Quantifying the Benefits and Harms of Connected and Automated Vehicle Technologies to Public Health and Equity

July 2021

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16. Abstract

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Abstract

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Acknowledgements

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Introduction

Although interest in the safety evaluation of automated vehicles (AVs) has increased (Boggs et al., 2020; Cui et al., 2019; Furlan et al., 2020; Sohrabi et al., 2021), the implications of AVs for underserved communities have not been sufficiently explored. Low-income communities are located near high-capacity roadways and interstates and have poor roadway infrastructure, which contributes to increased crash risk (Huang et al., 2010; Noland and Laham, 2018; Barajas, 2018). The socioeconomic characteristics of households have also been shown to correlate with motor vehicle safety in that low-income communities experience higher crash frequency and severity (Girasek and Taylor, 2010). Higher rates of risky driving behavior and traffic violations were also found in minority communities, which could be due to the language barriers and inability to read the traffic signs (Elias et al., 2016; Romano et al., 2005). In addition to the existing traffic-related risks, underserved and low-income communities may be the last ones to adopt AVs due to the high cost of these vehicles, and therefore may not be able to experience the increased safety benefits (Raj et al., 2019; Cohen and Shirazi, 2017). Hence, there is increasing concern about whether or not AV implementation will help to offset the discrepancies in roadway safety or will continue to exacerbate them.

To explore the potential inequity in AV safety, we first need to have realistic estimations. According to the National Highway Traffic Safety Administration (NHTSA), human error contributes to 94% of motor vehicle crashes (NHTSA, 2018). Since AVs have the potential to eliminate human error, in the most optimistic view they would be expected to prevent 94% of motor vehicle crashes. However, AVs are subject to system failure and associated safety risks, including sensor malfunctions in detecting objects, misinterpretation of data, and poorly executed responses (Bila et al., 2017). Although AVs have been developed to improve driver behavior, their driving operation and safety effectiveness (SE) need to be measured by field operational tests (Wang et al., 2020). The interaction between AV and driver may cause safety issues, particularly when the automated driving system must disengage and manual driving must resume (Boggs et al., 2020).

Given the limited field operational tests of AVs and the uncertainties associated with their operation and safety challenges, AV safety evaluation is not trivial. Although analyzing the target crash population is a practical approach for evaluating AV safety, there are certain limitations in target crash population studies. First, quantified benefits are considered optimistic because they do not explicitly account for the technical safety challenges of AV technologies—namely, system failure risks, the risk associated with disengagement from the ADS to manual driving, and the SE of advanced driver assistance systems (ADAS) and ADSs. Second, the selection of target crash scenarios that can be prevented by a specific AV technology is mainly arbitrary, and the literature lacks a structured mechanism for identifying preventable crashes. Third, despite the fact that AV safety implications are inconsistent at different automation levels, no comparison between the extent of the impacts has been made in the literature. Fourth, while previous studies quantified AV safety performance in terms of the number of preventable crashes and cost of crashes, the potential of AVs to prevent road injuries has not been considered.

This objective of this study is twofold: (1) develop a methodology to evaluate the SE of AVs; and (2) assess the SE of AVs in communities with different socioeconomic and demographic characteristics. We developed a methodology based on the target crash population methodology, which addresses the aforementioned limitations in the existing studies. We then conducted an empirical study using crash data from the Dallas-Fort Worth (DFW), Texas, the fourth-largest metropolitan area in the United States (World Population Review, 2019). We finally stratified preventable crashes and their severities based on socioeconomic and demographic characteristics to assess the equity implications of AVs.

Method

Figure 1 depicts the framework developed in this study to evaluate AV safety implications.

1. Task 1: Identify AV functionalities.
2. Task 2: Characterize conventional vehicle crashes and define potentially preventable crash scenarios.
3. Task 3: Identify target crash scenarios that are potentially preventable by the AV technologies found in Task 1.
4. Task 4: Based on the literature, identify the safety challenges of AVs, including safety effectiveness, system failure risk, and disengagement risk.
5. Task 5: Estimate the number of preventable crashes by each technology by incorporating the findings of Task 4 and exploring the target crashes in a historical conventional vehicle crash database.

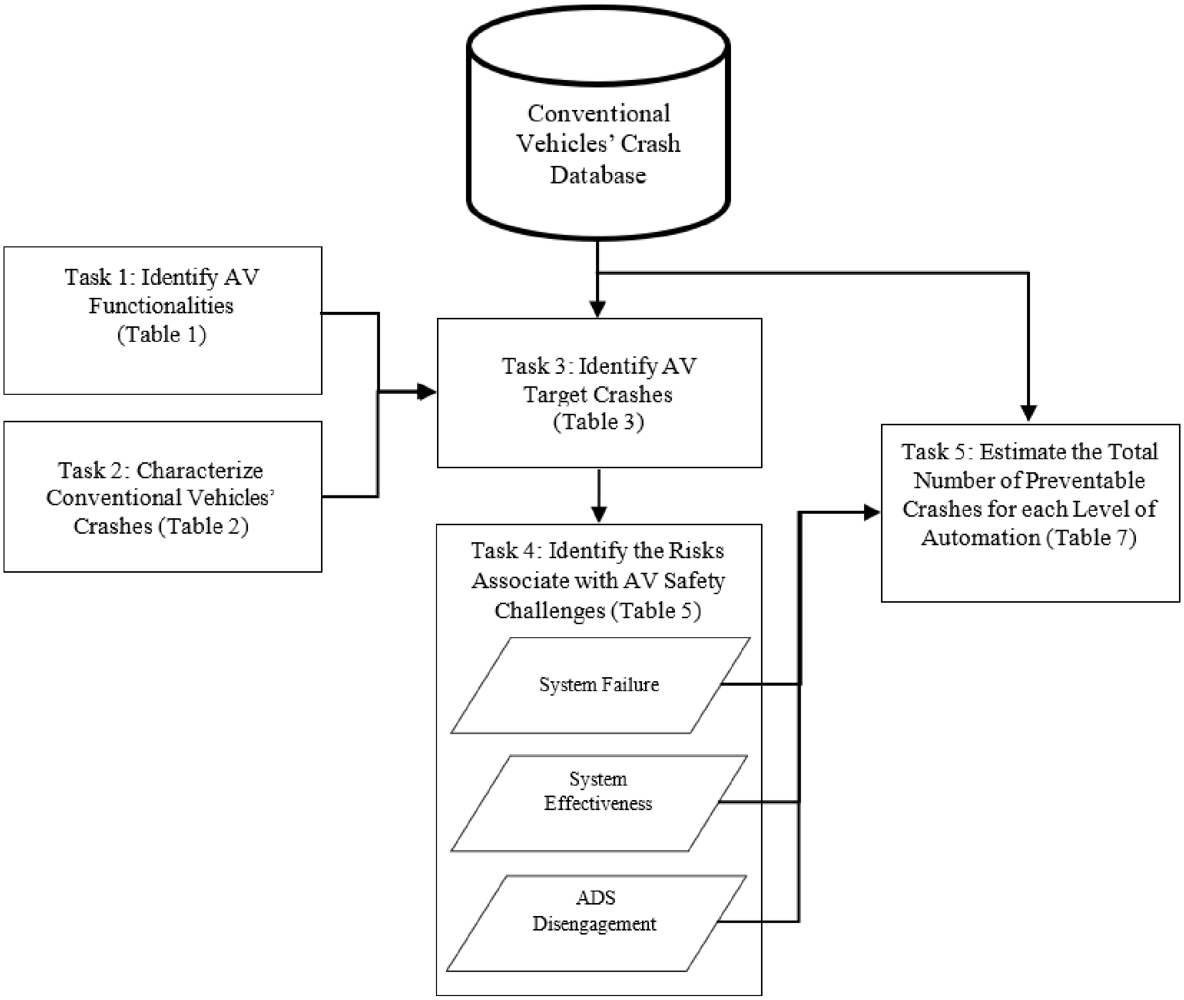


Figure 1. Flowchart. AV safety quantification framework.

Task 1: Identifying AV Functionality

Before identifying AV functionalities, we provide a brief overview of how the different levels of automation are defined in terms of the dynamic driving task (DDT), object and event detection and response (OEDR), driver responsibilities, and operational design domain (ODD). SAE defines six levels of automation (Society of Automotive Engineers [SAE], 2018). Level 0 represents no automation. At Level 1 and 2, most of the DDT is performed by the driver, and an ADAS occasionally helps with some of the driving tasks (SAE, 2018) and has the potential to correct some driver error. At Level 3, ADS performs OEDR and is responsible for most of the DDT (SAE, 2018). However, when the ADS is disengaged, a fallback-ready user is needed to intervene. Levels 4 and 5 are able to perform all of the DDT with no fallback-ready user, but differ in terms of ODD; Level 5 has an unlimited ODD. It is expected that Level 4 and 5 ADS will eliminate most driver errors; however, Level 4's impacts are limited to its ODD.

We identified AV functionalities at different levels of automation by investigating their capabilities in terms of performing the DDT, OEDR, and ODD. Table 1 summarizes AV technologies and their functionalities (SAE, 2018). First, we explored levels of automation and their functions. Then, based on this analysis, we identified the ADAS and ADS technologies by level of automation. Eight ADASs with the capability of performing longitudinal and lateral automated driving tasks, collision alert, collision mitigation, parking assistance, and driving aids are considered for Levels 1 and 2. For Levels 3, 4, and 5, the ADS performs the DDT, and crash avoidance capability is characterized based on the ADS functionalities. Based on the definitions, Level 5 has an unlimited ODD. Since there is no universal design for Level 3 and Level 4 ADS ODDs, we assume that they can only operate on well-mapped roads.

Table 1. AV Technologies and Functionality

Level of Automation	Functionality	ADS and ADAS
Level 0	Performs no driving task	NONE
Level 1	Performs either longitudinal or lateral vehicle motion control but does not complete OEDR.	Forward Collision Warning (FCW) Lane Departure Warning (LDW) Blind Spot Warning (BSW) Pedestrian Detection (PD) Automatic Emergency Braking (AEB) Electronic Stability Control (ESC) Adaptive Cruise Control (ACC) or Lane Keeping Assistance (LKA)
Level 2	Performs both longitudinal and lateral vehicle motion control but not complete OEDR.	Level 1 ADAS, including both ACC and LKA
Level 3	Performs the complete DDT, but not DDT fallback within a limited ODD.	Level 3 ADS
Level 4	Performs the entire DDT and is capable of responding to DDT fallback if needed, within a limited ODD.	Level 4 ADS
Level 5	Performs the entire DDT and is capable of responding to DDT fallback if needed, with unlimited ODD.	Level 5 ADS

Task 2: Investigating Crash Characteristics and Defining Crash Scenarios

In this task, we investigated conventional vehicle crashes and defined target crash scenarios using four criteria: contributing factors, manner of collision (MC), first harmful event (FHE), and crash location (CL) as depicted in Figure 2. NHTSA categorizes crash contributing factors into three broad groups: driver error (DE), environmental factors, and vehicle-related factors (NHTSA, 2018). In general, crashes can be attributed to one or more contributing factors.

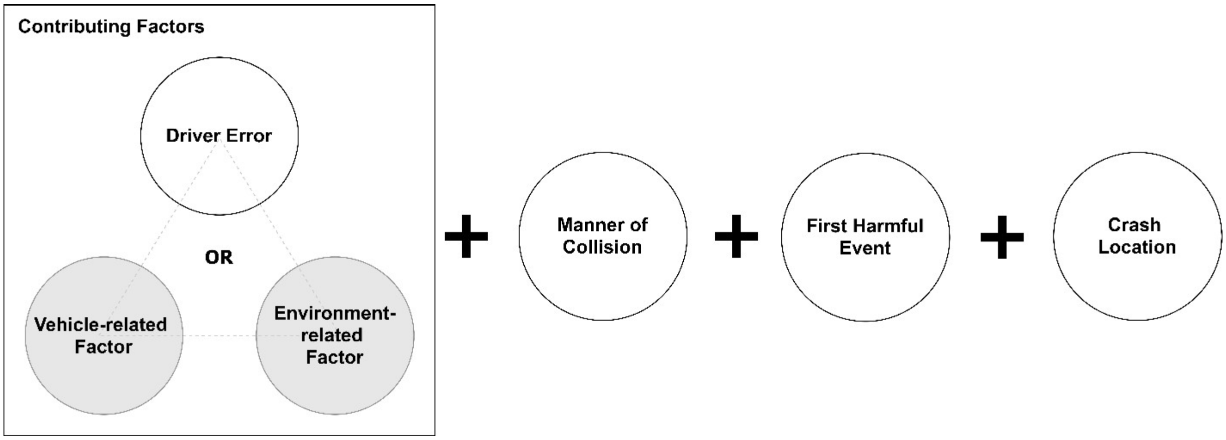


Figure 2. Diagram. Criteria for characterizing conventional vehicle crashes.

Per the objectives of this study, we explored the contributing factors for DE-related crashes, which can be divided into four types: recognition error, decision error, performance error, and non-performance error (NHTSA, 2018). We further analyzed driver errors using 11 subcategories. MC refers to the manner in which a crash occurred and is divided into six types of multiple-vehicle (MV) or single-vehicle (SV) crashes: angle (MV), rear-end (MV), backing (MV or SV), run-off-the-road (SV), sideswipe (MV), and head-on (MV). The FHE is the first event that leads to the crash and represents the road users that were involved in the crash and who were at-fault for the crash. This is divided into six types: pedestrian at-fault, cyclist at-fault, vehicle, animal, object, and pedestrian and cyclist. In this study, we did not account for crashes where the pedestrian or cyclist was at fault. Finally, ADAS and ADS crash avoidance capabilities are limited to certain locations. For example, ACC operates at high speeds and can prevent crashes on roads with higher speed limits. As discussed before, we assume Level 3 and 4 ADSs can only operate on well-mapped roads and hence that they would not be able to prevent crashes on local rural roads. To address the limitations of AV ODDs, we categorized crash locations into five groups to define crash scenarios: (1) intersections; (2) parking; (3) freeways, highways, and arterials; (4) urban collector and local roads; and (5) rural collector and local roads.

A crash scenario was then defined as a combination of DE, MC, FHE, and CL. Table 2 lists the critical crash scenario elements used in this study. There are 11 driver crash-contributing factors, 6 MCs, 5 FHE types, and 5 location types. Consequently, the crashes studied can be investigated by exploring a total number of 1,650 unique crash scenarios (Equation 1):

$$Driver\ Error\ (11) \times Manner\ of\ Collision\ (6) \times FHE\ (5) \times Crash\ Location\ (5) = 1{,}650 \quad (1)$$

Table 2. Critical Crash Scenario Elements

Crash Characteristics Criteria	Critical Descriptors
Driver Error (DE)	Recognition error: 1- Distraction and inattention (DE1) 2- Looked, did not see (DE2) Decision error: 3- Driving too fast for conditions and road rage (DE3) 4- False assumption of others' actions (DE4) 5- Misjudgment of gap and speed (DE5) 6- Traffic violation (DE6) 7- Unsafe maneuver and lane change (DE7) Performance error: 8- Poor directional and longitudinal control, and overcompensation (DE8) 9- Failure to drive between lanes (DE9) Non-performance error: 10- Drowsiness, taking medication, and illness (DE10) 11- Alcohol and drug impairment (DE11)
Environment-related Factors	1- Slick roads (ice, loose, etc.) 2- Glare 3- View obstructions 4- Adverse weather (fog, heavy rain, snow, etc.) 5- Sign/signals 6- Road design
Vehicle-related Factors	1- Steering, suspension, transmission, and engine-related 2- Defective lights 3- Tire and wheels 4- Brake related
Manner of Collision (MC)	1- Angle (MV*) (MC1) 2- Rear-end (MV) (MC2) 3- Backing (MV or SV**) (MC3) 4- Off the road (SV) (MC4) 5- Sideswipe crash (MV) (MC5) 6- Head-on (MV) (MC6)
First Harmful Event (FHE)	1- Pedestrian, with driver at fault (FHE1) 2- Cyclist, with driver at fault (FH2) 3- Vehicle (FHE3) 4- Animal (FHE4) 5- Object (FHE5) 6- Pedestrian and cyclist, with pedestrian and cyclist at fault (FHE6)
Crash Location (CL)	1- Intersections (CL1) 2- Parking (CL2) 3- Freeways, highways, and arterials (CL3) 4- Urban Collector and local roads (CL4) 5- Rural Collector and local roads (CL5)

* MV: Multi-vehicle
** SV: Single-vehicle

Task 3: Identify Target Crash Scenarios

Based on AV technologies at different levels of automation and their functionalities, we developed a list of target crash scenarios that can potentially be prevented by ADAS and ADS technology. For example, ACC is able to control acceleration and/or braking to maintain a prescribed distance between the following and leading vehicles. According to these functions, we expect that ACC can potentially prevent crashes caused by (1) recognition error due to distraction and inattention (DE1); (2) decision error attributed to the false assumption of other vehicles' actions as well as a misjudgment of the gap between the leading and following vehicles and consequently speed choice (DE2); and (3) performance error such as poor longitudinal control of the vehicle (DE3). These driver errors may result in rear-end collision (MC2) of a vehicle (FHE3) on a high-speed freeway, highway, or arterial (CL3). The combination of these crash characteristics leads to four crash scenarios that can be prevented by ACC:

1. Scenario 1: DE1 + MC2 + FHE3 + CL3
2. Scenario 2: DE4 + MC2 + FHE3 + CL3
3. Scenario 3: DE5 + MC2 + FHE3 + CL3
4. Scenario 4: DE8 + MC2 + FHE3 + CL3

Table 3 shows the target crash scenarios that each technology can prevent.

Table 3. Number of Target Crash Scenarios

System	Functions and Capabilities	DE	MC	FHE	CL	# of Target Crash Scenarios
ACC	Controls acceleration and/or braking to maintain a prescribed distance between it and a vehicle in front. May be able to come to a stop and continue.	DE1, DE4, DE5, DE8	MC2	FHE3	CL3	4
LKA	Controls steering to maintain the vehicle within the driving lane. May prevent the vehicle from departing lane or continually center vehicle.	DE8, DE9, DE10	MC1 to MC6	FHE2, FHE3	CL3, CL4	60
FCW	Detects impending collision while traveling forward and alerts driver.	DE1, DE4, DE5	MC1, MC2, MC6	FHE3, FHE4, FHE5	CL1, CL3, CL4	81
LDW	Monitors vehicle's position within driving lane and alerts driver as the vehicle approaches or crosses lane markers.	DE8, DE9, DE10	MC1, MC4, MC5, MC6	FHE2, FHE5	CL3, CL4	48
BSW	Detects vehicles to rear in adjacent lanes while driving and alerts the driver to their presence.	RE2, RE4	MC1, MC5	FHE3	CL3, CL4	8
PD	Detects pedestrians in front of vehicle and alerts driver to their presence.	DE1, DE2, DE6, DE8, DE10	MC4	FHE1, FHE6	CL1 to CL4	40

System	Functions and Capabilities	DE	MC	FHE	CL	# of Target Crash Scenarios
AEB	Detects potential collisions while traveling and automatically applies brakes to avoid or lessen the severity of impact.	DE1, DE4, RE10	MC1, MC2, MC3, MC6	FHE1 to FHE5	CL1 to CL4	320
ESC	Improves a vehicle's stability by detecting and reducing loss of traction.	DE5, DE8	MC4, MC5	FHE3, FHE5	CL3	8
L3 ADS	Performs the complete DDT, but not DDT fallback, within a limited ODD. Eliminates Level 2 crashes and crashes due to driver recognition error and performance error.	DE1 to DE9	MC1 to MC6	FHE1 to FHE5	CL2, CL3	720
L4 ADS	Performs the complete DDT, and DDT fallback, within a limited ODD.	DE1 to DE11	MC1 to MC6	FHE1 to FHE5	CL1 to CL4	1,320
L5 ADS	Performs the complete DDT, and DDT fallback, without ODD limitation.	DE1 to DE11	MC1 to MC6	FHE1 to FHE5	CL1 to CL5	1,650

Task 4: AV Safety Challenges

The three important safety concerns of AVs are (1) SE , (2) system failure risk; and (3) disengagement risk. In general, SE can be defined in terms of the number of AV-preventable crashes compared to conventional vehicles (Equation 2). Since driving simulator and traffic simulation studies use surrogate safety measures (SSMs) to evaluate AV safety impacts, in this study, the SE of AVs is estimated using SSMs. Equations 3 and 4 are examples of using two SSMs—time to collision (TTC) and traffic conflicts (TC)—to estimate the SE of ADASs and ADSs:

$$\boldsymbol{SE = 1 - \frac{AV crash\ rate}{Conventional\ vehicle\ crash\ rate}} \tag{2}$$

$$\boldsymbol{SE^{TTC} = 1 - \frac{AV\ time\ to\ collision<treshold}{Conventional\ vehicle\ time\ to\ collision<treshold}} \tag{3}$$

$$\boldsymbol{SE^{TC} = 1 - \frac{AV\ \ \ frequency\ of\ traffic\ conflicts}{Conventional\ vehicle\ frequency\ of\ traffic\ conflicts}} \tag{4}$$

Wang et al. (2020) synthesized the results of previous traffic simulations and field experiments that estimated the SE of AVs. Conducting a meta-analysis on 89 studies, the authors estimated the SE of seven ADASs in descending order: PD, LDW, FCW, ESC, BSW, AEB, ACC. Given the limited number of studies on the LKA impacts, we assumed that the effectiveness of LKA would be similar to that of the ACC. ADS SE was found to be different for intersections and road segments. We sourced the ADS effectiveness at intersections from Morando et al. (2018), which evaluated the safety impacts of AVs in terms of changes in the conflicts between vehicles after

AV implementation using traffic microsimulations. Using Equation 4, we then converted changes in the number of conflicts to the SE of AVs. The effectiveness of ADS in road segments was extracted from Kockelman et al. (2016), which used traffic microsimulations to evaluate AV safety impacts under various operational conditions and measured the safety impacts in terms of the number of conflicts between vehicles.

Another challenge with AV operation and safety is system failure, which can happen due to malfunctioning sensors, misinterpretation of data, and poorly executed responses that can jeopardize the reliability of AVs and cause serious safety concerns in an automated environment (Bila et al., 2017). The failure rate of each AV component was synthesized by Bhavsar et al. (2017). To this end, ADAS and ADS components were examined individually, and the failure rate was determined based on the evidence from the existing literature. Bhavsar et al. (2017) developed a hierarchical model to synthesize the AV failure rates associated with the vehicle. According to this study, the failure risks of the hardware system (sensor and integration platform) and software system are 4.2% and 1.0%, respectively.

The third safety concern of AVs is disengagement risk, which refers to an AV being involved in a crash as a result of the transition from automated driving mode to manual driving. For Levels 3 and 4, drivers need to take over control of the vehicle in case of technology failure or unsafe driving conditions. The disengagement from ADS to manual driving was studied using driving simulators and was shown to impose crash risks (Desmond et al., 1998; Happee et al., 2017). In Happee et al. (2017), the effects of automation in take-over scenarios were investigated in a high-end, moving-base driving simulator. Drivers encountered a blocked lane in highway driving, and their performance while executing evasive maneuvers in manual driving was compared to their performance in the automated driving environment with a disengagement to manual driving using TTC measures. Using Equation 3 and assuming a 4-second threshold for TTC (Sultan and McDonald, 2003), the disengagement risks were estimated to be 49%. We assumed a similar disengagement risk for both Level 3 and 4 automation due to the limitations in the literature on this topic. It is also assumed that AVs would disengage from the ADS before encountering a crash scenario, and so the driver is not able to respond to 49% of crash scenarios appropriately. Table 4 summarizes the AV safety challenges considered in this study.

Table 4. Safety Challenges of AVs

System	SE	Confidence Interval	Source
ACC	9.3%	[5.0, 0.14]	Wang et al., 2020
AEB	25.7%	[2.0, 31.0]	Wang et al., 2020
BSW	15.0%	[10.0, 20.0]	Wang et al., 2020
ESC	43.2%	[38.0, 48.0]	Wang et al., 2020
FCW	21.1%	[17.0, 25.0]	Wang et al., 2020
LDW	21.0%	[10.0, 33.0]	Wang et al., 2020
PD	38.9%	[36.0, 42.0]	Wang et al., 2020

System	SE	Confidence Interval	Source
LKA	9.3%	Not reported	Speculated, no source available
L3 ADS (Intersection)	64.0%	Not reported	Morando et al., 2018
L3 ADS (Highway	87.0%	Not reported	Kockelman et al., 2016
L4 ADS (Intersection)	64.0%	Not reported	Morando et al., 2018
L4 ADS (Highway)	87.0%	Not reported	Kockelman et al., 2016
L5 ADS (Intersection)	64.0%	Not reported	Morando et al., 2018
L5 ADS (Highway)	87.0%	Not reported	Kockelman et al., 2016

Task 5: Estimate Preventable Crashes

Incorporating the findings from Task 4 and exploring AV target crashes in the conventional vehicle crash database, the total number of preventable crashes can be estimated using Equation 5:

$$\boldsymbol{PC^t = TC^t \times SE^t \times (1 - FR) \times (1 - DR)} \tag{5}$$

where PC^t is the number of preventable crashes by technology t, TC^t is the number of target crashes by technology t, SE^t is the safety effectiveness of AV technologies, FR is the AV's software and hardware failure risk, and DR is the disengagement risk for Levels 3, 4, and 5.

Empirical Study

We designed an empirical analysis to examine the proposed AV safety quantification framework and to assess the equity implications of AVs. The proposed framework quantifies AV safety implications in terms of the number of preventable crashes. We further investigated the quantified preventable crashes to explore (1) the role of levels of automation, and the technologies behind them, in preventing different levels of crash severity; and (2) the relationship between preventable road fatalities and communities' socioeconomic and demographic characteristics to assess the equity implications of AVs.

Study Setting

The safety implications of AVs were quantified in the DFW metropolitan area for the year 2017. We assumed that the percentage of vehicles equipped with ADS was at a negligible level in 2017. Moreover, since a few changes were made to Crash Records Information System (CRIS) crash data collection methods in 2016, it is preferred to use crash data after this date. Hence, in this study, we use 2017 as the baseline year. We first defined five counterfactual scenarios for AV deployment, in which the existing vehicle fleets (including passenger cars, buses, and trucks) in the DFW area are replaced by five levels of automation. Using the proposed framework, we estimated the potentially preventable crashes for each scenario and compared them against the base scenario of no automation in the transportation system. The estimated numbers represent the potential safety implications of different levels of automation if the DFW transportation system were automated. We chose the DFW area as the case study since it is the fourth most populated metropolitan area in the United States, with more than 7.5 million residents in 2018 (US Census Bureau, 2019). The study area contains all road functional classes (both rural and urban roads), including interstate, freeway and highway, principal and minor arterials, major and minor collectors, and local roads.

Equity Assessment

AV safety implications were investigated based on the socioeconomic and demographic characteristics of communities, assuming 100% market penetration of AVs and no financial restrictions to adoption. This study considers median household income and household ethnicity as proxies for socioeconomic and demographic status. Moreover, we explored the communities' characteristics at the census tract level. Assuming that the vehicles' occupants lived in the same zip code as the vehicles' owners, we mapped the road fatalities to the zip codes where the vehicle owners lived, as opposed to the census tract where the crash happened. The estimated preventable fatalities can then be stratified based on median household income and household ethnicity at the census tract level.

This approach has certain limitations in that we cannot account for the crash location, which was one of the factors used for developing the preventable crash scenarios. However, since the scope of this project was to develop a framework for safety and equity assessment, we did not explore how a crash happening at certain location (e.g., intersection). This particular question will be explored in more detail in future study.

Datasets

Crash Characteristics

The crash data was sourced from the Texas Department of Transportation's (TxDOT) CRIS. The crash dataset includes the crash location, crash characteristics (Table 5), the vehicle owner's residential zip code, and the crash severity. We focused on crash records from 2017, given that only a limited number of vehicles were equipped with ADASs before the year 2018, which would be in line with our no-automation assumption for the base scenario. A total of 151,881 crashes were collected, of which 738 resulted in fatalities (0.5%), 34.7% resulted in injuries or possible injuries, and 64.8% resulted in no injury. The crashes were mostly MV crashes that included more than two vehicles. The rest of the crashes were distributed as follows: 15.2% fixed object, 1.7% vulnerable road user, and 0.5% wildlife. Table 5 provides a summary of the 2017 crash characteristics.

Table 5. Summary of DFW Crash Characteristics

	Fatal (#)	Incapacitating (#)	Non-Incapacitating Injury (#)	Possible Injury (#)	Non-injury (#)	# of Crashes
Distraction and inattention (DE1)	173	1439	6511	11696	74056	39053
Looked, did not see (DE2)	9	95	325	569	3292	1636
Driving too fast for conditions and road rage (DE3)	144	387	947	1057	6182	4659
False assumption of others' actions (DE4)	14	157	678	1137	6544	3902
Misjudgment of gap and speed (DE5)	31	185	1237	3222	30097	12443
Traffic violation (DE6)	207	1229	7093	14032	65382	29955
Unsafe maneuver and lane change (DE7)	94	529	3108	6720	66676	27899
Poor directional and longitudinal control, and overcompensation (DE8)	105	777	4377	10099	66881	28532
Failure to drive between lanes (DE9)	54	245	800	1215	7485	5337
Drowsiness, taking medication, and illness (DE10)	17	165	467	745	2394	2168
Alcohol and drug impairment (DE11)	57	227	613	647	4626	3187
Angle (MV*) (MC1)	196	1866	11305	24470	146361	62333
Rear-end (MV) (MC2)	262	2193	13373	34354	231692	84268
Backing (MV or SV**) (MC3)	9	34	150	184	5078	5253
Off the road (SV) (MC4)	507	2135	6814	7797	46357	45671
Sideswipe crash (MV) (MC5)	97	562	2932	6822	75560	30416
Head-on (MV) (MC6)	220	479	1180	1498	7466	3605
Pedestrian, with the driver at fault (FHE1)	141	292	653	446	2223	1516
Cyclist, with driver at fault (FH2)	7	77	277	204	877	628
Vehicle (FHE3)	878	6229	35506	80433	528265	209915
Animal (FHE4)	17	62	179	165	2463	1843
Object (FHE5)	288	1419	5045	6621	45,090	45109
Pedestrian and cyclist, with pedestrian and cyclist at fault (FHE6)	6	5	11	10	90	48
Intersections (CL1)	342	3383	19,514	42282	237524	101943
Parking (CL2)	2	18	143	374	7847	5042
Freeways, highways, and arterials (CL3)	861	3852	17733	36229	255266	106828
Urban collector and local roads (CL4)	404	3810	21137	46869	279218	133638
Rural collector and local roads (CL5)	129	736	3600	5316	45216	20373

Household Income and Ethnicity

The median household income and household ethnicities were collected from the American Community Survey (ACS) at the census tract level (available at https://data.census.gov/cedsci). The studied area comprises 1,185 census tracts. The average median household income at the census tract level in 2017 was $67,797, while the lowest and highest median household incomes at the census tract level were $13,947 and $249,219, respectively. In 2017, the ethnic composition of the DFW population was 47% White and 53% Black and Hispanic. Table 5 shows descriptive statistics of the ethnicity and median household income at the census tracts.

Table 6. Descriptive Statistics of the Ethnicity and Median Household Income at the Census Tracts

Socioeconomic Factors	Number of Census Tracts	Min	Max	Mean	Median
Median Household Income ($)	1,185	13,947	249,219	67,797	58,814
Ethnicity, White (%)	1,185	5.6	100.0	65.6	72.3
Ethnicity, Black (%)	1,185	0.0	93.4	16.1	9.7
Ethnicity, Hispanic (%)	1,185	0.0	95.9	30.24	22.30

Results

Preventable Crashes by AV Technologies

Implementing the proposed AV safety quantification framework for DFW crashes, we estimated the number of preventable crashes for the five levels of automation. Table 7 presents the estimation results. As expected, the total number of preventable crashes was higher for higher levels of automation; overall, it is estimated that Level 1 AVs can potentially prevent 8,172 crashes, while Level 5 AVs can prevent 70,464 crashes. Table 8 compares the specific AV technologies. Among the ADAS technologies, FCW showed superior safety performance. A higher level of uncertainty resulted in Level 3 and 4 AVs due to the potential impacts of disengagement risk, which have not been estimated.

Table 7. Estimated Number of Preventable Crashes by Automation Level

Level of Automation	Preventable Crashes
Level 1	8,172
Level 2	8,797
Level 3	32,485
Level 4	65,157
Level 5	70,464

Table 8. SE, Failure Risk, and Disengagement Risk by Technology

AV Technology	SE	Failure Risk	Disengagement Risk
ACC	9.3%	5.2%	NA
FCW	21.1%	5.2%	NA
LDW	21.0%	5.2%	NA
BSW	15.0%	5.2%	NA
PD	38.9%	5.2%	NA
AEB	25.7%	5.2%	NA
ESC	43.2%	5.2%	NA
Level 1 ADASs	-	-	NA
LKA	9.3%	5.2%	NA
Level 3 ADS (Intersection)	64.0%	5.2%	49.0%
Level 3 ADS (Highway)	87.0%	5.2%	49.0%
Level 4 ADS (Intersection)	64.0%	5.2%	NA
Level 4 ADS (Highway)	87.0%	5.2%	NA
Level 5 ADS (Intersection)	64.0%	5.2%	NA
Level 5 ADS (Highway)	87.0%	5.2%	NA

Preventable Crash Severities by AV Technologies

We further analyzed AVs' potential to prevent crashes with different levels of severity. To this end, the ratio of preventable crashes (number of preventable crashes/total crashes) and preventable injuries (e.g., number of preventable incapacitating/total number of incapacitating) were estimated. Figure 3 shows the ratio of preventable crashes and injuries for different levels of automation. Levels 1 and 2 can prevent 5% and 6% of crashes, respectively. Upgrading to Level 3 would result in preventing up to 23% of crashes. While Level 4 can prevent 46% of crashes, switching to fully automated vehicles (Level 5) could maximize the safety benefits of AVs by preventing 50% of crashes. At this level of automation, we can potentially observe up to a 30% reduction in fatal, suspected serious injury, and non-incapacitating injuries. In general, AVs are more effective at preventing non-injury crashes.

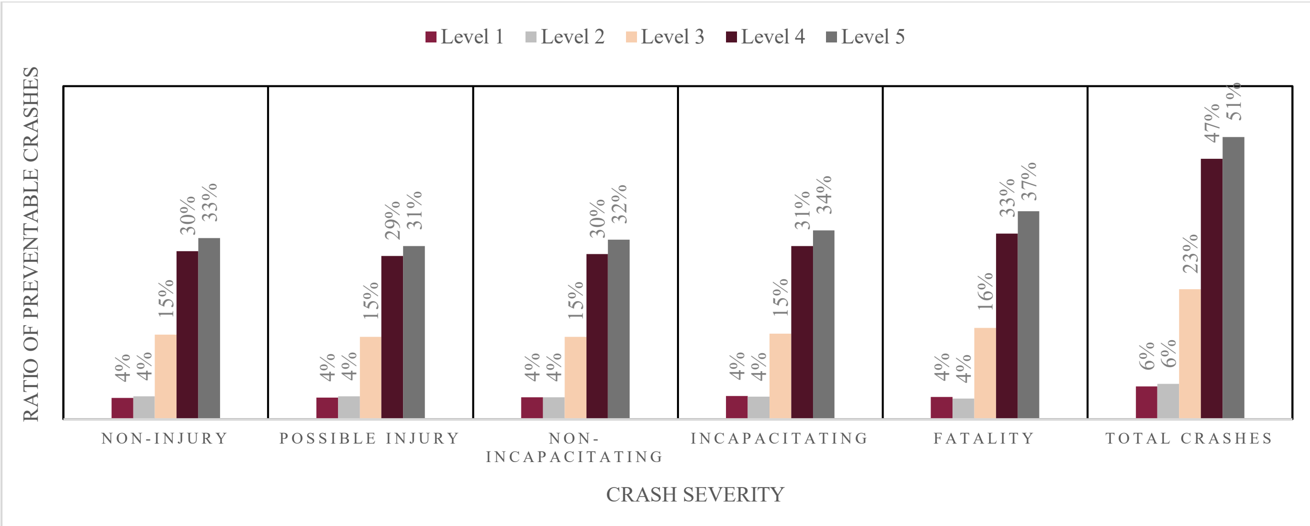


Figure 3. Chart. Safety implications of automation levels in terms of crash severity.

Figure 4 depicts the ratios of preventable crashes for ADAS technologies. LDW had the most significant impact on preventing severe crashes: about 1.6% of fatal crashes and 1.3% of suspected serious injury crashes. Although ESC and PD could prevent a lower percentage of crashes (1.2% and 0.2%, respectively), they are more effective in terms of preventing fatal crashes (1.3% and 1.0%, respectively). This is in line with the fact that ESC and PD target crashes involving vulnerable road users and run-off-the-road crashes with higher severity rates. Most of the ADAS technologies are more effective at preventing non-injury crashes compared to injury crashes.

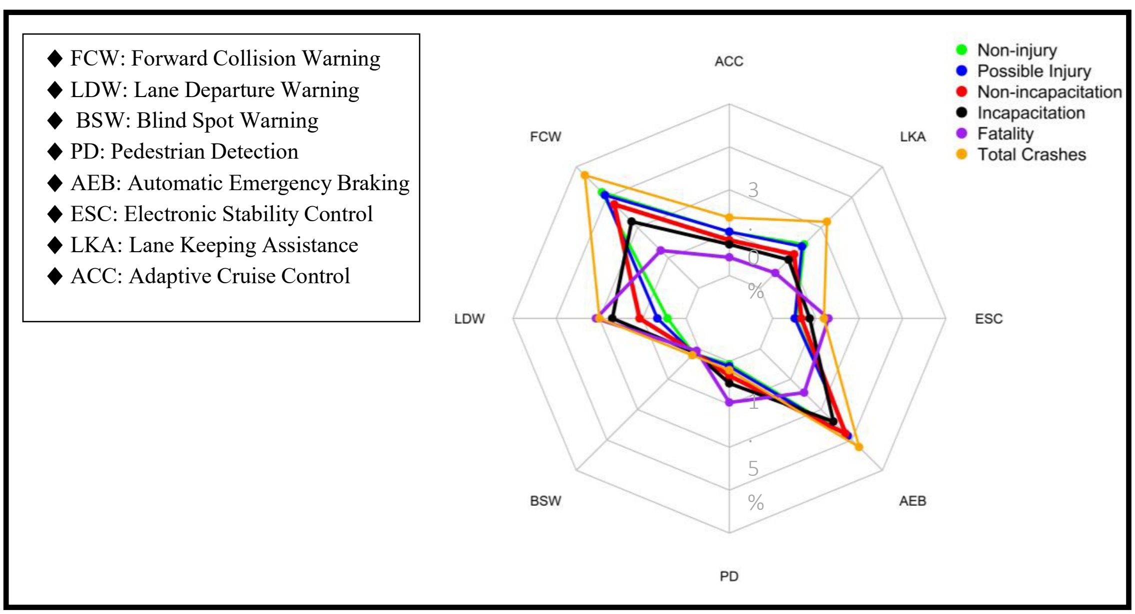
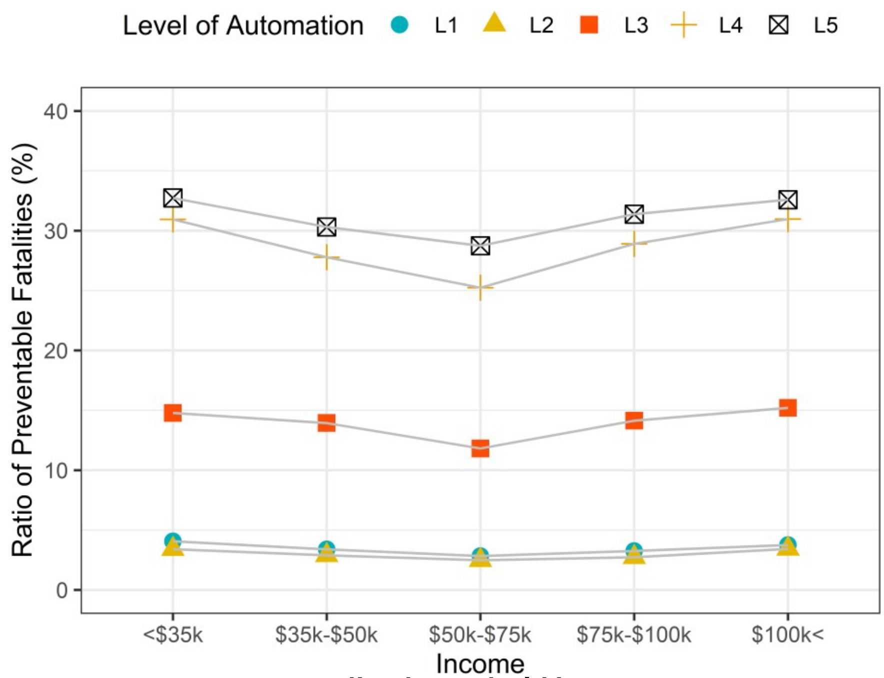


Figure 4. Chart. ADAS estimated preventable crashes by severity.

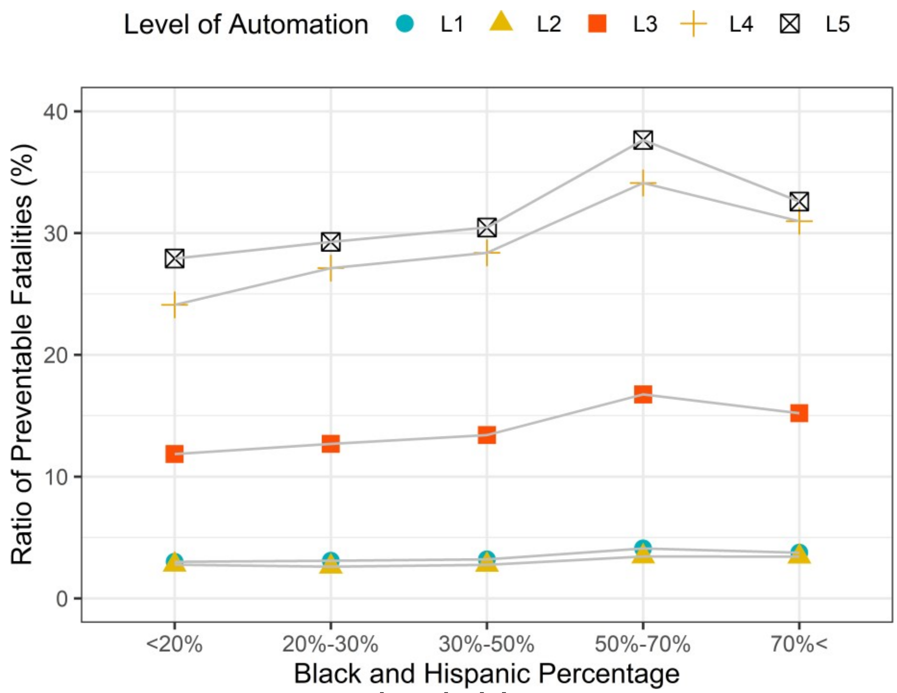
Fatalities by Community Characteristics (Equity Assessment)

We stratified AV preventable fatalities by communities' socioeconomic and demographic characteristics at the census tract level. The results of analyzing preventable fatalities by median household income are shown in Figure 5(a). Based on this analysis, AVs are expected to have the most profound positive impacts on communities with median household income less than $35,000, where a higher rate of preventable fatalities was observed. AVs' role in preventing fatalities is the lowest among medium-income communities ($35,000 to $75,000). More fatalities can be prevented in high-income communities as well.

We also explored the relationship between ethnic diversity and AV-preventable fatal crashes by stratifying the fatal crashes. The results show AVs having a greater safety contribution in communities with a higher Black and Hispanic population percentage (Figure 5(b)). Ethnically diverse communities are expected to benefit more from AV implementation, particularly at higher levels of automation.



(a) Median household income



(b) Ethnicity

Figure 5. Chart. Percentage of AV-preventable traffic crash fatalities in different communities.

Discussion

Key Findings and Implications

The results of implementing the proposed AV safety quantification framework on DFW crashes showed that Level 5 automation has the potential to prevent 50% of crashes and 31% of fatalities. This figure is significantly lower than speculations that eliminating all driver errors will consequently prevent 94% of crashes. The results showed that Level 1 automation has the potential to prevent 5% of crashes, and upgrading to Level 4 can prevent 46% of crashes. Eliminating Level 4 ODD limitations—by upgrading to Level 5—could result in a 4% increase in the number of preventable crashes. Most of the ADAS technologies are more effective at preventing non-injury crashes compared to injury crashes. LDW, ESC, and PD, on the other hand, showed a more significant contribution to injury crashes, perhaps because these systems target crashes that include vulnerable road users and higher speeds. A similar observation was found for ADSs, which were more effective in preventing non-injury crashes.

A U-shape relationship between AV safety impact and median household income was observed. AVs are expected to have a greater contribution to lowering road fatalities in communities with low and high income, as well as those with a higher percentage of Black and Hispanic residents, whereas the impact is expected to be lower for median income communities and those with a higher percentage of White residents. This could be because of the fact that road fatalities are higher among communities with lower income levels (Marshall and Ferenchak, 2017). Other contributing factors mentioned in the literature are the ownership of older and less maintained vehicles (Girasek and Taylor, 2010) and riskier driving behavior (Elias et al., 2016) in these population groups, which could be prevented by AV deployment. This may also be explained by the poor transportation infrastructure in low-income communities, assuming most of the crashes occur in the same zip code where the vehicle owner lives. The greater impacts of AVs on high-income communities, on the other hand, can be because of more miles driven in these communities (mainly because of living in suburban areas and owning more vehicles).

Our findings have important policy implications. The initial assessment conducted in this study indicates that low-income and ethnically diverse communities will benefit more from the implementation of AV technologies more than middle-income communities; hence, the cost-benefit ratio of AV deployment will be much higher for low-income and ethnically diverse communities. However, due to the high cost of the technology, low-income communities will be the last ones to adopt the technology, and therefore they may not enjoy the safety benefits of AVs. City and state planning and transportation agencies may want to consider policies and strategies for making these technologies available to low-income and ethnically diverse communities at a lower cost. Potential policies could also target facilitating automated transit and/or shared AVs in low-income communities.

The proposed framework can be considered as a tool for policymakers to envision AV safety implications for more informed decision-making regarding AV policies. Despite the fact that the results of the empirical analysis study stemmed from a retrospective analysis of 2017 crashes and the defined counterfactual scenarios may be unrealistic (at least in the near future), understanding the potential safety impact of AVs can inform decisions on future investments and development plans for AV technologies. Knowing the potential of AVs to prevent road fatalities and the relationship to household socioeconomic and demographic characteristics can benefit decision-making regarding adoption strategies and incentives. We expect that the disparities in AV safety impacts would facilitate the involvement of the health sectors in the policymaking process. Given this study's results, decision-makers can adopt policies to make AVs accessible to underserved communities through shared mobility services or subsidies.

Strengths and Limitations

The proposed framework augments existing target crash population studies and is a starting point for future AV safety research. Although the proposed framework accounts for some of the challenges, the following factors were not considered: mixed-traffic safety issues (interaction of AVs and conventional vehicles at different market penetration rates), the driver's pre-crash reaction to a hazard, potential riskier behavior by the driver or passengers as a result of overreliance on the system, and changes in travel demand after AV implementation (Sohrabi et al., 2021). Given these limitations, the framework proposed here is expected to represent a theoretical upper bound (or optimistic scenario) of the potential safety benefits of AVs, not their actual benefits. Uncertainties are inherited in variables incorporated in this study, including the estimations of AV SE, system failure risk, and disengagement risk. Given that only a limited number of studies have evaluated or tested AV safety, we could not account for the uncertainties in our analysis. Also, the accuracy of our empirical analysis depends on the reliability of the variables in the proposed safety quantification framework. Since the number of studies on AV is growing, future research can benefit from more accurate estimates of AV SE, system failure risk, and disengagement risk. The results of this analysis are based on exploring police-reported crashes, and, therefore, many minor crashes were not considered. We did not consider the risk that AVs can impose outside the crash scenarios—e.g., the riskier behavior of passengers not using a seatbelt. This would result in overestimating AVs' safety. Moreover, we evaluated AV safety impacts of a counterfactual implementation scenario (100% market penetration for all levels of automation) for the sake of comparing the safety implications of different levels of automation. The counterfactual scenario was compared with a base scenario where we assumed that no vehicles were equipped with ADASs. More realistic AV implementation scenarios would result in a more accurate estimation. We assigned the crashes to census tracts based on the driver's residential area and assumed that any other passengers lived in the same area as well. We also did not account for the location of vulnerable road users, as such information was not available. These assumptions need to be addressed in the future studies. The safety impacts of AVs are also not limited to preventing crashes and can also mitigate crashes by reducing crash severity. This study solely focused on preventable crashes, and the impact of AVs on mitigating crash severity was not considered.

Conclusions and Recommendations

This study has tried to assess the future safety impacts of AVs in communities with various socioeconomic backgrounds for the first time. Although the safety impacts of AVs have been evaluated in numerous studies, an equity assessment of AV safety implications has never been quantified. Another contribution of the paper is the application of a much-improved safety quantification framework that accounts for some of the safety challenges of AV operation, including SE, system failure risk, and the potential risk of disengagement from an automated system to manual driving. The proposed framework uses more robust estimations of AV safety implications and provides insights into the potential safety impacts of AVs. The comparison between the safety implications of AVs and levels of automation showed the contribution of each technology and the variation in their impacts. The analysis of AV safety impacts on communities with different socioeconomic backgrounds showed that the AVs would most impact low-income communities and communities with a higher percentage of Black and Hispanic population.

Future research is required to address some of the limitations of the proposed framework, including accounting for AV safety evaluation challenges and conducting an equity assessment analysis. The empirical analysis can be improved by using a more reliable estimation of AV safety quantification framework variables, defining empirical studies that consider realistic scenarios regarding AV market penetration, and using more accurate information regarding roadway crashes. Moreover, future studies are required to investigate the relationship between AV safety implications and communities' socioeconomic characteristics. Although the preliminary findings of this study indicate that underserved and ethnically diverse communities may benefit the most from AV deployment, there are limitations in the approach in that the crash location and drivers' zip codes (where the crash was mapped) are inconsistent. Future work is needed to identify pathways through which AVs can affect safety and equity and quantify the extent of their impacts.

Additional Products

The Education and Workforce Development (EWD) and Technology Transfer (T2) products created as part of this project can be downloaded from the project page on the Safe-D website. The final project dataset is located on the Safe-D Dataverse.

Education and Workforce Development Products

This project resulted in two scientific papers:

1. Sohrabi, S., A. Khodadadi, S. M. Mousavi, B. Dadashova, and D. Lord. Quantifying the Automated Vehicle Safety Performance: A Scoping Review of the Literature, Evaluation of Methods, and Directions for Future Research. *Accident Analysis &Prevention*, Vol. 152, 2021, p. 106003. https://doi.org/10.1016/j.aap.2021.106003

2. Sohrabi, S., B. Dadashova, D. Lord, H. Khreis, I. Sener, and J. Zmud. Safety and Equity Impacts of Automated Vehicles: A Quantification Framework and Empirical Analysis. *Accident Analysis & Prevention* (Revise & Resubmit).

The findings of the work presented in this report will become part of the doctoral thesis of the graduate student (Soheil Sohrabi).

Data Products

The data used in this project is the property of Texas Department of Transportation and cannot be made publicly available. The ACS data is publicly available at https://data.census.gov/cedsci.

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