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Rise of the machines: crash experiences of highly automated vehicles and human drivers

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Contents

ABSTRACT

Introduction: As highly automated (SAE Level 4 [L4]) vehicles accrue more mileage and operate in more areas, it is important to understand how their crash involvement rates compare with human drivers. Doing so is challenging, largely because of differences in crash-reporting requirements and practices.

Method: Data on L4 vehicles' crashes were obtained from federally required reports on crashes involving automation. Human drivers' crash involvements were obtained from state databases of police-reported crashes. Regional data on vehicle miles traveled (VMT) were obtained from the Federal Highway Administration and from Waymo. Incident narratives about driverless vehicle crash involvements were manually coded to determine whether a reasonable person would have reported such an incident to police and the crash type and circumstances. Rates of police-reportable Waymo L4 crash involvements and human driver police-reported crash involvements per million VMT were computed and compared.

Results: Overall, 22% of L4 crash involvements were deemed police-reportable or maybe police-reportable, and two thirds of these occurred in driverless operation. L4 vehicles were unlikely to be the striking vehicle or primary contributor to crashes. Waymo L4 vehicles in driverless operation had police-reportable crash involvement rates 68% lower than human drivers in the same areas and years. Waymo's rate of rear-ending another vehicle was 91% lower; its vehicles' rate of being rear-ended was 40% lower. These results apply only to the L4 vehicles in driverless operation that were studied.

Conclusions: The results provide further evidence that Waymo's current L4 vehicles have lower crash involvement rates than human drivers. The method of coding narratives is unsustainable as these deployments and the number of incidents continue to grow.

Practical application: This study identifies ways in which national crash and VMT data collection for L4 vehicles can be improved for more timely and accurate safety evaluations.

Keywords: SAE Level 4, automated driving system, autonomous vehicle, driving automation, self-driving, motor vehicle crashes, highway safety

1. INTRODUCTION

The highest level of driving automation deployed today corresponds to a Level 4 (L4) on the scale outlined in SAE International’s J3016 standard (SAE International, 2021). In this level of automation, the vehicle is entirely responsible for the driving task without the required presence of a human driver within a specified set of conditions (e.g., location, weather). While L4 systems may be supervised by a human driver during development and testing, their ability to operate without one distinguishes them from lower levels of automation (L1–L3). L4 vehicles, particularly those developed and operated by Waymo (formerly the Google self-driving car project), have expanded rapidly over recent years across more cities and more parts of those cities and have logged an increasing number of miles each year. For example, Waymo began its publicly accessible robotaxi service in Phoenix in 2020, adding San Francisco in 2022 and Los Angeles in 2023, and seeks to expand to several more cities (Waymo LLC, n. d.-a). Waymo’s vehicle miles traveled (VMT) without a human driver also grew rapidly in these locations—from 0.074 million miles in Phoenix in 2020 to 20.9 million in 2024, from 0.070 million miles in San Francisco in 2022 to 13.5 million in 2024, and from 0.140 million in Los Angeles in 2023 to 5.03 million in 2024, according to the company’s own reports (Kusano et al., 2025). Other companies operating highly automated vehicles do not release VMT figures or release only very limited ones and there is currently no national requirement to report VMT.

These deployments and testing on public roads have not been without incident, and such incidents frequently gain substantial public attention. Recently, the National Transportation Safety Board (NTSB, 2026) opened an investigation into a crash in which a Waymo L4 vehicle struck a 9-year-old child in a school zone, resulting in minor injuries. Two infamous crashes were sufficient to reduce public confidence and shut down L4 programs: An Uber L4 development vehicle struck and killed a pedestrian in 2018 (NTSB, 2019) and a Cruise L4 vehicle dragged and likely further injured a pedestrian thrown into its path by an impact with another vehicle (National Highway Traffic Safety Administration [NHTSA], 2024). Although these high-profile events may not be representative of the broader crash experience of L4 vehicles, they play a role in the heightened public concern around the safety of L4 vehicles on our roadways.

Public evaluations of L4 safety rely on the availability of appropriate data. Beginning in 2014, California required companies testing L4 vehicles on public roads to submit Form OL316 for crash involvements that result in fatality, injury, or property damage of any amount. Consequently, the reports include many extremely minor incidents that would not meet the typical $1,000 threshold for reporting crashes to police that applies to human drivers. Since 2021, NHTSA has required companies operating vehicles with any level of automation above L1 on public roads to report crash involvements resulting or possibly resulting in fatality, injury, or property damage under the agency's Standing General Order (SGO) (NHTSA, n. d.). Although NHTSA was primarily concerned with defect identification and recalls, the SGO and the California data enable estimates of L4 crash rates when combined with VMT data.

However, comparing L4 crash rates with those of human drivers is challenging for many reasons, perhaps the greatest of which is differences in crash reporting. Initially, the SGO required reporting of incidents involving any physical contact (similarly to California's Form OL316). However, the third-amended SGO, effective June 16, 2025, set thresholds that were closer to those used for police-reported crashes involving human drivers (NHTSA, 2025). The SGO data reported prior to this change included many incidents that clearly do not meet police-reporting property damage thresholds, are not true crashes (e.g., turning left into a parking lot and scraping the undercarriage, SGO report_id 30270-4274), occurred on private property, or occurred when the L4 vehicle was being driven manually. Compounding the differences in reporting thresholds and requirements is the well-known issue that drivers fail to report many crashes. For instance, Blincoe et al. (2023) found that over half of crashes in the United States during 2019 were not reported to police. Perhaps some of these did not meet the property damage threshold, but for crashes involving injury, about one third were not reported. This clearly illustrates that actual reporting practices differ from the legal requirements in many states. Finding ways to reconcile these crash reporting differences was a key recommendation of the RAVE (Retrospective Automated

Vehicle Evaluation) Checklist (Scanlon et al., 2025), a detailed list of challenges and ways to overcome them when conducting or evaluating studies comparing the crash rates of L4 vehicles and human drivers.

Several methods have been introduced in the literature to address the dilemma posed by human and L4 crash-reporting differences. One approach involves adding estimated numbers of crashes that human drivers did not report to police to the police-reported crash counts to produce an estimate of total crash population (e.g., Kusano et al., 2024; 2025; Schoettle & Sivak, 2015). While reasonable, this approach assumes that human drivers' self-reported crash involvements that were not reported to police are similar to the minor L4 crash involvements that were reported under the SGO or under California requirements. Another approach is to use inclusion criteria to focus on crashes in which underreporting is likely a lesser issue, like those involving serious or fatal injury or airbag deployments (Kusano et al., 2024; 2025). These factors are straightforward to identify in both SGO and police-reported data, but this greatly reduces the crash sample size of both L4 vehicles and human drivers. Another approach is to read L4 crash incident narratives and make a determination of whether the crash met police-reporting requirements (Teoh & Kidd, 2017). Of course, another approach is to use a different human driver data source altogether, such as naturalistic driving studies (Blanco et al., 2016; Teoh & Kidd, 2017) or insurance claims (Di Lillo et al., 2024), but these data have their own weaknesses, including limited availability of the data or being restricted to a given time period and location. In contrast, police-reported data from across the United States are broadly available to researchers and governments.

While Teoh and Kidd (2017) coded narratives of L4 crash involvements in terms of whether the crashes likely met the police-reporting threshold, they acknowledged that this would not address the underreporting issue. However, it is possible to address both the reporting threshold and underreporting simultaneously by coding the narratives differently—specifically, by providing an "in-our-best-judgement" answer to the question "Would a reasonable person have reported this incident to police, absent expensive automation sensors and prominent names printed on the sides of vehicles?" Coding narratives to answer this question is necessarily subjective, but it provides another way of addressing the challenge of crash-reporting differences.

As L4 VMT continue to rise and cover more locations, L4 crash involvements will inevitably rise too. It is important that researchers, policymakers, and other stakeholders have appropriate data systems to monitor safety in a straightforward and timely manner. The purpose of the current study is to adapt the methods used by Teoh and Kidd (2017) to address both crash-reporting thresholds and underreporting, evaluate the relative rates and types of crashes for L4 vehicles that report VMT (i.e., Waymo) versus human drivers, and use this experience to identify ways to improve current data systems.

2. METHOD

Data on L4 vehicles' crash involvements were obtained from NHTSA's SGO website (NHTSA, n. d.). The SGO requires companies operating L4 vehicles to submit reports of crash involvements in which the automation was engaged within 30 seconds of the crash. The first two versions of the SGO required reporting of crashes involving fatality, medical transport, tow-away, airbag deployment, or a vulnerable road user (VRU). This type of information is referred to as Request 1. Request 2 expanded data collection to incidents involving minor or alleged property damage, any physical impact with the L4 vehicle, any incident to which the L4 vehicle contributed or allegedly contributed. The SGO data contain some coded data elements as well as a narrative of the crash events, but whether a given crash incident was reported under Request 1 or Request 2 (both of which include incidents below the threshold for police crash reporting) is only mentioned in the narrative, if at all. This study used SGO data from July 2021 to December 2024.

SGO data were cleaned prior to analysis to remove redundant records, reducing 1,692 SGO records to 977 unique incidents. Reporting entities often submitted multiple reports or updates for a single crash. Moreover, multiple entities may have been required to submit a report for the same crash. For example, General Motors, which owned Cruise, submitted duplicative reports for each Cruise incident as both parties are named in the SGO. Similarly, the contractor handling Waymo's test drivers, Transdev, submitted duplicative reports for Waymo crash incidents in supervised driving operations. It is possible the current study did not always select the most ideal record for each crash incident.

Based on the information available in the database, the authors coded narratives based on the following characteristics:

- whether L4 automation was in operation immediately before impact
- whether the crash occurred on a public road
- crash type
- whether the L4 vehicle was the primary contributor to the crash
- whether the crash incident was severe enough that a reasonable person would have reported it to police (referred to as police-reportability).

Basing the police-reportability determination on a simple estimate of crash damage cost or towing would not produce a fair comparison with human-driven vehicles because L4 vehicles often use expensive sensors in exposed areas that could be damaged by very minor impacts and could render the vehicle inoperable. Instead, estimating police-reportability was based on the nature of the impact or impacts and property damage, the possible reasons a vehicle was towed, the types of reported injury (e.g., complaint of pain but leaving the scene was judged as not likely to have resulted in a police report), and other factors. If airbag deployment was noted in the SGO data, then the crash was considered police-reportable due to the higher impact speed and the airbag replacement cost, independent of other damage or injury. There were no fatal crash involvements reported in the SGO data during the study period. We assumed that none existed (i.e., unreported) because such a severe crash of an L4 vehicles would have garnered a lot of media attention.

Crashes in which a human supervisor disengaged the automation to perform an imminent avoidance maneuver were counted as L4 in operation. Incidents in which the L4 automation was not engaged in the time leading up to the crash, did not occur on a public road, or were determined not to be crashes accounted for about a quarter of the SGO sample and were excluded. Involvement of pedestrians, bicyclists, users of micromobility devices, and motorcyclists were identified from the narrative. Crash involvements were coded as "involved pedestrian" only if a pedestrian was contacted in the crash. (If, for example, a vehicle braked to yield to a pedestrian and was subsequently rear-ended, that would not be coded "involved pedestrian.) The same principle was followed for the other road user categories: The involvement of bicyclists, micromobility users and motorcyclists took precedence over other crash types, largely to align with the police-reported data; the same involved_X variables were created analogously in the analysis of the police-reported crash data to improve alignment. Crashes involving vulnerable road users are relatively rare, so it is important to identify them reliably, and doing so would not substantially affect counts of other types of crashes. Vulnerable road user involvement (in any way) is part of the SGO reporting requirements, so the SGO data are more likely to include extremely minor VRU events than police-reported data. The final coding for each case was based on agreement of two of the three authors. Remaining cases with disagreement were resolved through discussion among all three authors.

Although the SGO requires crash reporting for L4 vehicles, there is no national reporting requirement for L4 VMT. Consequently, comparisons between L4 vehicles and human drivers in the current study were restricted to Waymo, which voluntarily publishes VMT data. Table 2 in Kusano et al. (2025) contains VMT figures for Waymo L4 vehicles disaggregated by location and year covering the current study period. Waymo's VMT has increased dramatically from 2023 to 2024, and increased even more dramatically through December 2025 (Waymo LLC, n. d.-b). Waymo only reports VMT for their "rider only" configuration, meaning that there is no human driver seated in the driver's seat. In many cases, however, the vehicles were completely unoccupied (i.e., no rider), so the current paper uses the term "driverless operation" to refer to absence of a human driver in the vehicle. This is defined as SGO variable driver_operator_type values of "none" or "remote (commercial/test) individuals." The latter value does not distinguish between remote operation of vehicle controls and remote assistance.

Police-reported crash data on human driver crash involvements were obtained from California, Arizona, and Texas, where Waymo driverless operation occurred during the study period. In each state's data, the urbanized area was identified using latitude/longitude and a shape file obtained from U.S. Census Bureau. Geocoordinates were frequently missing in California's police-reported crash data, so city and region names were matched with descriptive maps of the relevant urbanized area defined in the shape file as accurately as possible. Data on driver involvements in police-reported crashes were extracted from locations and years aligning with Waymo's self-reported VMT. Since driverless Waymo vehicles did not operate on limited-access roads during the study period (Kusano et al., 2025), interstates and freeways were excluded from the current study's police-reported crash data using the road type variable where available. When road type was not coded, road names were categorized in relevant urbanized areas as being likely limited-access (e.g., road names beginning with "I-" or "SR-" based on examining Google Maps satellite view). No restriction was made on vehicle type or time of day, as the human drivers' VMT data could not be disaggregated by these without making certain assumptions. Police-reported crashes typically exclude those occurring on private property like parking lots, garages or driveways, so any such crashes identified in the SGO were excluded from the analyses. While the SGO data begin in July 2021, the full year of 2021 was used for police-reported data because monthly human-driver VMT data by urbanized area were not available. Sensitivity analyses showed that including or excluding 2021 altogether did not change the overall results or conclusions. For this reason, the year was kept in the analysis despite the data alignment discrepancy.

For human drivers, VMT data were obtained by urbanized areas from the Federal Highway Administration's Highway Statistics Series (Federal Highway Administration, 2026) Table HM-71 for each year. These disaggregate total VMT by roadway function class. VMT on interstates and freeways were excluded, similarly to the police-reported crash data. The Highway Statistics Series VMT data by urbanized area and roadway function class were not further disaggregated by time of day or vehicle type, so no restriction was made on these factors. All Waymo vehicles in driverless operation were passenger vehicles, and passenger vehicles comprise over 90% of human drivers' VMT in urban areas (Federal Highway Administration, 2026, Table VM-1 for 2021–24), so no adjustment was made.

3. RESULTS

Exclusions from the SGO sample, aside from data cleaning, are outlined in Table 1. Based on the narratives, similar numbers of incidents were excluded from the analysis because they occurred somewhere other than a public road (e.g., parking garage, hotel driveway), involved the L4 vehicle being driven manually by a human (longer than as an avoidance maneuver), or were not considered a crash (e.g., running over small road debris, being struck by a parking gate arm). More than one of these could have been true and, together, they accounted for 24.5% of the total sample. Two narratives were incomplete to the point that a police-reportability determination could not be made, leaving a final sample size of 736.

Table 1

Exclusions for L4 vehicles' SGO-reported crash involvements, 2021–2024

	N	%
Unique SGO crash incidents	977	100.0
Not on public road [a]	88	9.0
Not a crash [a]	76	7.8
L4 not engaged [a]	107	11.0
Any of the above	239	24.5
Missing narrative	2	0.2
Final study sample	736	75.3

[a] These characteristics were coded from SGO narratives.

Overall, 22% of L4 crash involvements in the SGO were estimated to be possibly police-reportable (Table 2). We use the term "possibly police-reportable" to include those that we consider police-reportable with a high degree of certainty and those that we consider maybe police reportable. The proportion of crash involvements that were possibly police-reportable was higher in Phoenix (33%) than in San Francisco or Austin (19%) and lowest in Los Angeles (13%). Police-reportability (including maybe) was higher among Cruise vehicles (35%) than others (18%–19%). Vehicles coded as having a remote operator or assistant also had higher police-reportability (34%–37% vs. 17%–19%). The two observed associations are related because all L4 crash involvements coded as driver_operator_type = 'none' were Waymo and all coded as remote operator/assistant were Cruise.

Eighteen percent of SGO-reported L4 crash involvements on roads with speed limits of 25 mph or less were judged to be possibly police-reportable. On roads with 30–45 mph speed limits, that number was 29%, while on roads with speed limits higher than 45 mph, it was 44%. A similar trend was observed with the L4 vehicles' pre-impact speeds reported in the SGO data, with 14% of L4 crash involvements possibly police-reportable when the vehicle was stopped, 24%–26% when the L4 was traveling at 1–10 mph, 43% when traveling at 11–44 mph, and 55% when traveling at 45 mph or greater.

Police-reportability (including maybe) was highest for head-on and T-bone crashes (83% and 72%, respectively) and lowest for crashes involving pedestrians (15%), sideswipe opposite direction (15%), sideswipe same direction (11%), and backing (7%). Police-reportability was higher when the crash involved three or more vehicles, the L4 vehicle was the striking vehicle, and when the L4 vehicle could have been the primary contributing vehicle in the crash. A monotonically increasing relationship was observed between the proportion of L4 crash involvements that were police-reportable (or maybe) and the highest injury severity reported in the SGO. No fatal crash involvements of L4 vehicles were reported during the study period.

As a check, police-reportability was compared with information in the SGO data about police involvement (e.g., a police agency was investigating, some data came from a police report, or the source of the incident report was the police). For crash involvements coded as not police-reportable, 16% had police involvement noted in the SGO. For maybe police-reportable, it was 42%, and for crash involvement deemed police-reportable, it was 68%. This reflects consistency in coding police-reportability. It also suggests that the true level of reporting to police for L4 crashes may be even lower than our estimates of police reportability, and thus our method produced conservative results.

Table 2

L4 vehicles' SGO-reported crash involvements by police-reportability determination, 2021–2024

	Total	Police-reportable			% Yes/maybe
		No	Maybe	Yes	
Total	736	577	79	80	21.6
Location					
San Francisco	442	360	41	41	18.6
Phoenix	136	91	21	24	33.1
Los Angeles	54	47	5	2	13.0
Austin	37	30	2	5	18.9
Other	67	49	10	8	26.9
Year of crash					
2021	38	29	6	3	23.7
2022	112	90	9	13	19.6
2023	224	157	31	36	29.9
2024	362	301	33	28	16.9
Entity					
Waymo	488	399	50	39	18.2
Cruise	141	91	17	33	35.5
Zoox	53	43	5	5	18.9
Other	54	44	7	3	18.5
Type of operator					
None [a]	372	308	39	25	17.2
Remote operator/assistant [b]	112	71	14	27	36.6
Driver and remote	36	24	5	7	33.3
Driver in vehicle	211	170	21	20	19.4
Unknown	5	4	0	1	20.0
Speed limit					
<=25 mph	504	414	48	42	17.9
30–40 mph	177	125	24	28	29.4
45 mph	35	25	4	6	28.6
>45 mph	16	9	3	4	43.8
Unknown	4	4	0	0	0.0
Crash type					
Front-to-rear	262	209	24	29	20.2
Backing	94	87	2	5	7.4
Head-on	6	1	2	3	83.3
T-bone	36	10	8	18	72.2
Angle	52	33	13	6	36.5
Sideswipe—same direction	134	119	13	2	11.2
Sideswipe—opposite direction	33	28	3	2	15.2
Fixed object	9	7	1	1	22.2
Involved pedestrian	39	33	3	3	15.4
Involved bicyclist	20	15	4	1	25.0
Involved micromobility	10	6	3	1	40.0
Involved motorcyclist	14	9	2	3	35.7
Other/unknown	27	20	1	6	25.9

	Total	Police-reportable No	Maybe	Yes	% Yes/maybe
Number of vehicles					
1	61	49	8	4	19.7
2	651	524	66	61	19.5
3+	24	4	5	15	83.3
L4 vehicle was striking vehicle					
Yes	68	46	12	10	32.4
No	665	528	67	70	20.6
Unknown	3	3	0	0	0.0
L4 vehicle was primary contributor					
Yes	52	38	10	4	26.9
Maybe	25	16	5	4	36.0
No	657	521	64	72	20.7
Unknown	2	2	0	0	0.0
L4 vehicle's pre-crash speed					
Stopped	429	368	27	34	14.2
1–5 mph	122	93	14	15	23.8
6–10 mph	62	46	10	6	25.8
11–24 mph	82	47	17	18	42.7
25–44 mph	28	16	6	6	42.9
45+ mph	11	5	5	1	54.5
Unknown	2	2	0	0	0.0
Highest injury severity in crash					
None	641	537	59	45	16.2
Minor	56	31	14	11	44.6
Moderate	13	3	2	8	76.9
Serious	6	0	0	6	100.0
Fatal	0	0	0	0	n/a
Unknown (but nonfatal)	20	6	4	10	70.0

Note. Police-reportability, crash type, number of vehicles, and whether the L4 vehicle was the striking vehicle or the primary contributor were coded from SGO narratives.

[a] All were Waymo, which is known to use remote assistance (Waymo LLC, 2024).

[b] All were Cruise. The SGO database does not distinguish between remote operation and remote assistance.

Table A1 in the Appendix breaks down possibly police-reportable L4 crash involvements by whether the L4 vehicle was the striking vehicle or the likely primary contributor to the crash. The L4 vehicle was the striking vehicle in 22 crash involvements and was likely the primary contributor in 23 crashes—each of which corresponds to 14% of the 159 police-reportable (or maybe) L4 crash involvements. Among front-to-rear crashes, the L4 vehicle was the striking vehicle in about 6% and likely the primary contributor in 13% of these crashes. The L4 vehicle was the striking vehicle in only 3 of the 20 collisions involving VRUs, either because the VRU struck the L4 vehicle or the crash involved multiple vehicles and at least one VRU.

Table 3 shows the distribution of crash circumstances by entity among possibly police-reportable L4 crash involvements, restricted to those in driverless operation. Higher percentages do not necessarily indicate higher rates of crashes, as these could result from lower rates in other categories. Cruise crash involvements were far more likely to have been in San Francisco than Waymo (78% vs. 39%), to have been in 2023 (93% vs. 25%) (Cruise ceased driverless operations in October of that year [Levy, 2023]), and to have been on roads with speed limits of 25 mph or less (88% vs. 48%). These differences largely reflect differences in where and when Cruise and Waymo conducted driverless operation of their L4 vehicles. Cruise L4 crash involvements were less likely to have been front-to-rear crashes than Waymo's (17% vs. 30%), more likely to have been backing crashes (12% vs. 2%), more likely to have been T-bone (29% vs. 17%), and Cruise vehicles were slightly more likely to have been considered the likely primary contributor by the authors (22% vs. 16%). Overall, 41 of Cruise's 50 possibly police-reportable crash involvements, or 82%, were in driverless operation, compared with 64 out of Waymo's 89, or 72%.

Table 3

Crash circumstances distribution of L4 vehicles' SGO-reported crash involvements while in driverless operation deemed possibly police-reportable by company, 2021–2024

	Cruise		Waymo	
	N	%	*N*	%
Total	41	100.0	64	100.0
Location				
San Francisco	32	78.0	25	39.1
Phoenix	1	2.4	31	48.4
Los Angeles	0	0.0	6	9.4
Austin	5	12.2	2	3.1
Other	3	7.3	0	0.0
Year of crash				
2021	0	0.0	1	1.5
2022	3	7.3	0	0.0
2023	38	92.7	16	25.0
2024	0	0.0	47	73.4
Speed limit				
≤25 mph	36	87.8	31	48.4
30–40 mph	4	9.8	29	45.3
45 mph	1	2.4	4	6.2
>45 mph	0	0.0	0	0.0
Crash type [a]				
Front-to-rear	7	17.1	19	29.7
Backing	5	12.2	1	1.6
Head-on	1	2.4	3	4.7
T-bone	12	29.3	11	17.2
Angle	5	12.2	12	18.8
Sideswipe–same direction	2	4.9	6	9.4
Sideswipe–opposite direction	1	2.4	3	4.7
Fixed object	0	0.0	1	1.6
Involved pedestrian	2	4.9	1	1.6
Involved bicyclist	1	2.4	3	4.7
Involved motorcyclist	1	2.4	1	1.6
Other/unknown	4	9.8	3	4.7
Number of vehicles [a]				
1	3	7.3	4	6.2
2	36	87.8	51	79.7
3+	2	4.9	9	14.1
L4 was striking vehicle [a]				
Yes	6	14.6	11	17.2
No	35	85.4	53	82.8
L4 was primary contributor [a]				
Yes	6	14.6	5	7.8
Maybe	3	7.3	5	7.8
No	32	78.0	54	84.4

	Cruise		Waymo	
	N	%	*N*	%
L4 pre-crash speed				
Stopped	13	31.7	28	43.8
1–5 mph	11	26.8	6	9.4
6–10 mph	5	12.2	6	9.4
11–24 mph	12	29.3	16	25.0
25–44 mph	0	0.0	7	10.9
45+ mph	0	0.0	1	1.6
Highest injury severity in crash				
None	29	70.7	43	67.2
Minor	5	12.2	11	17.2
Moderate	3	7.3	1	1.6
Serious	2	4.9	2	3.1
Fatal	0	0.0	0	0.0
Unknown (but nonfatal)	2	4.9	7	10.9

Note. Possibly police reportable = police reportable + maybe police-reportable.

[a] Coded from SGO narratives.

Waymo's and human drivers' crash rates are compared in Table 4. Waymo vehicles traveled about 50 million miles in driverless operation during the study period, compared with about 222 billion miles by human drivers in the same period and locations (Table A2 in the Appendix). In every location except Austin, Waymo's crash rate per million VMT was lower than that of human drivers. However, the sample size for Austin was relatively small for both Waymo and human drivers. Across study years, Waymo's crash rate was 76% lower than that of human drivers in Phoenix, 35% lower in San Francisco, 71% lower in Los Angeles, and 3% higher in Austin.

Overall, when including police-reportable crashes, Waymo's crash rate was 68% lower than that of human drivers. These include crashes of all severities, but the pattern of results was similar for crashes involving injury. Arizona's property damage threshold for police-reported crashes was $300, compared with $1,000 in California and Texas.

Table 4

Crash involvements of Waymo L4 vehicles in driverless operation and human drivers per million vehicle miles traveled by crash severity, excluding interstates and freeways, 2021–2024

		Crash involvements per million VMT									
		Police-reported/possibly police-reportable crashes					Injury crashes				
		2021	2022	2023	2024	Total	2021	2022	2023	2024	Total
Phoenix	Waymo	3.05	0	1.53	0.96	1.1	0	0	0.61	0.14	0.25
	Human	4.42	4.21	4.56	5.55	4.63	1.24	1.21	1.32	1.61	1.33
San Francisco	Waymo		0	2.44	1.41	1.56		0	0.81	0.22	0.31
	Human		2.55	2.72	2.03	2.4		1.39	1.39	1.09	1.27
Los Angeles	Waymo			0	1.19	1.16			0	0.40	0.39
	Human			4.09	3.93	4.01			1.77	1.70	1.73
Austin	Waymo				3.6	3.6				0	0
	Human				3.48	3.48				1.42	1.42
Total	Waymo	3.05	0	1.75	1.18	1.28	0	0	0.66	0.20	0.28
	Human	4.42	3.81	4.09	4.02	4.06	1.24	1.25	1.59	1.57	1.49

Note. Waymo crashes were coded as possibly police-reportable based on SGO narratives.

Table 5 compares Waymo's possibly police-reportable and human police-reported crash involvements by crash type, number of vehicles, and injury severity. T-bone and angle crashes were coded similarly in the human police-reported crash data, so they were combined. Micromobility devices could not be identified in police-reported data, so crashes involving them were excluded. T-bone/angle and rear-end-struck (in two-vehicle crashes) were the most frequent type of crash involvements for Waymo vehicles, but these occurred at lower rates per mile traveled than for human drivers (61% lower and 40% lower, respectively). Waymo vehicles were involved in 85% fewer single-vehicle crashes per VMT than human drivers and were involved in 81% fewer injury/fatal crashes per VMT.

Table 5

Possibly police-reportable crash involvements of Waymo L4 vehicles in driverless operation and police-reported crash involvements of human drivers per million vehicle miles traveled by crash severity, excluding interstates and freeways, by crash type, 2021–2024

	Waymo		Human drivers		
	N	Rate per million VMT	*N*	Rate per million VMT	Rate ratio (95% confidence interval)
Total	64	1.28	900,509	4.06	0.32 (0.25, 0.40)
Crash type [a]					
Front-to-rear	19	0.38	282,754	1.27	0.30 (0.19, 0.47)
Front-to-rear-striking / two-vehicle crash	2	0.04	96,452	0.43	0.09 (0.02, 0.37)
Front-to-rear-struck / two-vehicle crash	13	0.26	96,452	0.43	0.60 (0.35, 1.03)
Backing	1	0.02	11,746	0.05	0.38 (0.05, 2.69)
Head-on	3	0.06	29,897	0.13	0.45 (0.14, 1.38)
T-bone / angle	23	0.46	261,607	1.18	0.39 (0.26, 0.59)
Sideswipe	9	0.18	171,746	0.77	0.23 (0.12, 0.45)
Fixed object	1	0.02	28,914	0.13	0.15 (0.02, 1.09)
Involved pedestrian	1	0.02	18,723	0.08	0.24 (0.03, 1.69)
Involved bicyclist	3	0.06	11,198	0.05	1.19 (0.38, 3.69)
Involved motorcyclist	1	0.02	11,234	0.05	0.40 (0.06, 2.81)
Single-vehicle rollover	0	0.00	2,435	0.01	0.00
Number of vehicles [a]					
1	4	0.08	119,707	0.54	0.15 (0.06, 0.40)
2	51	1.02	625,297	2.82	0.36 (0.28, 0.48)
3+	9	0.18	140,802	0.63	0.28 (0.15, 0.55)
Highest injury severity in crash					
None	43	0.86	522,731	2.35	0.37 (0.27, 0.49)
Nonfatal injury	14	0.28	330,541	1.49	0.19 (0.11, 0.32)
Fatal	0	0.00	4,895	0.02	0.00
Unknown [b]	7	0.14	43,358	0.20	0.72 (0.34, 1.50)

[a] Coded from SGO narratives for L4 vehicles; adapted from crash type codes in police-reported data.

[b] Not fatal in SGO; unlikely fatal in police-reported data.

The environments in which L4 vehicles are operated are more limited than where humans drive, which could explain some of the observed differences in crash rate, type, and severity. No Waymo crash involvements occurred on interstates or freeways, as these roads were not part of their operational design domain (ODD) at the time of this study. In contrast, 22% of human drivers' police-reported crash involvements occurred on interstates and freeways. These roads were excluded from the crash data and from VMT data. Table 6 shows the environmental circumstances of Waymo vehicles and human drivers involved in crashes in the current study, which excluded interstates and freeways. Nearly half of Waymo crash involvements occurred on roads with a 25 mph or lower speed limit, compared with only 8% of human drivers' crash involvements. The share of crash involvements that were in wet conditions was similar, and the share in dark conditions was higher for Waymo than for human drivers (41% vs. 27%). Data on VMT were not available to compute crash involvement rates disaggregated by these factors, so these percentages cannot be interpreted as relative likelihood of crashing.

Table 6

Waymo L4 vehicles' SGO-reported crash involvements while in driverless operation deemed possibly police-reportable and human-drivers' police-reported crash involvements, excluding interstates and freeways, by crash environment, 2021–2024

	Waymo		Human drivers	
	N	%	*N*	%
Total	64	100.0	901,525	100.0
Speed limit				
≤25	31	48.4	68,881	7.6
30–40	29	45.3	282,058	31.3
45	4	6.3	161,422	17.9
>45	0	0.0	176,240	19.5
Unknown	0	0.0	212,924	23.6
Surface condition				
Wet	2	3.1	44,602	4.9
Dry	62	96.9	851,038	94.4
Other/unknown	0	0.0	5,885	0.7
Lighting condition				
Dark	26	40.6	241,006	26.7
Light (including dawn/dusk)	38	59.4	640,710	71.1
Other/unknown	0	0.0	19,809	2.2

Unlike human-driven vehicles, L4 vehicles cover many miles without any occupant—driver or passenger. Based on the seat belt use variable in the SGO data, only about half of the Waymo vehicles involved in possibly police-reportable crashes during driverless operation had occupants (Table 7) and, therefore, there were fewer people at risk of injury.

Table 7

Waymo L4 vehicles' SGO-reported crash involvements while in driverless operation deemed possibly police-reportable by vehicle occupancy, 2021–2024

	N	%
Total	64	100.0
Vehicle occupancy		
Occupied, all belted	28	43.8
Occupied, at least one unbelted	5	7.8
No occupants in vehicle	31	48.4

4. DISCUSSION

These results provide further evidence that Waymo's deployments of L4 vehicles in driverless operation have lower crash rates than human drivers in comparable areas—68% lower in Waymo's current state of technology and current locations. This figure is consistent with earlier studies, which found that the Google self-driving car program's crash rates were 64% lower (Teoh & Kidd, 2017) and Waymo's were 55% lower (Kusano et al., 2024), and indicates that the company is maintaining a level of safety as its technology develops and its ODD is expanded. However, these results may not apply to future locations where Waymo deploys or to companies other than Waymo with L4 vehicles in driverless operation. For this reason, it is important to have appropriate data systems in place to enable the independent researchers and federal, state, and local governments to monitor the safety of new and existing L4 deployments relative to human drivers. These data systems should (a) contain the necessary information to compute L4 crash involvement rates that are comparable with those of human drivers and (b) be structured in such a way that results can be produced quickly.

The current study illustrates the need for a means of continually—and quickly—monitoring and evaluating the crash rates of L4 vehicles, especially as their deployments continue to increase. For instance, to specify an L4 crash involvement population comparable with human drivers, the authors removed redundant crash records in the SGO (a time-consuming process prone to errors), read crash narratives to extract important information for all reported incidents, and incorporated VMT data that only Waymo chose to release publicly. This process could be greatly improved by future updates to the reporting of L4 crash involvements. Some of this has already happened with the third-amended SGO (NHTSA, 2025), which added minimum property damage thresholds similar to those of police crash reports that, while not addressing humans' underreporting issue, could drastically reduce the number of records that must be examined. The current study estimated that 78% of the 736 L4 crash involvements are less severe than what a reasonable person would report to police and were excluded from further analyses.

While it would be ideal if NHTSA curated the SGO database to include only one record per crash, a faster alternative could be to include a variable identifying the primary (most complete and most up-to-date) record for each crash incident. Moreover, the same_incident_id variable in the SGO data should be at the crash level, not entity level, as multiple L4 vehicles can be involved in a crash. For example, two minor Cruise-to-Cruise sideswipe incidents occurred in April and May of 2023. The SGO already contains the same_vehicle_id variable to index individual vehicles.

The current study inferred police-reportability from the crash incident narratives, nearly all of which contained redacted information and some of which were redacted in their entirety. The SGO could provide more guidance regarding redactions and prohibit the complete redaction of a narrative. Current SGO narratives often indicate damage severity, but these descriptions often are inconsistent and vague (e.g., "sustained minor damage" can mean many things). Quantification of crash damage would be more consistent if there were more standardized coding of common types of damage such as a scratched bumper, deformed bumper, dented body panels, structural intrusion, inoperable headlight or taillight, broken glass, or damaged L4 sensor. The SGO database could incorporate crash type coding schemes similar or identical to the acc_type variable in NHTSA's Fatality Analysis Reporting System (FARS) and Crash Report Sampling System (CRSS) to further reduce reliance on crash incident narratives. Wiacek et al. (2026) coded SGO narratives to determine crash type using the acc_type FARS/CRSS coding scheme and, while that analysis did not code police-reportability, the crash type findings are consistent with those of the current study. That analysis included SGO data through June of 2025 and included nearly 50%

more crash incidents than the current study (before applying exclusion criteria) that went through December of 2024. This illustrates that while coding narratives is informative, relying on this procedure is an unsustainable approach as L4 vehicle deployments and resulting crash incidents continue to expand.

The SGO data should also indicate the mode of operation (L4, human driver, remote operator) immediately before impact, not just the within-30-seconds inclusion criteria. Moreover, the coding should distinguish between remote operation (directly manipulating vehicle control) versus remote assistance and define what these classifications entail carefully. The SGO records highest injury severity in the crash as none, minor, moderate, severe, and fatal, but these do not directly correspond with other coding schemes. It would be more appropriate to use the KABCO scale, which is used in FARS and CRSS, as well as other police-reported crash databases. While the SGO injury severity categories appear similar to KABCO codes, directly using KABCO coding and guidance in the SGO would improve its alignment with databases of police-reported crashes. Lastly, standardized VMT reporting should be required by month and location, as well as operating condition (driverless operation or supervised operation, whether remote or in-vehicle). These recommendations can be summarized as follows: (a) recognize the value in having a national L4 crash reporting system, (b) structure and manage this data system like other NHTSA crash databases, (c) and ensure the data are of such quality that a researcher can download the latest version and produce immediate results as is currently possible with other national crash databases (e.g., FARS, CRSS).

This study compared Waymo L4 vehicles with human drivers, which is an important baseline for comparison. Nevertheless, simply having lower crash rates than humans does not mean an L4 deployment is "safe." Humans' crash rates include impaired, distracted, and aggressive drivers. Including these in the human driver benchmark compares L4 vehicles with the way humans actually drive, on average, rather than comparing L4 with how well a human could drive. Both are legitimate research questions, and more detailed human benchmarks can be calculated, but there is value in using straightforward benchmarks like overall human driver police-reported crash involvements per VMT, especially in terms of timeliness and ease of use. A key difficulty, however, is that national crash data systems for human drivers either focus only on high-severity crashes (i.e., FARS) or cannot be restricted to individual urbanized areas or even individual states (i.e., CRSS). Thus, crash data must be collected from individual states and the inclusion criteria, coding, and data structure of these vary widely by state. Data and reporting practices can vary by jurisdiction within a state as well. Identifying urbanized areas within these crash databases to align with standardized VMT reporting (Federal Highway Administration, 2026) can be challenging or impossible. However, it is straightforward if crashes are geocoded with latitude and longitude so that the urbanized area can be coded using shape files. States and localities should ensure that these fields are recorded consistently.

Human-driven vehicles, by definition, have at least one occupant, but L4 vehicles can be operated without any occupants, resulting in fewer people exposed to possible injury. Indeed, 25 of the 31 (or 81%) Waymo vehicles without occupants in possibly police-reportable crashes reflected in Table 7 were in property-damage-only crashes, compared with 18 of 33 (55%) for occupied Waymo vehicles in driverless operation. This is one reason L4 vehicles have lower injury crash involvement rates than human drivers. While this is a statistical bias, having fewer people exposed to injury may be reasonably considered a benefit at a population level (Kusano et al., 2025). However, that population-level benefit can be reduced or reversed if robotaxi operation increases the volume of traffic on the road. In the future, it could be of interest to develop a fuller understanding of the relationship between miles traveled (VMT or person-level miles) for human-driven rideshare and robotaxi services. It also may be of interest to compute crash rates restricted to occupied vehicles, but the analog for human-driven vehicles is not straightforward and VMT disaggregated by passenger presence is not available for Waymo or for human drivers.

The current study has several limitations, perhaps chief of which is the subjective nature of inferring police-reportability (i.e., would a reasonable person report such an incident to police) based on narratives that often lack detail. Unlike an earlier analysis (Teoh & Kidd, 2017), the current study included a ‘maybe’ category for police-reportability, which was combined with "yes" in all analyses to be conservative (Scanlon et al., 2025). On the other hand, no assumptions were made about what humans did or didn't report to police. Ultimately, the results are consistent with those of studies using other methods (Blanco et al., 2016; Di Lillo et al., 2024; Flannagan et al., 2023; Kusano et al., 2024; 2025; Teoh & Kidd, 2017). The use of multiple approaches, each with their own set of assumptions, strengths, and weaknesses, results in stronger evidence. A major goal of this analysis was to identify ways to improve data systems, as opposed to inventing the strongest possible method of analysis.

Another limitation is that it is possible the current study did not always select the most ideal record for each crash incident from the duplicate ones in the SGO data. It is also possible that the human driver VMT estimates included L4 VMT. However, those numbers would be a tiny proportion of the total, so it is reasonable to think of these estimates as human drivers' VMT. Some of the VMT numbers (e.g., Phoenix and San Francisco) changed dramatically in 2024, possibly due to an underlying data error or change in state reporting. Even so, the numbers were used directly and basic sensitivity analyses showed that these did not substantively impact the analyses or conclusions.

Finally, it was not possible to directly align L4 vehicles' ODD with the VMT data reported by the Federal Highway Administration, and the ODDs were proper subsets of their urbanized areas. For example, Waymo's ODD in the San Francisco region during the study period is generally understood to be approximately within San Francisco County (i.e., the northern part of the peninsula), whereas the San Francisco urbanized area includes Oakland and other surrounding areas. While these do not align, the broader region still is a reasonable comparison for L4 crash involvement rates since humans drive throughout urbanized areas. Moreover, urbanized areas are straightforward to define. Refining human VMT data to the county level, while still excluding interstates and freeways, would involve making certain assumptions about how the various VMT data tables are related and would be time-consuming.

Overall, this study provides further evidence that Waymo's L4 vehicles in driverless operation have lower crash involvement rates than human drivers in reasonably similar deployment areas and they are involved in less egregious types of crashes (e.g., less likely to be the striking vehicle, especially in rear-end crashes). Moreover, it highlights opportunities to improve the only national data system on L4 crash involvements to enable L4 deployment monitoring and evaluation that is faster and more accurate.

5. PRACTICAL APPLICATIONS

This study identifies ways in which national crash and VMT data collection for L4 vehicles can be improved for more timely and accurate safety evaluations. This will help ensure that high levels of safety continue as these technologies develop and become more prevalent.

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7. REFERENCES

Blanco, M., Atwood, J., Russell, S., Trimble, T., McClafferty, J., & Perez, M. (2016). *Automated vehicle crash rate comparison using naturalistic data. Final report.* Virginia Tech Transportation Institute.

Blincoe, L., Miller, T. R., Wang, J. S., Swedler, D., Coughlin, T., Lawrence, B., Klauer, S., & Dingus, T. (2023). *The economic and societal impact of motor vehicle crashes, 2019 (revised)* National Highway Traffic Safety Administration https://crashstats.nhtsa.dot.gov/Api/Public/ViewPublication/813403.pdf

Di Lillo, L., Gode, T., Zhou, X., Scanlon, J. M., Chen, R., & Victor, T. (2024). *Do autonomous vehicles outperform latest-generation human-driven vehicles? A comparison to Waymo's auto liability insurance claims at 25.3m miles*. Waymo LLC.

Federal Highway Administration. (2026). *Highway statistics series*. Retrieved 02/13/2026, from https://www.fhwa.dot.gov/policyinformation/statistics.cfm

Flannagan, C. A., Leslie, A., Kiefer, R., Bogard, S., Freeman, C.-J., Huang, L., Walsh, R., & Joseph, D. (2023). *Establishing a crash rate benchmark using large-scale naturalistic human ridehail data* (Technical Report). University of Michigan Transportation Research Institute.

Kusano, K. D., Scanlon, J. M., Chen, Y. H., McMurry, T. L., Chen, R., Gode, T., & Victor, T. (2024). Comparison of Waymo rider-only crash data to human benchmarks at 7.1 million miles. *Traffic Injury Prevention*, *25*(sup1), s66-s77. https://doi.org/10.1080/15389588.2024.2380786

Kusano, K. D., Scanlon, J. M., Chen, Y. H., McMurry, T. L., Gode, T., & Victor, T. (2025). Comparison of Waymo rider-only crash rates by crash type to human benchmarks at 56.7 million miles. *Traffic Injury Prevention*, *26*(sup1), S8-S20. https://doi.org/10.1080/15389588.2025.2499887

Levy, D. (2023). *Cruise takes all its driverless vehicles off public roads following a pedestrian collision, expands safety investigation*. Tech Startups. Retrieved 04/13/2026, from https://techstartups.com/2023/11/16/cruise-takes-all-its-driverless-vehicles-off-public-roads-following-a-pedestrian-collision-expands-safety-investigation/

National Highway Traffic Safety Administration. (n. d.). *Standing General Order on crash reporting for incidents involving ADS and Level 2 ADAS*. Retrieved 02/04/2025, from https://www.nhtsa.gov/laws-regulations/standing-general-order-crash-reporting

National Highway Traffic Safety Administration. (2024). *NHTSA announces consent order with Cruise after company failed to fully report crash involving pedestrian*. Retrieved 04/07/2026, from https://www.nhtsa.gov/press-releases/consent-order-cruise-crash-reporting

National Highway Traffic Safety Administration. (2025). *Third amended Standing General Order 2021-01*. https://www.nhtsa.gov/sites/nhtsa.gov/files/2025-04/third-amended-SGO-2021-01_2025.pdf

National Transportation Safety Board. (2019). *Collision between vehicle controlled by developmental automated driving system and pedestrian, Tempe, Arizona March 18, 2018* (Highway Accident Report). https://www.ntsb.gov/investigations/accidentreports/reports/har1903.pdf

National Transportation Safety Board. (2026). *Automated driving system-equipped vehicle collision with student pedestrian*. Retrieved 04/072026, from https://www.ntsb.gov/investigations/Pages/HWY26FH008.aspx

SAE International. (2021). *Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles* (SAE Standard No. J3016_202104).

Scanlon, J. M., Teoh, E. R., Kidd, D. G., Kusano, K. D., Bärgman, J., Chi-Johnston, G., Di Lillo, L., Favarò, F. M., Flannagan, C. A., Liers, H., Lin, B., Lindman, M., McLaughlin, S., Perez, M. A., & Victor, T. (2025). RAVE checklist: Recommendations for overcoming challenges in retrospective safety studies of automated driving systems. *Traffic Injury Prevention*, *26*(5), 608-621. https://doi.org/10.1080/15389588.2024.2435620

Schoettle, B., & Sivak, M. (2015). *A preliminary analysis of real-world crashes involving self-driving vehicles*. University of Michigan Transportation Research Institute.

Teoh, E. R., & Kidd, D. G. (2017). Rage against the machine? Google's self-driving cars versus human drivers. *Journal of Safety Research*, *63*, 57-60. https://doi.org/10.1016/j.jsr.2017.08.008

Waymo LLC. (n. d.-a). *Our history*. Retrieved 04/07/2026, from https://waymo.com/about/#story

Waymo LLC. (n. d.-b). *Waymo safety impact*. Retrieved 04/07/2026, from https://waymo.com/safety/impact/

Waymo LLC. (2024). *Fleet response: Lending a helping hand to Waymo's autonomously driven vehicles*. Retrieved 04/10/2026, from https://waymo.com/blog/2024/05/fleet-response/

Wiacek, C. J., Espeland, S., Shull, E., Khan, M., Lee, G., & Valentin-Ruiz, J. (2026, January 22, 2026). *Characterization of ADS performance by pre-crash movement and crash type using the SGO data*. SAE Government/Industry Meeting, Washington, DC. https://www.nhtsa.gov/sites/nhtsa.gov/files/2026-03/16935%20SAE%20GIM%202026%20Wiacek%20Characterization%20of%20ADS%20Performance%20tag.pdf

8. APPENDIX

Table A1

L4 vehicles' SGO-reported crash involvements deemed possibly police-reportable by role, 2021–2024

		L4 was striking vehicle [a]		L4 was primary contributor (Yes/maybe) [a]	
	Total	*N*	%	*N*	%
Total	159	22	13.8	23	14.5
Crash type [a]					
Front-to-rear	53	3	5.7	7	13.2
Backing	7	1	14.3	0	0.0
Head-on	5	0	0.0	0	0.0
T-bone	26	4	15.4	3	11.5
Angle	19	6	31.6	3	15.8
Sideswipe—same direction	15	1	6.7	1	6.7
Sideswipe—opposite direction	5	1	20.0	0	0.0
Fixed object	2	2	100.0	2	100.0
Involved pedestrian	6	2	33.3	2	33.3
Involved bicyclist	5	1	20.0	3	60.0
Involved micromobility	4	0	0.0	1	25.0
Involved motorcyclist	5	0	0.0	0	0.0
Other/unknown	7	1	14.3	1	14.3
Number of vehicles [a]					
1	12	5	41.7	7	58.3
2	127	17	13.4	15	11.8
3+	20	0	0.0	1	5.0
Location					
San Francisco	82	13	15.9	14	17.1
Phoenix	45	7	15.6	5	11.1
Los Angeles	7	0	0.0	2	28.6
Austin	7	1	14.3	0	0.0
Other	18	1	5.6	2	11.1
Year of crash					
2021	9	2	22.2	2	22.2
2022	22	2	9.1	0	0.0
2023	67	10	14.9	14	20.9
2024	61	8	13.1	7	11.5
Entity					
Waymo	89	12	13.5	10	11.2
Cruise	50	8	16.0	10	20.0
Zoox	10	1	10.0	1	10.0
Other	10	1	10.0	2	20.0
Type of operator					
None [a]	64	11	17.2	10	15.6
Remote operator/assistant [b]	41	6	14.6	9	22.0
Driver and remote	12	3	25.0	1	8.3
Driver in vehicle	41	1	2.4	3	7.3
Unknown	1	1	100.0	0	0.0
Highest injury severity in crash					
None	104	15	14.4	12	11.5
Minor	25	3	12.0	7	28.0
Moderate	10	1	10.0	0	0.0
Serious	6	1	16.7	2	33.3
Fatal	0	0	--	0	--
Unknown (but nonfatal)	14	2	14.3	2	14.3

Note. Police-reportability, crash type, number of vehicles, and whether the L4 vehicle was the striking vehicle or the primary contributor were coded from SGO narratives.

[a] All were Waymo, which is known to use remote assistance (Waymo LLC, 2024).

[b] All were Cruise. The SGO database does not distinguish between remote operation and remote assistance.

Table A2

Waymo vehicles' SGO-reported crash involvements while in driverless operation deemed possibly police-reportable and human driver police-reported crash involvements per million vehicle miles traveled (VMT), excluding interstates and freeways, 2021–2024

		Police-reportable/reported crash involvements					VMT (millions)					Crash involvements per million VMT				
		2021	2022	2023	2024	Total	2021	2022	2023	2024	Total	2021	2022	2023	2024	Total
Phoenix [a]	Waymo	1	0	10	20	31	0.328	0.454	6.52	20.9	28.202	3.05	0.00	1.53	0.96	1.10
	Humans	110,846	109,205	111,012	110,130	441,193	25,100	25,910	24,342	19,840	95,192	4.42	4.21	4.56	5.55	4.63
San Francisco	Waymo		0	6	19	25		0.07	2.46	13.5	16.03		0.00	2.44	1.41	1.56
	Humans		20,939	22,203	21,254	64,396		8,221	8,153	10,477	26,851		2.55	2.72	2.03	2.40
Los Angeles	Waymo			0	6	6			0.14	5.03	5.17			0.00	1.19	1.16
	Humans			182,554	180,539	363,093			44,590	45,918	90,508			4.09	3.93	4.01
Austin	Waymo				2	2				0.555	0.555				3.60	3.60
	Humans				32,843	32,843				9,440	9,440				3.48	3.48
Total	Waymo	1	0	16	47	64	0.328	0.524	9.12	39.985	49.957	3.05	0.00	1.75	1.18	1.28
	Humans	110,846	130,144	315,257	344,262	901,525	25,100	34,131	77,085	85,675	221,992	4.42	3.81	4.09	4.02	4.06

Note. Police-reportability for Waymo crashes was coded from SGO narratives.

[a] Arizona's police-reporting property damage threshold was $300, compared with $1,000 in California and Texas. No adjustments were made, but a sensitivity analysis was conducted.

Table A3

Waymo vehicles' SGO-reported injury/fatal crash involvements while in driverless operation deemed possibly police-reportable and human driver police-reported injury/fatal crash involvements per million vehicle miles traveled, excluding interstates and freeways, 2021–2024

		Police-reportable/reported crash involvements					VMT (millions)					Crash involvements per million VMT				
		2021	2022	2023	2024	Total	2021	2022	2023	2024	Total	2021	2022	2023	2024	Total
Phoenix [a]	Waymo	0	0	4	3	7	0.328	0.454	6.52	20.9	28.202	0	0	0.61	0.14	0.25
	Humans	31,727	31,971	32,938	32,475	129,111	25,100	25,910	24,342	19,840	95,192	1.26	1.23	1.35	1.64	1.36
San Francisco	Waymo		0	2	3	5		0.07	2.46	13.5	16.03		0	0.81	0.22	0.31
	Humans		11,511	11,424	11,470	34,405		8,221	8,153	10,477	26,851		1.40	1.40	1.09	1.28
Los Angeles	Waymo			0	2	2			0.14	5.03	5.17			0	0.40	0.39
	Humans			79,716	78,645	158,361			44,590	45,918	90,508			1.79	1.71	1.75
Austin	Waymo				0	0				0.555	0.555				0	0
	Humans				13,559	13,559				9,440	9,440				1.44	1.44
Total	Waymo	0	0	6	8	14	0.328	0.524	9.12	39.985	49.957	0	0	0.66	0.20	0.28
	Humans	31,727	43,482	124,078	136,149	335,436	25,100	34,131	77,085	85,675	221,992	1.26	1.27	1.61	1.59	1.51

Note. There were no fatal crash involvements in the SGO data for the study period, so the Waymo crashes are all injury crashes. Police-reportability for Waymo crashes was coded from SGO narratives.

[a] Arizona's police-reporting property damage threshold was $300, compared with $1,000 in California and Texas. No adjustments were made, but a sensitivity analysis was conducted.