could be due to several factors. As noted in Scanlon et al. (2023), although geographic location is controlled for in the benchmarks used in this paper, other driving environment factors are not. For example, the ride-hailing benchmark from San Francisco in Flannagan et al. (2023) will have some amount of differing driving exposure (e.g., time of day, location/routes) than the overall passenger vehicle populations derived from police report data because the drivers studied in Flannagan et al. (2023) were primarily using their vehicles to offer ride-hailing services. Another possible explanation for this discrepancy is that the underreporting adjustment used to estimate *any property damage or injury* crashes could also vary by driving environment. The available underreporting estimates are few, and are derived from large, nationally representative surveys that may not capture reporting differences in different driving environments. Last, it is still not clear if the minimum severity for reporting is consistent between different benchmark sources and the ADS fleet. The effect of including or excluding low delta-V crashes can also be observed in the ADS crash data. Excluding vehicle-to-vehicle crashes with low delta-V (less than 1 mph) reduced the ADS crashed vehicle rates by 48% in Phoenix and 52% in San Francisco.

The assumed crash underreporting used in Scanlon et al. (2023) to adjust police-reported data to estimate the *any property damage or injury* outcome level are subject to uncertainties. When surveying people about underreporting, there is subjective judgment on what is considered a crash. The survey studies used as part of the underreporting adjustment in Blincoe et al. (2022) and subsequently used by Scanlon et al. (2023) were open-ended and asked respondents to report whether they were involved in a crash, without defining what a crash constitutes in terms of vehicle damage. On the NDS side, there can be similar difficulties judging property damage status of crashes. Most

NDS will identify most crashes in the data reduction phase based on kinematic triggers and manual review of the sensor and video data. Data reductionists need to make subjective judgements on the severity of these crashes without the benefit of retrospective vehicle damage investigations. Although this NDS-based method may discover most crashes, there are certain types of low impact severity crashes that may be more likely to be missed (e.g., while the equipped vehicle is stationary and thus do not trigger kinematic triggers or those that occur outside the camera views of the instrumentation). Further complicating property damage crash reporting, ADS vehicles are equipped with high cost sensors that may be damaged in even minor crashes. If a property damage value approach is used, ADS vehicles may have higher repair costs, and thus have a higher property damage crash rate for a similar set of benchmark crash with similar impact energy characteristics.

In addition to underreporting uncertainty, as discussed in Scanlon et al. (2023), a stated limitation of the state-wide police report database in California (SWITRS) is that there is no requirement that non-injury police-reported (within a jurisdiction) crashes be reported to SWITRS (the state). This potential incomplete reporting of property damage crashes, even those that meet the reporting requirement, could explain why San Francisco has a lower police-reported crashed vehicle rate than Phoenix, even though the expectation is that there are more crashes in more densely populated areas. Although San Francisco had a lower *any property damage or injury* crashed vehicle rate compared with Phoenix, San Francisco had the highest *any-injury-reported* crashed vehicle rate. It is unclear whether this result is because San Francisco indeed has a higher ratio of *any-injury-reported* to *any property damage or injury* crashes than other locations, or if this is an artifact of this underreporting that affects SWITRS data specifically.

Because of these discrepancies and difficulties, it is difficult to draw conclusions about the relative performance of an ADS like the Waymo Driver and a benchmark crashed vehicle rate for *any property damage or injury* crashes. Although the results show that the Waymo ADS has, in general, a lower crashed vehicle rate in *any property damage or injury* crash outcome group, it is not clear what the appropriate benchmark should be. For example, in San Francisco the *any property damage or injury* benchmark from Scanlon et al. (2023) is between 10.5 and 17.9 IPMM (depending on the underreporting modeling adjustment methodology), while the ride-hailing driver benchmark in San Francisco reported in Flannagan et al. (2023) is 64.9 IPMM. Given the available data, it's unclear if this discrepancy is because the underreporting adjustment used in Scanlon et al. (2023) is not representative of San Francisco, whether the SWITRS police report database is underreporting property damage only reports at a higher rate than elsewhere, or if the different characteristics of the driving populations (all drivers vs ride-hail drivers using rental vehicles) are affecting the rates. In order to better understand *any property damage or injury* crashed vehicle rates, there is a need for metrics or data sources that can more accurately define a more objective lower reporting threshold than exists today.

In this study, the ADS *any property damage or injury* crashes were reported in two severity levels: all reported contacts and those that excluded crashes with delta-V less than 1 mph. The availability of accurate sensor data enables accurate reconstructions of ADS crashes to estimate their severity (e.g., delta-V or impact speed). Estimating crash severity is often not possible from most police report databases without detailed reconstructions. The Crash Investigation Sampling System (CISS), maintained by NHTSA, is a nationally representative database where some crashes have an accompanying crash reconstruction based on vehicle damage and scene evidence. This sampled, nationally representative database might be difficult to apply to different driving environments, however. As shown in the benchmarks of Scanlon et al. (2023), crashed vehicle rates can vary widely in different locations. Another potential source of severity estimates in a benchmark is estimating severity from NDS data. Advances in computer vision may enable crash reconstructions from limited vehicle sensor and video data (see for example Campolettano et al. (2023)).

### *4.1.2. Police-Reported and Any-Injury-Reported*

Observed *police-reported* crashes, in contrast to *any property damage or injury* crashes, may be a comparison with less inherent systematic variability. Although reporting thresholds and reporting practices may differ by jurisdiction (Scanlon et al., 2023), if observed police reports in the ADS and human benchmark are from the same jurisdictions and time periods, then the reporting practices should be comparable in both populations.

This comparison of *police-reported* crashed vehicle rates is likely a conservative comparison for several reasons. Private citizens often do not report police-reportable events (M. Davis & Co., 2015). Again, in California, only injury crashes are required to be reported to the state databases, which means some jurisdictions in California may have different PDO police-reported crashes reporting practices. Conversely for ADS crashes, this study conservatively used the "Law Enforcement Investigating?" field of the NHTSA SGO reports because the authors have knowledge that Waymo's operational policies where it is likely police took information that could be used to file a report or indicated they would file a report. Although the *police-reported* outcome is often associated with a certain level of property damage, factors other than property damage may influence whether an ADS fleet operator would report collisions to the police. Future research should investigate police reporting differences between businesses (like an ADS fleet operator) and the general population. In some cases, Waymo was not provided with a filed report. Because most of the crashes in this dataset occurred in 2022 and 2023, for which state police-reported databases have not been published at the time of writing, the authors could not verify whether the ADS crashes in this study in the *police-reported* outcome group indeed were recorded. The benchmark from Scanlon et al. (2023) used for comparison in the *police-reported* outcome group was recorded in the respective crash databases.

*any-injury-reported* crashes may also serve as a useful comparison metric between ADS and a benchmark. It has been shown that there is less underreporting in injury crashes compared to crash with no injuries Blincoe et al. (2022). Because the magnitudes of underreporting are smaller, the variance and the impact on the comparisons may also be lower. The injury rates, however, can also suffer from similar surveillance biases than the property damage and police report data related to underreporting. The minimum threshold of an injury is often unclear. The timing of presentation of injury can also affect the results. Injury determination as reported in police reports is often reported on scene when the report is filed. A police report may not reflect injuries that are reported days after a crash. ADS reported crashes are often filed days, weeks, or up to a month after the event, allowing for more time to become aware of alleged injuries from those involved.

## 4.2. Comparison to Insurance Claims-based Analyses

The benchmarks and ADS data presented in this paper are overall crash involvement rates which do not consider crash contribution of those involved. Di Lillo et al. (2023) compared third party liability property damage and bodily injury insurance claims rate between the Waymo ADS operations and a human benchmark. In this study, only liability claims that were resolved or were likely to be resolved with a payment were included as these types of claims are a proxy for responsibility. Di Lillo et al. (2023) found that the Waymo RO service had a lower property damage and bodily injury claims rate compared to a human benchmark over 3.8 million miles of RO driving. Examining liability claims allows an analysis of the safety impact of a population (here the Waymo RO service) towards other road users in the way the ADS contributes to causing crashes. The results of this study, in contrast, examine the overall crashed vehicle rate regardless of the contribution to the crash's causation. Indeed, many of the crashes in the RO dataset examined in this paper featured the Waymo ADS parked or stopped appropriately at a traffic control device where the ADS's behavior had little or no contribution to the crash's cause. Examining ADS performance from both a crash causation and overall crash rate are important and can provide information on the overall safety impact of an ADS. Di Lillo et al. (2023) reported that Waymo RO operations reduced property damage liability claims by 76% and bodily injury liability claims by 100% (zero observed RO bodily injury liability claims). This magnitude of claims reduction is similar to the magnitude in *police-reported* (51% to 70% reduction) and *any-injury-reported* (76% and 90% reduction) reductions reported in this study, which did not consider contribution to causing the crash.

## 4.3. Considerations for Safety Impact Assessment for Serious Injury and Fatal Crashes

Conclusions regarding serious injury alone, or fatalities alone, require more data because they are subsets of the *any-injury-reported* outcome group which combines all injury and fatality results into one data category. ADS developers use multiple, complementary safety assurance methods to mitigate risk of high severity outcomes across architectural, behavioral, and operational layers (e.g., platform verification and validation, hazard analysis, see Webb et al. 2020, Favaro et al. 2023a). Traditionally, automotive safety systems have used prospective safety benefit analyses that use test track data and simulations as risk assessment tools and to determine potential high severity benefits. These types of prospective studies have also been performed for ADS. For example, one study that used reconstructions of all fatal crashes in Chandler, AZ found that a level 4 ADS was able to prevent 100% of crash when placed in the initiator role and prevent 82% and mitigate 10% when placed in the responder role (Scanlon et al., 2021).

Furthermore, ADS are designed to be able to follow applicable speed limits on the roads they drive on. Reducing speeding is a core pillar of the Vision Zero and Safe Systems approach to reducing serious injuries and fatalities on roadways. The Safe Systems approach has been adopted as a policy initiative by the U.S. Department of Transportation (United States Department of Transportation, 2022). The results of this study show that the ADS evaluated had a statistically significant lower *any-injury-reported* crashed vehicle rate. Serious injury and fatalities are a subset of this *any-injury-reported* benchmark, but no statement on these outcome levels can be made at this time based on this retrospective data. In a Safe Systems approach, it is not a requirement to prove efficacy of countermeasures before they are deployed in the field. Due to the statistical requirements, like the ones presented in Scanlon et al. (2023) or Kalra and Paddock (2016), assessing the safety impact of a system on serious injury or fatal crashes is impractical in many situations. The Safe Systems approach instead uses known causal factors that contribute to a large amount of serious injury and fatal crashes (e.g., excessive speed, or excessive energy transfer) and attempts to control these factors to stay below the tolerances to lead to these outcomes.

As ADS RO miles increase, the likelihood of observing a serious injury or fatality also increases. As discussed in the statistical power analysis of Scanlon et al. (2023), hundreds of millions to billions of miles of VMT would be necessary to detect a statistically significant difference in fatal crashed vehicle rates, depending on the magnitude of the difference in crashed vehicle rate of the ADS and benchmark. The national rate of crashed passenger vehicles involved in fatal crashes while traveling on surface streets is 22.3 incidents per billion miles (IPBM) (Scanlon et al., 2023). Consider a fictive driver who experiences 1 fatal crash after driving 10 million miles. At the time of this fictive fatal crash, the driver's fatal crashed vehicle rate would be 100 IPBM with 95th percentile confidence intervals of [3, 557] IPBM. Although the point estimate of 100 IPBM is higher than the benchmark, due to the low event count relative to the miles, this fictive driver's crashed vehicle rate is not statistically different from the benchmark. Consider another fictive driver involved in 1 fatal crash in 100 million VMT, which is a rate of 10 IPBM. The 95th percentile confidence intervals of this fictive driver is [0.3, 56] IPBM, which is still overlapping with the benchmark and not significantly different.

## 4.4. Limitations

This study has several limitations. The results in this study examine crashed vehicle rates aggregated by operating location and do not attempt to evaluate crashed vehicle rates within subgroups, for example, by crash partner or crash type. As discussed above, the method used for estimating an overall crashed vehicle rate, and particularly underreporting assumptions, affect the ability to draw conclusions about *any property damage or injury* crashed vehicle rate performance. Past studies that reported ADS crash data have found that ADS vehicles may have different proportions of different crash rates than the general population (Victor et al., 2023).

As noted above, this study attempted to compare the ADS crashed vehicle rate to the most comparable benchmark available in the literature. Although these benchmarks could adjust for some factors that are related to crashed vehicle rate (e.g., geographical area, types of roads, vehicle type), other pertinent factors were not controlled for. These include time of day adjustments and adjustments for the driving density within the geographic areas. As the Waymo ADS is being used as a ride-hailing service, the routes the ADS drives are likely differently dispersed than the general driving population and may be biased toward more densely populated areas. There are challenges when matching benchmark crash and VMT data sources that can be adjusted by these parameters. Even if the origin and destinations of the ADS ride-hailing trips match closely to a comparable human driving population, there still may be differences in the route selection between the ADS vehicle and human drivers that affects crash rates. An aggregate-level analysis comparing the ADS to the current crash status quo should include these route choices if the research question is to determine the safety impact of replacing human driving with ADS vehicle driving. It may also be of interest, however, to compare the ADS vehicle crashed vehicle rate compared to human drivers driving the same routes as the ADS vehicle. This latter comparison is closer to an event-level analysis (Favaro et al., 2023a) than an aggregate-level analysis that is the purpose of the current study and different methods than an outcome-based approach may be more effective in this case.

This study relied on fields in the NHTSA SGO crash data to determine ADS outcome groups. There may be differences in how different ADS fleet operators fill out the fields in the NHTSA SGO reports. For example, other ADS fleet operators may interpret the "Law Enforcement Investigating?" field differently than what was described in this study.

An ADS vehicle operating in a ride hailing context is not always occupied by a human (e.g., before or in between picking up passengers). Therefore, when examining injury outcomes, if the ADS vehicle is unoccupied, there would be a reduced risk of injury for a similar human-only crash. More broadly, risk of injury in a motor vehicle crash can be affected by many factors, such as seat belt use and vehicle model year (as a proxy for available safety systems). A risk-based approach that uses an injury risk function to compute probability of an injury outcome given some set of inputs can be advantageous in normalizing risk in both the benchmark and ADS crashes for comparison, as has been traditionally done in prospective safety benefit analyses (for example, Kusano and Gabler (2012); Scanlon et al. (2017)).

The Waymo RO service studied in this paper was operating over multiple years on different vehicle platforms and with evolving software versions. Just as the human driving population has changing characteristics over time, certain aspects of the Waymo RO ride-hailing service have changed. The operating environment and territory has expanded during this time period. Starting in the area around Chandler, Arizona in 2020, today the Waymo RO ride-hailing service operates in an area that includes multiple cities in metropolitan Phoenix and over the entire area of San Francisco. A limitation of this study is that the entire history of the Waymo RO crash record was compared to human crash data over different time periods. As the results of this study show, several millions of miles are needed to detect differences between an ADS fleet and benchmarks. As ADS fleets continue to increase the number of VMT, additional analyses that are restricted to certain periods of time or platforms could be enabled. One difficulty in comparing ADS and human crash data is that ADS data is published at a much faster cadence than human crash data. The NHTSA SGO crash data is submitted every month and published shortly after. Complete human crash databases generally are published by the calendar year and can take up to 2 years after the completion of the calendar year to be published.

## 5. Conclusions

This study compared the crashed vehicle rate of the Waymo RO service to human benchmarks for *any property damage or injury*, *police-reported*, and *any-injury-reported* outcomes. The results show that the Waymo RO service has a lower *police-reported* and *any-injury-reported* crashed vehicle rate compared to the benchmarks. When considering all locations together, the any-injury crashed vehicle rate was 0.41 incidents per million miles (IPMM) for the ADS vs 2.78 IPMM for the human benchmark, an 85% reduction or a 6.8 times lower rate. *Police-reported* crashed vehicle rates for all locations together were 2.1 IPMM for the ADS vs. 4.85 IPMM for the human benchmark, a 57% reduction or 2.3 times lower rate. Because the *police-reported* and *any-injury-reported* crashed ADS vehicle rates were much lower than the benchmark rates, the ADS *any-injury-reported* and police-report crashed vehicle rates were statistically significant over a total of 7.14 million RO miles when compared individually in Phoenix and San Francisco and when compared overall. The comparison for Los Angeles was not statistically significant for zero observed ADS events but few miles. The results are more difficult to interpret for the *any property damage or injury* outcome comparison. In general, the ADS had a lower crashed vehicle rate than the benchmarks. The benchmark rates themselves, however, varied considerably between locations and within the same location. This raises questions whether the benchmark data sources have comparable reporting thresholds (surveillance bias) or if other factors that were not controlled for in the benchmarks (time of day, mix of driving) is affecting the benchmark rates. We assume that the *police-reported* and *any-injury-reported* rates are not as affected by this surveillance bias because of a higher lower threshold for reporting. This is the first study to compare overall crashed vehicle rates of ADS RO data only (as opposed to a mix of ADS testing with a human behind the wheel) to human benchmarks that also corrected for biases reported in the literature. The comparison of crash rates to benchmarks are part of the safety determination lifecycle, which itself is a part of a broader ADS safety case. The results show that the Waymo ADS operating in RO configuration has a lower crashed vehicle rate than human drivers when considering *police-reported* and *any-injury-reported* crashes. This result provides directional confirmation of the predictions and analyses used prior to deploying RO operations.

## CRediT authorship contribution statement

**Kristofer D. Kusano:** Conceptualization, Data curation, Formal analysis, Writing - original draft. **John M. Scanlon:** Conceptualization, Data curation, Writing - review & editing. **Yin-Hsiu Chen:** Methodology, Validation. **Timothy L. McMurry:** Methodology, Validation. **Ruoshu Chen:** Validation. **Tilia Gode:** Conceptualization, Supervision. **Trent Victor:** Conceptualization, Supervision, Writing - review & editing.

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# A. Appendix

The table below lists all the crashes included in this analysis. The SGO report ID can be used to look up further details of these events that are published by NHTSA. The "Waymo 1M Mile RO Event #" column lists the integer event identifier that was reported in Victor et al. (2023) that described all contact events (regardless of whether they were reported as part of the NHTSA SGO). Of the 20 events reported in Victor et al. (2023), 11 were reported as part of the NHTSA SGO. Waymo started to operate in RO before the NHTSA SGO was enacted in July 2021 and as a result, 4 contact incidents that were previously reported in Victor et al. (2023) were not subject to the SGO reporting requirements. The authors retroactively reviewed these 4 contact incidents and determined that 2 of the contact incidents would have qualified for NHTSA SGO reporting. These two (2) incidents were included in the data analyzed for this paper. The location column refers to the market the crash occurred in (PHX for Phoenix, SFO for San Francisco, and LA for Los Angeles). The remaining columns indicate whether the SGO-reported crash belonged to each of the groups analyzed in this paper and described in the methodology section. As noted in the Methods section, two crashes occurred before the NHTSA SGO reporting requirements were enacted but were retroactively reviewed and deemed to meet the SGO reporting requirements (events #1 and #4 from Victor et al. (2023).

Police-reported status was determined using a combination of the NHTSA SGO field "Law Enforcement Investigating?" and internal Waymo records. Of the 10 SGO-reported crashes that indicated "Yes" for the "Law Enforcement Investigating?" field. The two SGO-reported crashes with an "Unknown" reported in the "Law Enforcement Investigating?" field also likely had a police report generated based on review of Waymo operations records. Additionally, in two events (30270-6548 and 30270-1583), the SGO field "Law Enforcement Investigating?" is "No", but operational records indicate a police report may have been filed. These two events are also conservatively included in the SGO police-reported category. Event #1 from Victor et al. (2023) occurred before the NHTSA SGO-reporting period but was reported to police based on review of operational records.

**List of Included NHTSA SGO Crash Events in this Analysis.**

| SGO Report ID | Waymo 1M Mile RO Event # (Victor et al., 2023) | Location | NHTSA SGO-Reported | NHTSA SGO In-Transport | NHTSA SGO In-Transport Exclude Low DV | NHTSA SGO Police-Reported | NHTSA SGO Any Injury |
|---|---|---|---|---|---|---|---|
| 30270-6668 | NA | PHX | True | True | True | False | False |
| 30270-6667 | NA | SFO | True | True | False | False | False |
| 30270-6666 | NA | SFO | True | True | False | False | False |
| 30270-6664 | NA | PHX | True | True | False | False | False |
| 30270-6663 | NA | SFO | True | True | True | False | False |
| 30270-6662 | NA | SFO | True | True | False | False | False |
| 30270-6661 | NA | SFO | True | True | True | False | False |
| 30270-6566 | NA | PHX | True | True | False | True | True |
| 30270-6561 | NA | PHX | True | True | False | True | False |
| 30270-6548 | NA | PHX | True | True | False | True | False |
| 30270-6542 | NA | PHX | True | False | False | False | False |
| 30270-6521 | NA | PHX | True | True | False | False | False |
| 30270-6520 | NA | PHX | True | True | False | False | False |
| 30270-6519 | NA | PHX | True | True | True | True | False |
| 30270-6518 | NA | SFO | True | False | False | False | False |
| 30270-6517 | NA | SFO | True | True | False | False | False |
| 30270-6516 | NA | PHX | True | True | True | False | False |
| 30270-6515 | NA | SFO | True | True | True | False | False |
| 30270-6514 | NA | SFO | True | True | False | False | False |
| 30270-6405 | NA | SFO | True | True | True | True | False |
| 30270-6385 | NA | SFO | True | True | True | False | False |

Continuation of Event List

| SGO Report ID | Waymo 1M Mile RO Event # (Victor et al., 2023) | Location | NHTSA SGO-Reported | NHTSA SGO In-Transport | NHTSA SGO In-Transport Exclude Low DV | NHTSA SGO Police-Reported | NHTSA SGO Any Injury |
|---|---|---|---|---|---|---|---|
| 30270-6368 | NA | PHX | True | True | True | True | False |
| 30270-6352 | NA | SFO | True | True | True | True | False |
| 30270-6347 | NA | LA | True | True | True | False | False |
| 30270-6346 | NA | SFO | True | True | False | False | False |
| 30270-6342 | NA | SFO | True | True | False | False | False |
| 30270-6338 | NA | PHX | True | True | True | False | False |
| 30270-6337 | NA | PHX | True | False | False | False | False |
| 30270-6336 | NA | SFO | True | True | True | True | True |
| 30270-6335 | NA | PHX | True | False | False | False | False |
| 30270-6198 | NA | PHX | True | True | True | True | False |
| 30270-6150 | NA | PHX | True | True | True | False | False |
| 30270-6149 | NA | PHX | True | True | True | True | False |
| 30270-6133 | NA | SFO | True | True | False | False | False |
| 30270-6132 | NA | SFO | True | True | False | False | False |
| 30270-6131 | NA | PHX | True | False | False | False | False |
| 30270-5997 | NA | PHX | True | True | True | True | True |
| 30270-5961 | NA | SFO | True | True | False | False | False |
| 30270-5960 | NA | SFO | True | False | False | False | False |
| 30270-5959 | NA | SFO | True | True | True | False | False |
| 30270-5958 | NA | SFO | True | False | False | False | False |
| 30270-5957 | NA | SFO | True | True | False | False | False |
| 30270-5896 | NA | PHX | True | True | True | True | False |
| 30270-5760 | NA | PHX | True | True | False | False | False |
| 30270-5758 | NA | SFO | True | True | True | False | False |
| 30270-5756 | NA | PHX | True | True | True | False | False |
| 30270-5612 | NA | PHX | True | True | False | False | False |
| 30270-5611 | NA | PHX | True | True | False | False | False |
| 30270-5593 | NA | SFO | True | False | False | False | False |
| 30270-5592 | NA | SFO | True | True | True | False | False |
| 30270-5591 | NA | PHX | True | True | True | False | False |
| 30270-5588 | NA | PHX | True | True | False | False | False |
| 30270-5456 | NA | SFO | True | True | True | False | False |
| 30270-5319 | NA | PHX | True | True | False | False | False |
| 30270-5318 | NA | SFO | True | True | False | False | False |
| 30270-5208 | NA | SFO | True | True | False | False | False |
| 30270-5114 | NA | SFO | True | True | False | False | False |
| 30270-5085 | NA | SFO | True | True | True | False | False |
| 30270-5083 | NA | SFO | True | True | True | False | False |
| 30270-5081 | NA | SFO | True | True | False | False | False |
| 30270-4882 | NA | PHX | True | True | True | False | False |
| 30270-4880 | 19 | PHX | True | True | False | False | False |
| 30270-4768 | 20 | PHX | True | True | True | False | False |
| 30270-4484 | 16 | PHX | True | True | False | True | False |
| 30270-4363 | 17 | PHX | True | True | False | False | False |
| 30270-3842 | 14 | SFO | True | True | True | False | False |
| 30270-3838 | 13 | PHX | True | True | False | False | False |

**Continuation of Event List**

| SGO Report ID | Waymo 1M Mile RO Event # (Victor et al., 2023) | Location | NHTSA SGO-Reported | NHTSA SGO In-Transport | NHTSA SGO In-Transport Exclude Low DV | NHTSA SGO Police-Reported | NHTSA SGO Any Injury |
|---|---|---|---|---|---|---|---|
| 30270-1730 | 6 | PHX | True | False | False | False | False |
| 30270-1583 | 7 | PHX | True | True | True | True | False |
| 30270-1501 | 5 | PHX | True | True | True | False | False |
| NA | 4 | PHX | True | True | True | False | False |
| NA | 1 | PHX | True | True | True | True | False |

As stated in the Methods section (section 2), the "NHTSA SGO In-Transport Exclude Low delta-V (DV)" category was derived by applying a impulse-momentum collision model for vehicle-to-vehicle crashes. Each of the 7 ADS crashes with a fixed or non-fixed object was examined individually to estimate a delta-V. All but 2 of the 7 vehicle-to-object crashes were excluded from the low delta-V category. Three (3) crashes resulted in underbody damage when the Waymo vehicle "bottomed out" entering a parking lot driveway (30270-5612, 30270-5611) or tire damage after driving through a pothole (30270-5114) which resulted in less than the 1.0 mph threshold. Two (2) crashes involved non-fixed objects with low mass (<100 kg): a cardboard box (30270-5081) and a swinging parking lot gate that was not fixed (30270-4363).

Of the two vehicle-to-object crashes included, SGO report 30270-6548 involved a Waymo ADS vehicle that was driving in a construction zone and "entered a lane undergoing construction ..., encountered a section of roadway that had been removed, and the front driver's side wheel dropped off the paved roadway." After reviewing the on-board data from this crash event, the front wheel dropping likely caused a delta-V of 1 to 3 mph. SGO report 30270-6561 involved a Waymo ADS vehicle "exited a parking lot..., when the passenger's side sensors and side mirror made contact with an automatic gate that was in the process of closing." Based on review of the sensor data, the contact with the closing gate caused damage to a sensor housing and side view mirror of the vehicle, which are unlikely to result in a delta-V above 1 mph. Because the event in report 30270-6561 was police-reported, we decided to not exclude this event from the low delta-V category.