Safety and Equity Impacts of Automated Vehicles: A Quantification Framework and Empirical Analysis

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ABSTRACT

Automated Vehicles (AVs) have the potential to improve traffic safety by preventing crashes. Given the limitations in AV road tests, the safety quantification studies are limited and trivial. Moreover, the AVs' safety implications can vary across communities with different socioeconomic and demographic characteristics. Low-income communities are located near high-capacity roadways, and interstates with poor roadway infrastructure increase the crash risk in these communities. The household's socioeconomic characteristics were shown to be in correlation with motor vehicle safety features, and therefore, higher risk of crashes. Riskier driving behavior and more traffic violation were found in minorities. In this study, we proposed a framework to quantify the potential AVs' safety implications in terms of preventable crashes and fatalities, accounting for some of the safety challenges of AVs' operation, including AV technologies' safety effectiveness, system failure risk, and the risk of disengagement from the automated system to manual driving. The framework consists of five tasks: (1) identifying the safety functionalities of AVs, (3) identifying the AV technologies target crashes, (2) characterizing conventional vehicles with crash scenarios, (4) exploring AVs' safety challenges, (5) estimating the number of crashes preventable by different AV technologies at different levels of automation. We further defined an empirical study to examine the proposed framework and investigate inequity in AVs' potential safety implications. To this end, the relationship between communities' socioeconomic and demographic characteristics and preventable fatalities by AVs is explored. The empirical analysis was conducted using 2017 crash data from the Dallas-Fort Worth area, the fourth largest metropolitan area in the United States. The results showed that AVs could potentially prevent up to 50%, 46%, 23%, 6%, and 5% crashes for automation levels 5 to 1, respectively. AVs were shown to be more effective in preventing non-injury crashes. Among advanced driver assistance systems (ADASs), pedestrian detection, electronic stability control, and lane departure warning have more significant potential in reducing fatal crashes. We found a U-shaped relationship between preventable fatalities and AVs and household median income and more significant safety impacts on ethnically diverse communities. We expect that our results indicate the theoretical higher bound of AV safety implications. In case we assume no financial barriers in adopting AVs among communities, low-income, and ethnically diverse communities will benefit most from the implementation of AV technologies; hence, the cost-benefit of AVs' deployment will be much higher for those communities. However, in reality, due to the high cost of AVs, these communities will be the last to adopt this technology, and therefore they may not take advantage of the benefits of AVs. Potential policies could also target facilitating vehicle automation and/or shared AVs in low-income communities. The city and state planning and transportation agencies may consider implementing 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.

Keywords: Automated vehicle; Preventable crashes; Target crash population; Safety; Equity.

ABBREVIATIONS

Abbreviation	**Description**
ADAS	Advanced Driving Assistance System
ACC	Adaptive Cruise Control
ACS	American Community Survey
ADS	Automated Driving System
AEB	Automatic Emergency Braking
AV	Automated Vehicle
BSW	Blind Spot Warning
CL	Crash Location
CRIS	Crash Records Information System
DDT	Dynamic Driving Task
DE	Driver Error
DFW	Dallas-Fort Worth
DR	Disengagement Risk
ESC	Electronic Stability Control
FCW	Forward Collision Warning
FHE	First Harmful Event
FR	Failure Risk
LDW	Lane Departure Warning
LKA	Adaptive Cruise Control
MC	Manner of Collision
MV	Multi-Vehicle
NHTSA	National Highway Traffic Safety Administration
ODD	Operation Design Domain
OEDR	Object and Event Detection and Response
PD	Pedestrian Detection
SAE	Society of Automotive Engineers
SE	Safety Effectiveness
SSM	Surrogate Safety Measure
SV	Single Vehicle
TC	Traffic Conflict
TTC	Time to Collision
TxDOT	Texas Department of Transportation

INTRODUCTION

According to the National Highway Traffic Safety Administration (NHTSA), human error contributes to 94 percent of motor vehicle crashes (NHTSA, 2018). Autonomous Vehicles (AVs) have the potential to eliminate human error, and therefore, in optimistic views, are expected to prevent 94 percent of motor vehicle crashes. However, AVs are prone to system failure and the associate safety risks, including, sensors malfunction in detecting objects (pedestrians, bikes and cyclists, vehicles, obstacles, etc.), misinterpretation of data, and poorly executed responses (Bila et al., 2017). Although AVs, and its technologies, have been developed to improve driver behavior, their driving operation and safety effectiveness (e.g., in mix-traffic environment) needs to be measured by field operational tests (Wang et al., 2020). Risky behavior of AV users because of over reliance on AV technologies was discussed in the literature as one of the AV safety challenges (Sohrabi et al., 2021). The interaction between AV driver system may cause safety issues, particularly when the system is disengaged from automated driving system to manual driving mode (Boggs et al., 2020). Cybersecurity risks is another potential safety concerns of AVs that can result in motor vehicle crashes (Cui et al., 2019).

In the past years, the interest in the safety evaluation of AVs has increased (Sohrabi et al., 2021, Furlan et al., 2020), however AVs' implications for underserved communities has not been explored. Low-income communities are located near high-capacity roadways and interstates, and have poor roadway infrastructure, which increases the crash risk in these communities (Huang et al., 2010, Noland and Laham, 2018, Barajas, 2018). Socioeconomic characteristics of household was shown to be in correlation with motor vehicle safety features, in that low-income communities were found to observe higher crash frequency and severity (Girasek and Taylor, 2010). Riskier driving behavior and more traffic violation was found in minority communities (Elias et al., 2016, Romano et al., 2005). Moreover, due to their high cost, only wealthy consumers might be able to afford AVs as personal vehicles (Raj et al., 2019, Cohen and Shirazi, 2017). This social inequity in AV adoption could lead to uneven distribution of

AVs across households and could result in even further segregation of low-income and ethnic communities. In this regard, it is not clear how AVs will affect inequity in low-income communities. Hence, there is an increasing concern about whether or not the AV implementation will help to offset these discrepancies or will contribute to exacerbate it.

To explore the inequity in AV safety implications, we first need to have realistic estimations regarding AV safety. Given the limited field operational tests of AVs and the uncertainties associated with their operation and safety challenges, AV safety evaluations is not trivial. Sohrabi et al. (2021) have identified six approaches used to quantify the safety effectiveness of AVs, with varying levels of reliability and data availability—including target crash population, road test data analysis, traffic simulation, driving simulator, system failure assessment and safety effectiveness estimation. Among these methods target crash population was widely used in the literature to evaluate the AVs' safety implications (Sohrabi et al., 2021).

The target crash population approach quantifies the safety performance of AVs by identifying the AV technologies functionalities and their potential to prevent certain crash types, hence the "target" (Kusano and Gabler, 2014, Detwiller and Gabler, 2017, Li and Kockelman, 2016, Lubbe et al., 2018, Hendrickson and Harper, 2018, Combs et al., 2019, Agriesti et al., 2019). Target crash population methods were used for evaluating the safety of different levels of automation (Lubbe et al., 2018, Agriesti et al., 2019) and individual or combined Automated Driving Systems(ADSs) and Advanced Driving Assistance Systems (ADASs) functions (Kusano and Gabler, 2014, Li and Kockelman, 2016, Detwiller and Gabler, 2017, Hendrickson and Harper, 2018, Combs et al., 2019). Given the limitations in AV road tests, one of the advantages of this method is that it relies on the existing conventional vehicle crash databases rather than limited AV crashes (Sohrabi et al., 2021). In this method, the target crashes for each technology are identified with respect to the crash characteristics. Depending on the ADAS/ADS system function and capabilities, the AV technology is then attributed to either specific crash types (e.g., rear-end collision, pedestrian crashes) (Detwiller and Gabler, 2017, Hendrickson and Harper, 2018, Combs et al., 2019), specific crash-contributing factors (e.g., distracted driving, speeding, etc.), or critical pre-crash events (e.g., running a red light, vehicle failure) (Yanagisawa et al., 2017, Lubbe et al., 2018, Li and Kockelman, 2016, Kusano and Gabler, 2014). After identifying the target crashes, preventable crashes are extracted from the historical conventional vehicle crash databases. The safety benefits of AVs are finally quantified in terms of the number of preventable crashes (Kusano and Gabler, 2014, Yanagisawa et al., 2017, Detwiller and Gabler, 2017, Lubbe et al., 2018, Hendrickson and Harper, 2018, Agriesti et al., 2019, Combs et al., 2019) and/or reduced cost of crashes (Li and Kockelman, 2016, Yanagisawa et al., 2017, Hendrickson and Harper, 2018).

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 safety challenges AV technologies—namely, system failure risks, the risk associated with disengagement from ADS to manual driving, and safety effectiveness of ADASs and ADSs. Second, the selection of target crash scenarios that can be prevented by a specific AV technology was 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 was made in the literature. Fourth, while previous studies quantified AV safety performance in terms of the number of preventable crashes and cost of crashes, AVs' potential in preventing road injuries and were not considered.

This study is developed to (1) address the limitations of the target crash population approach by proposing a new AV safety quantification framework; and (2) assess the potential equity implications of AVs. The proposed framework for conducting safety assessment comprises of five tasks: (1) exploring the functionalities of AV technologies, (2) characterizing crashes by generating 1,650 crash scenarios (i.e., the sequence of events leading to crash) using four criteria, consisting of crash characteristics and crash-contributing factors, (3) identifying target crash scenario for each AV technologies, (4) incorporating some of the AV safety challenges, including system failure risk, disengagement risk, and AV safety effectiveness, (5) estimating the number of preventable crashes and crash severities per AV technologies. We designed an empirical study to examine the proposed framework and further investigate AVs' potential safety and equity implications. In the empirical study, we utilized the crash data from Dallas-Fort Worth metropolitan area, the fourth-largest metropolitan area in the United States (World Population Review, 2019). We selected 2017 as the base year of the analysis, given that a limited number of vehicles were equipped with ADASs in 2017. The AV safety implications are then quantified for contrafactual scenarios in which we assume that 100% of the 2017 traffic fleet consisted of AVs. We finally stratified preventable crashes and their severities based on the communities' socioeconomic and demographic characteristics to assess the equity implications of AVs. In this study, we explore communities' characteristics at the census tract level.

The remainder of this paper is organized as follows. In the next section, we delineate the proposed framework for quantifying AVs' safety implications and the methodologies behind it. This section is followed by introducing the empirical study design, including the study area and the datasets. Then, we report the results of implementing the proposed framework in the studied area. We discuss the key findings of this study, their implication, and the study limitations. Finally, we conclude the paper and suggest avenues for future studies.

METHODOLOGY

In this paper, we propose an AVs' safety quantification framework that accounts for the safety implications and challenges of different levels of automation (Figure 1). The safety quantification is executed/performed in five tasks:

<u>Task 1:</u> The AVs' functionalities are identified.

Task 2: The conventional vehicle crashes are characterized, and potential crash scenarios are defined.

Task 3: The target crash scenarios for each AV technology are identified using information from Task 1 and 2.

Task 4: The safety challenges of AVs', including system effectiveness, system failure risk, and disengagement risk, are identified.

Task 5: The number of preventable crashes is estimated for each technology by incorporating the findings of Task 4 and exploring the target crashes in the historical conventional vehicles' crash database.

In the subsequent sections, we discuss each task in more detail.

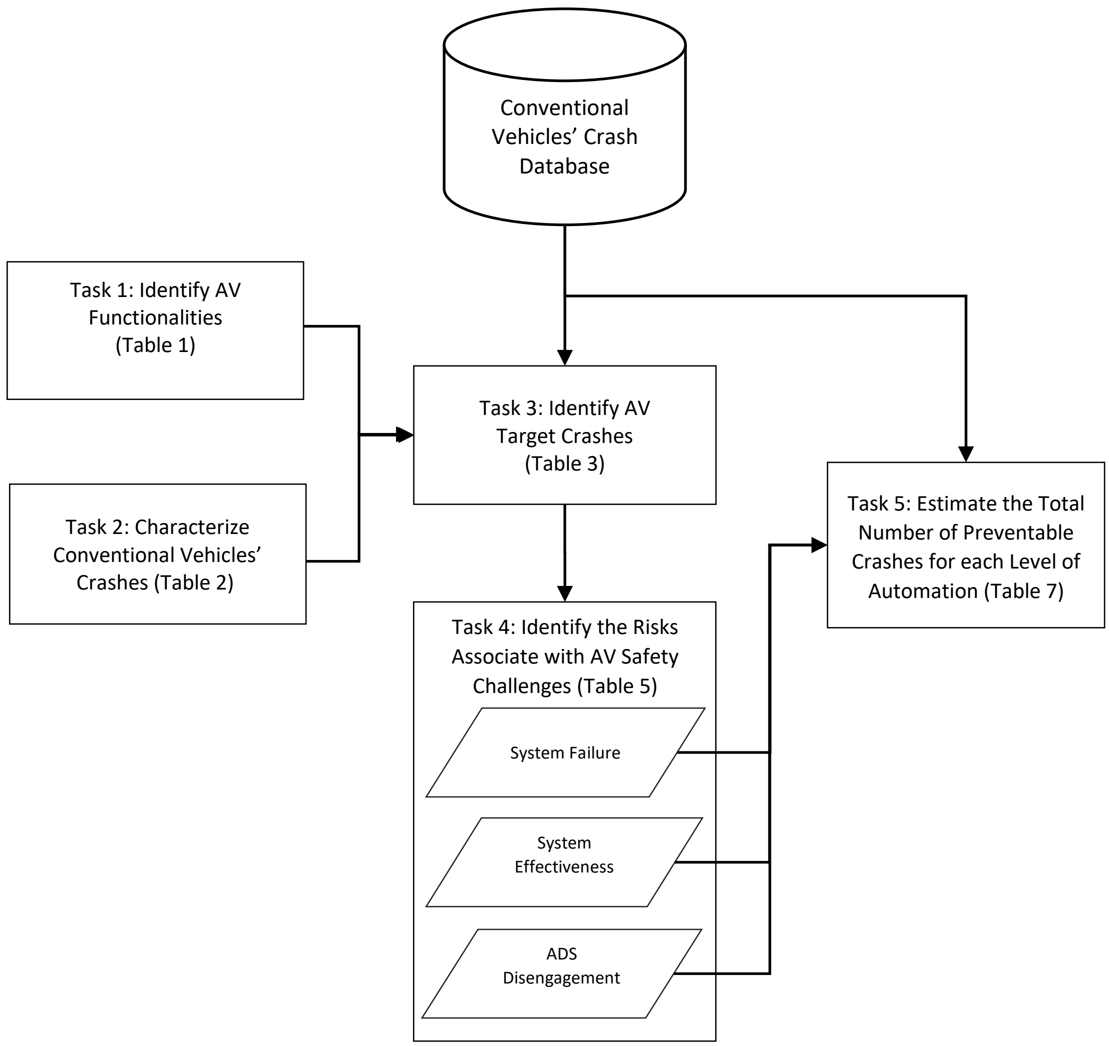


Figure 1. AVs' Safety Quantification Framework

Task 1: Identify AV functionalities

Before identifying the AVs' functionalities, we provide a brief overview of how the different levels of automation are defined in terms of the dynamic driving tasks (DDT), object and event detection and response (OEDR), driver responsibilities, and operation design domain (ODD). As known, there are six levels of automation (Society of Automotive Engineers [SAE], 2018). Level 0 of automation represents no-automation. At levels 1 and 2 of automation, most of the DDTs are performed by the driver, while ADASs occasionally help the driver with some of the driving tasks (SAE, 2018). Given that, the ADASs have the potential to correct some of the driver's error. At level 3 of automation, ADS performs OEDR and is responsible for most of the DDT (SAE, 2018). However, the fallback-ready users should intervene when the ADS is disengaged. Levels 4 and 5 of automation are able to perform all of the DDT with no fallback-ready user. Levels 4 and 5 also differ in terms of ODD, where level 5 has unlimited ODD. It is expected that levels 4 and 5 ADS eliminate most of the driver's errors; however, level 4's impacts are limited to its ODD.

We identified the AVs' functionalities at different levels of automation by investigating their capabilities in terms of performing DDTs, OEDR, and ODD. Table 1 summarizes AV technologies and their functionalities (SAE, 2018). As noted earlier, there are six levels of automation, and each level comes with various technologies, such as forward collision warning or adaptive cruise control. To this end, first, we explored levels of automation and their functions and then, based on this analysis, identify the ADAS and ADS technologies per 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 of automation in this study. For levels 3, 4, and 5 of automation, ADS performs DDT, and crash avoidance capability is characterized based on the ADS functionalities. Based on the definitions, level 5 of automation has unlimited ODD. Since there is no universal design for level 3 and level 4 ADS ODD, we assume 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 or lateral vehicle motion control but does not complete OEDR.	Level 1 ADASs, including both ACC and LKA
Level 3	Performs the complete DDT, but does 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

We investigated the conventional vehicle crashes-and defined target crash scenarios using four criteria: contributing factors, manner of collision, first harmful event (FHE), and crash location (Figure 2). NHTSA categorized crash contributing factors into three broad groups–driver error, environmental factors, and vehicle-related factors (NHTSA, 2018). In general, crashes can be attributed to one or more contributing factors. Per the objectives of this study, we explored the contributing factors for driver error-related crashes, which can be divided into four types: recognition error, decision error, performance error, and non-performance error (NHTSA, 2018). We further analyzed the driver errors using 11 subcategories, as listed in Table 2. Manner of collision refers to the manner in which a crash occurred and is divided into six multiple vehicles (MV) or single vehicle (SV) crash types–angle (MV), rear-end (MV), backing (MV or SV), run-off-the-road (SV), sideswipe crash (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, ADASs and ADSs 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 operate on well-mapped roads. Hence, we assume they would not be able to prevent crashes on local rural roads. To address the limitations of AVs' ODD, we categorized crash locations into five groups to define crash scenarios: 1) intersections, 2) parking, 3) freeway, highway, and arterials, 4) urban collector and local roads, and (5) rural collector and local roads.

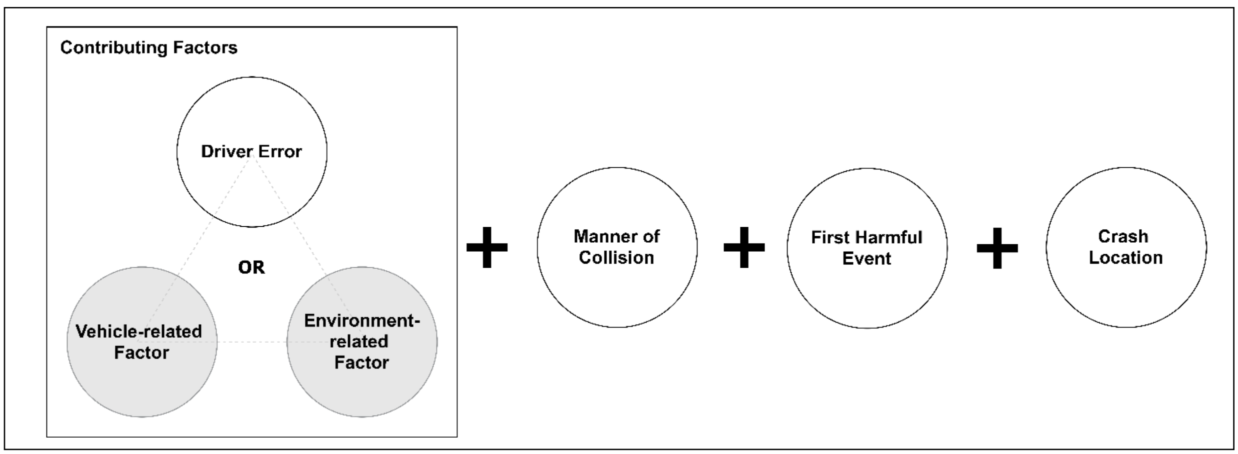


Figure 2. Criteria for characterizing conventional vehicle crashes

A crash scenario is defined as a combination of driver error, manner of collisions, FHE, and crash location. Table 2 lists the critical crash scenario elements used in this study. There are 11 driver crash-contributing factors, six manners of collisions, five FHE types, and five location types. Consequently, the crashes studied in this study 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. Crash Characteristics

Crash Characteristics Criteria		**Critical descriptors**
Contributing Factor	Driver Error (DE)	<u>Recognition error:</u> 1- Distraction and inattention (DE1) 2- Looked, did not see (DE2) <u>Decision error:</u> 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) <u>Performance error:</u> 8- Poor directional and longitudinal control, and overcompensation (DE8) 9- Fail to drive between lanes (DE9) <u>Non-performance error:</u> 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- Brakes 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 Vehicles ** 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, the 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 inattentions (DE1); (2) decision error attributed to the false assumption of other vehicles action 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) at a high-speed freeway, highway, and arterial (CL3). The combination of these crash characteristics hence leads to four crash scenarios that can be prevented by ACC that by definition controls acceleration and/or braking to maintain prescribed distance between the vehicle and leading vehicle.:

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 level of automation, and its technologies, can prevent.

Table 3. Number of target crashes

Systems		Functions and Capabilities	Crash Characteristics				# of Target Crash Scenarios
			DE	MC	FHE	CL	
ADAS	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
	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
ADS	L3 ADS	Performs the complete DDT, but not DDT fallback, within a limited ODD. Eliminates level 2 crashes and crashes dues 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

As indicated earlier, the three important safety concerns of AVs are: (1) safety effectiveness (SE) of ADAS and ADS technologies, (2) system failure risk, and (3) disengagement risk. In general, the *safety effectiveness* (SE) can be defined in terms of the number of preventable crashes by AVs compared to conventional vehicles (Equation 2). Since driving simulator and traffic simulation studies use surrogate safety measures (SSMs) to evaluate the AV safety impacts, in this study, the safety effectiveness 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 safety effectiveness of ADASs and ADSs:

$$\mathrm{SE} = 1 - \frac{\text{AVs}'\text{crash rate}}{\text{Conventional vehicles}'\text{ crash rate}} \tag{2}$$

$$\mathrm{SE}^{TTC} = 1 - \frac{\text{AVs}'\text{ number of time to collision} < \text{treshold}}{\text{Conventional vehicles}'\text{number of time to collision} < \text{treshold}} \tag{3}$$

$$\mathrm{SE}^{TC} = 1 - \frac{\text{AVs}'\text{ number of traffic conflicts}}{\text{Conventional vehicles}'\text{number of traffic conflicts}} \tag{4}$$

Wang et al. (2020) synthesized the results of previous traffic simulation and field experiments that estimated the *safety effectiveness* of AVs (2020). Conducting a meta-analysis on 89 studies, the authors estimated the safety effectiveness of seven ADASs—in descending order of safety effectiveness PD, LDW, FCW, ESC, BSW, AEB, ACC (reported in Table 4). Given that there is a limited number of studies on the LKA impacts, we assumed that the effectiveness of LKA would be similar to ACC. ADS' safety effectiveness was found to be different for intersections and road segments. We sourced the ADS effectiveness at intersections from the Morando et al.'s study (2018), in which they evaluated the safety impacts of AVs in terms of changes in the conflicts between vehicles after AVs' implementation using traffic microsimulations (Morando et al., 2018). Using Equation 4, we converted changes in the number of conflicts to the safety effectiveness of AVs. The ADS effectiveness in road segments was extracted from Kockelman et al. (2016) study, which used traffic microsimulations to evaluate AVs' safety impacts under various operational conditions and measured the safety impacts in terms of the number of conflicts between vehicles.

Another challenge in AVs' operation and safety is *system failure* (Koopman and Wagner, 2016). The system failure can happen due to malfunctioning sensors in detecting objects (pedestrians, bicyclists, vehicles, obstacles, etc.), 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 component of AVs was synthesized by Bhavsar et al. (2017). To this end, the components of the ADAS and ADS were examined individually, and the failure rate is determined based on the evidence from the existing literature. Bhavsar et al. (2017) developed a hierarchical model to synthesize the AVs' failure rates associated with the vehicle. According to the results of their model, the failure risk of hardware system (sensor and integration platform failure) and software system were 4.2% and 1.0%, respectively.

The third safety concern of AVs is related to the *disengagement risk*, which refers to the risk of AV being involved in a crash as a result of the transition from automated driving mode to manual driving. For levels 3 and 4 of automation, drivers need to take over the 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 showed to impose crash risks (Desmond et al., 1998, Happee et al., 2017). In a study by Happee et al. (2017), the effects of automation in take-over scenarios were investigated in a high-end moving-base driving simulator. Drivers performed evasive maneuvers encountering a blocked lane in highway driving, and the performance of drivers in the manual driving environment and the automated driving environment with a disengagement to manual driving were compared, using TTC measures. Using Equation 4 and assuming a four seconds threshold for TTC (Sultan and McDonald, 2003), the disengagement risks were estimated to be 49%. We assumed a similar disengagement risk for both levels 3 and 4 of 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.

A summary of the safety challenges of AVs that were considered in this study is summarized in Table 4.

Table 4. Safety Challenges of AVs

System	Safety Effectiveness	Source	System Failure		Source	Disengagement Risk	Source
			Software Failure Risk	Hardware Failure Risk			
ACC	9.3% [5.0,0.14]	(Wang et al., 2020)	1.0%*	4.2%*	(Bhavsar et al., 2017)	NA	
AEB	25.7% [2.0,31.0]	(Wang et al., 2020)				NA	
BSW	15.0% [10.0,20.0]	(Wang et al., 2020)				NA	
ESC	43.2% [38.0,48.0]	(Wang et al., 2020)				NA	
FCW	21.1% [17.0,25.0]	(Wang et al., 2020)				NA	
LDW	21.0% [10.0,33.0]	(Wang et al., 2020)				NA	
PD	38.9% [36.0,42.0]	(Wang et al., 2020)				NA	
LKA	9.3%**	-				NA	
L3 ADS (Intersection)	64.0%*	(Morando et al., 2018)				49.0%*	(Happee et al., 2017)
L3 ADS (Highway	87.0%*	(Kockelman et al., 2016)					
L4 ADS (Intersection)	64.0%*	(Morando et al., 2018)				NA	
L4 ADS (Highway)	87.0%*	(Kockelman et al., 2016)				NA	
L5 ADS (Intersection)	64.0%*	(Morando et al., 2018)				NA	
L5 ADS (Highway)	87.0%*	(Kockelman et al., 2016)				NA	

* Confidence interval is not reported.
** Speculated (no source available)

Task 5: Estimate preventable crashes

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

$$PC^t = TC^t \times SE^t \times (1 - FR) \times (1 - DR) \quad (5)$$

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

EMPIRICAL STUDY

We design an empirical analysis to examine the proposed AV safety quantification framework and AV equity implications. The proposed framework quantifies the AVs' safety implications in terms of the number of preventable crashes. We further investigate the quantified preventable crashes to explore (1) the role of levels of automation, and the technologies behind it, in preventing different levels of crash severity, (2) the potential relationship between preventable road fatalities and communities socioeconomic and demographic characteristics to assess the equity implications of AVs. In this section, we briefly describe the study setting, equity assessment method, and utilized datasets.

Study Setting

The safety implications of AVs are quantified in the DFW metropolitan area for the year 2017. To this end, first, we define five counterfactual scenarios about AVs' 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 estimate the potentially preventable crashes for each scenario and are compared against the base scenario, i.e., no-automation in the transportation system. The estimated numbers represent the potential safety implications of different levels of automation in case the DFW transportation system was 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 redisents 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. Since a limited number of vehicles were equipped with ADASs in 2017, crash records can be considered a representative of the DFW area safety with no-automation in the transportation system. According to our preliminary analysis of the DFW demographic, the DFW area is populated with diverse races and ethnicities.

Equity Assessment

The role of AVs' safety implications in communities is investigated based on their socioeconomic and demographic characteristics, assuming 100% market penetration of AVs, and therefore, no financial restriction in adopting AV in communities. This study considers median household income and household ethnicity as a proxy for communities' socioeconomic and demographic status. Moreover, we explored the communities' characteristics at the census tract level. Assuming that the vehicles' occupants are living in the same zip code as the vehicles' owners, we mapped the road fatalities to the zip codes in each census tract. The estimated preventable fatalities can then be stratified based on median household income and household ethnicity at the census tract level.

Datasets

Crash Characteristics

The crash data was sourced from the Texas Department of Transportation's (TxDOT) crash records information system (CRIS). The CRIS data were collected for the year 2017. The crash dataset includes the crash location, crash characteristics (Table 5), the vehicle's owner's residential zip code, and the crash severity. We focused on crash records from 2017, given that 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 number of 151,881 crashes were collected, of which 738 crashes resulted in fatalities (0.5%), 34.7% resulted in injuries or possible injuries, and 64.8% resulted in no injury. The crashes are mostly MV crashes that include more than two vehicles. The rest of the crashes are distributed as follows: 15.2% fixed object crashes, 1.7% vulnerable road user (bicycle, pedestrian and motorcycle) crashes, and 0.5% wildlife crashes. Table 5 represents a summary of crash characteristics in 2017.

Tables 5. Crash Characteristics

Crash Characteristics		**Count by Severity**					**# of Crashes**
		Fatal	***Incapacitating***	***Non-Incap. Injury***	***Poss. Injury***	***Non-injury***	
Driver Error	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
	Fail 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
Manner of Collision	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
First Harmful Event	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	45090	45109
	Pedestrian and cyclist, with pedestrian and cyclist at fault (FHE6)	6	5	11	10	90	48
Location	Intersections (CL1)	342	3383	19514	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[1]. 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 income at the census tract level was $13,947 and $249,219, respectively. In 2017, 47% of the DFW population consisted of white ethnicity, and 53% consists of black and Hispanic ethnicities. Table 6 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

ACS	Num. 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 of DFW crashes, we estimated the number of preventable crashes for five levels of automation. Table 7 presents the estimation results for different levels of automation and Levels 1 and 2 ADASs. As expected, the total number of preventable crashes was higher for higher levels of automation; level 1 AVs can prevent 8,172 crashes while level 5 AVs can prevent 70,464 crashes. Among the ADASs, FCW showed a superior safety

[1] Sourced from American Community Survey database available at https://data.census.gov/cedsci/

performance in the studied area. A higher level of uncertainty resulted in levels 3 and 4 ADSs' estimations due to the potential impacts of disengagement risk that is applicable to these technologies.

Table 7. Estimated Number and Percentage of Preventable Crashes by AVs

Level of Automation	ADAS and ADS	Safety Effectiveness	Failure Risk	Disengagement Risk	Preventable Crashes
Level 1	ACC	9.3%	5.2%	NA	8,172
	FCW	21.1%			
	LDW	21.0%			
	BSW	15.0%			
	PD	38.9%			
	AEB	25.7%			
	ESC	43.2%			
Level 2	Level 1 ADASs	-	-	NA	8,797
	LKA	9.3%	5.2%		
Level 3	Level 3 ADS (Intersection)	64.0%	5.2%	49.0%	32,485
	Level 3 ADS (Highway)	87.0%			
Level 4	Level 4 ADS (Intersection)	64.0%	5.2%	NA	65,157
	Level 4 ADS (Highway)	87.0%			
Level 5	Level 5 ADS (Intersection)	64.0%	5.2%	NA	70,464
	Level 5 ADS (Highway)	87.0%			

Preventable Crash Severities by AV Technologies

We further analyzed ADASs and ADSs' safety implications in terms of their potential to prevent crashes with different levels of severity. To this end, the ratio of preventable crashes ($\frac{\#\ prevenetbale\ crashes}{Total\ number\ of\ crashes}$) are estimated. Figure 3 shows the ratio of preventable crashes for different levels of automation. Levels 1 and 2 of automation can prevent 5% and 6% of crashes, respectively. Upgrading to level 3 would result in preventing up to 26% of crashes. While level 4 of automation can prevent 46% of crashes, switching to fully-automated vehicles (level 5) could maximize the safety benefits of AVs by preventing 50% of crashes. ADSs could prevent fatalities, incapacitation, and injuries from crashes by up to 31%. In general, and similar to most ADASs, the ADSs were more effective in preventing non-injury crashes.

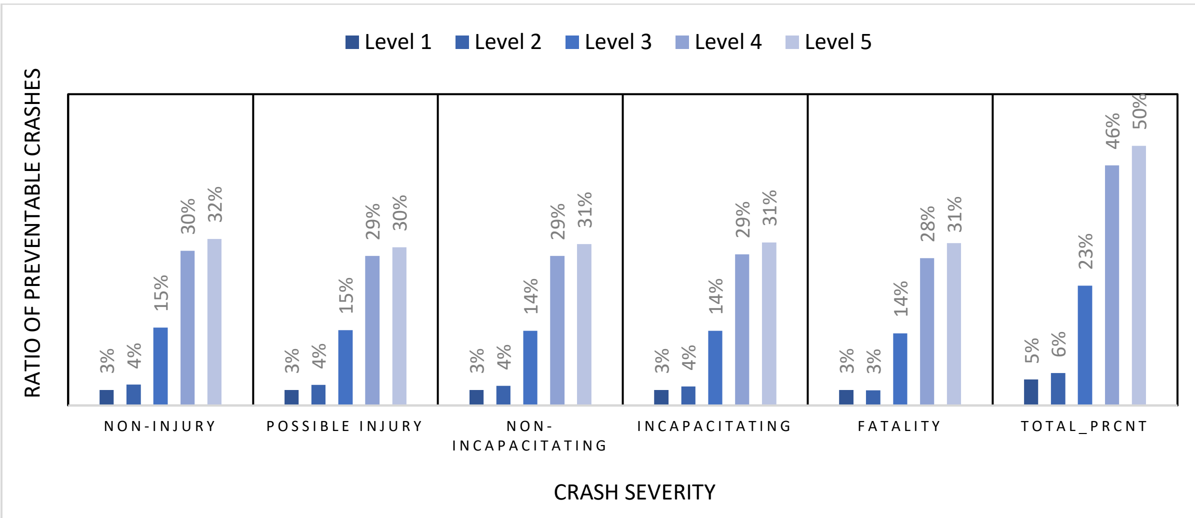


Figure 3. Safety implications of automation levels in terms of crash severity

Figure 4 depicts a graphical representation of the ratio of preventable crashes for ADAS. Among ADASs, LDW had the most significant impact on preventing severe crashes; they can prevent about 1.6% of fatalities and 1.3% of incapacitations (i.e., suspected serious injuries). Although the ESC and PD could prevent a lower percentage of crashes (1.2% and 0.2%, respectively), they are more effective in terms of preventing fatalities (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 ADASs are more effective in preventing non-injury crashes compared to injury crashes.

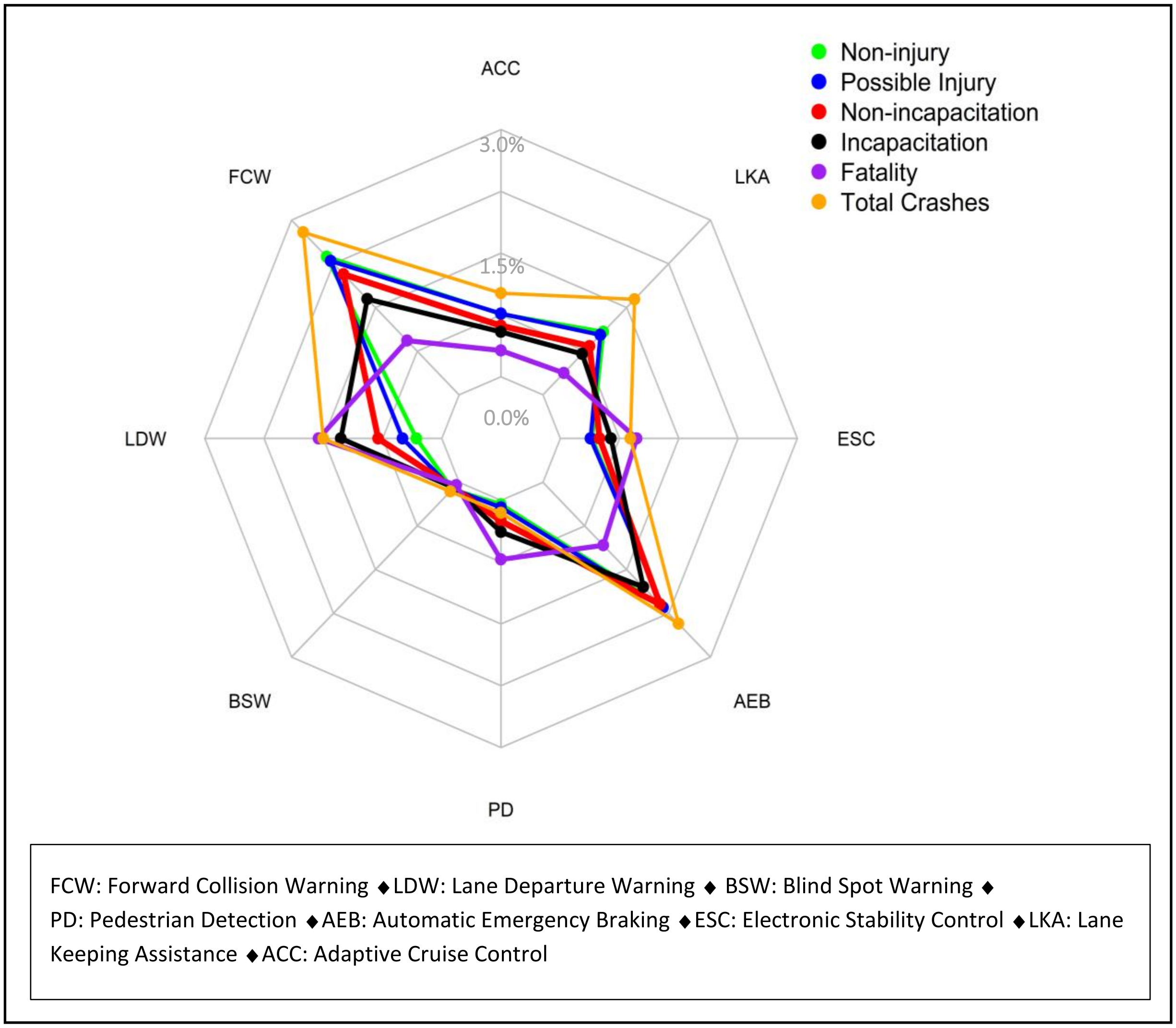
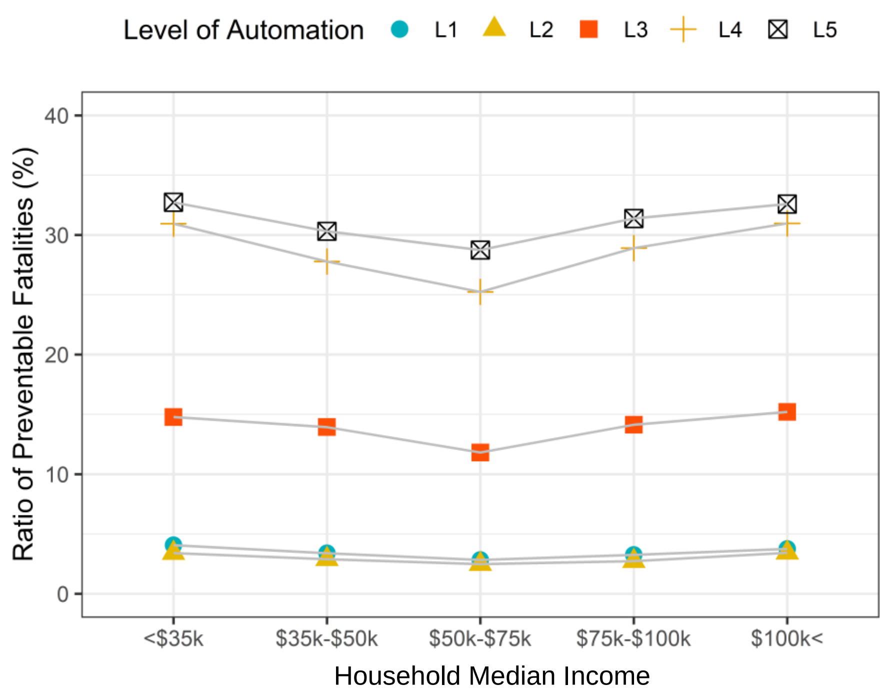


Figure 4. ADASs estimated preventable crashes by severity

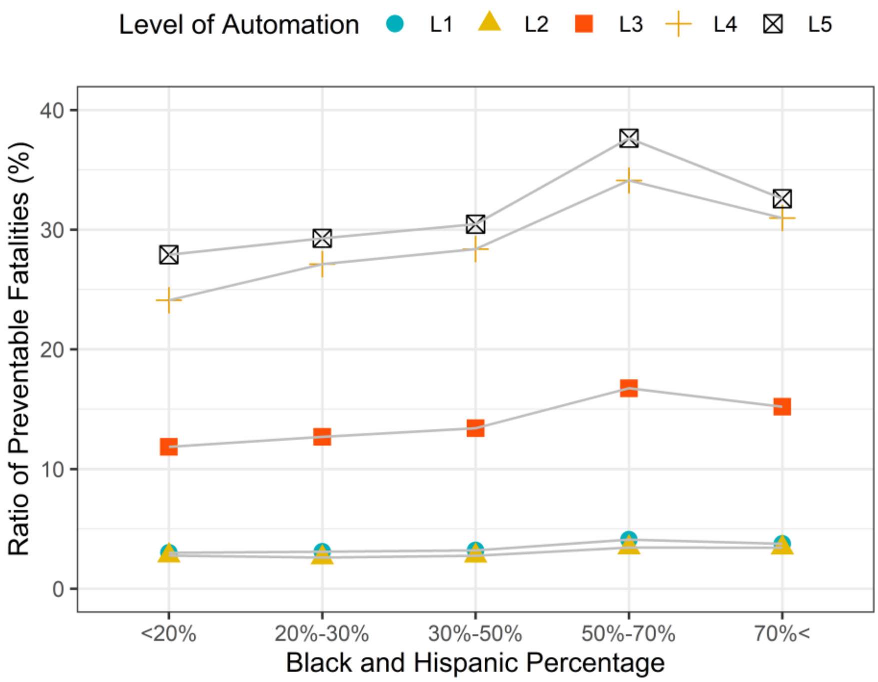
Preventable Fatalities by Community Characteristics (Equity Assessment)

We further 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 $35k, where a higher rate of preventable fatalities was observed. AVs' role in preventing fatalities is the lowest among medium-income communities ($35k to $75k). More fatalities can be prevented in high-income communities as well.

We also explored the relationship between ethnic diversity and preventable fatalities by AVs. The results of stratifying crash fatalities based on the percentage of people with Black and Hispanic ethnicities in the communities (Figure 5(b)) show a more dominant role of AVs in communities with a higher percentage of Black and Hispanic population. Ethnically diverse communities are expected to benefit more from AVs' implementation, particularly at higher levels of automation.



(a)



(b)

Figure 5. AVs' preventable fatalities by (a) median household income and (b) ethnicity at the Census tract level

DISCUSSION

Key Findings and Implications

The results of implementing the proposed AV safety quantification framework on DFW crashes showed that level 5 of automation has the potential to prevent 50% of crashes and 31% of fatalities. This figure is significantly lower than speculations regarding AVs' safety improvement impacts by eliminating all driver errors and consequently preventing 94% of crashes. The results showed that level 1 of 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 ADASs are more effective in 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, where they were more effective in preventing non-injury crashes.

A U-shape relationship between AVs' safety impacts and median household income was observed. Contributions of AVs to road fatalities are expected to be higher in communities with low and high income as well as those with a higher percentage of the Black and Hispanic population, while the impact is lower for median income communities and those with higher white ethnicity percentage. This could be because of the fact that road fatalities are higher in communities with lower income levels (Marshall and Ferenchak, 2017). Other contributing factors mentioned in the literature are the ownership of older and less maintained vehicle fleet (Girasek and Taylor, 2010) and riskier driving behavior (Elias et al., 2016), which could be addressed by AV deployment. This may also be explained by the poor transportation infrastructure in these low-income communities, in case we assume most of the crashes occur in the same zip code where the vehicle owner lives. Higher 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 than middle and higher-income communities; hence, the cost-benefit of AVs' deployment will be much higher for those communities. However, due to the high cost of the technology, these communities will be the last ones to adopt the technology, and therefore they may not take advantage of the benefits of AVs. The city and state planning and transportation agencies may consider implementing 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 and the results of the empirical analysis would help decision-makers and stakeholders. The proposed framework can be considered as a tool for policymakers to envision AV safety implications for more informed decision-making regarding AVs supporting policies. Despite the fact that the empirical analysis study results stemmed from a retrospective analysis of 2017 crashes and the defined contrafactual scenarios can be sought unrealistic (at least in the near future), understanding AVs' potential safety impact can benefit decision-makers in various ways. Providing insight into each technology's potential in preventing crashes can help make more informed decisions on future investments and development plans on AV technologies. Learning of AVs' potential in preventing road fatalities and its relationship with households' socioeconomic and demographic characteristics can benefit decision-making regarding AVs adoption strategies and incentives. We expect the disparities in AVs' safety impacts would facilitate the health sectors' intervention in the policymaking process. Given this study's promising results, the decision-makers can adopt policies to make the AVs accessible to underserved communities through shared mobility services or subsidies.

Strength and Limitations

The proposed framework augmented the existing target crash population studies and is a starting point for future AV safety research. Although the proposed framework accounts for some of AVs' challenges, the following factors were not considered in the target crash population approach: mixed traffic safety issues (interaction of AVs and conventional vehicles at different market penetration rates), driver pre-crash reaction to hazard, potential riskier behavior of driver/passenger (as a result of overreliance on the system), 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 scenarios) of the potential safety benefits of AVs, not their actual benefits. Uncertainties are inherited in variables incorporated in this study, including AV's safety effectiveness estimations, the system failure risk, and the disengagement risk. Given that there are a limited number of studies that evaluated or tested AVs' 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 studies on AVs' evaluation and testing are growing, future research can benefit from more accurate estimates of AVs' technology safety effectiveness, 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., riskier behavior of passengers by not using a seatbelt. This would result in overestimating AVs' safety. Moreover, we evaluated AVs' safety impacts of a contrafactual implementation scenario (100% market penetration for all levels of automation) for the sake of comparing the safety implications of different levels of automation. More realistic AV implementation scenarios would result in a more accurate estimation. AVs' safety impacts are not limited to preventing crashes and can also mitigate crashes by reducing crash severity. This study solely focuses on preventable crashes, and the AVs' impacts on mitigating crash severity were not considered.

SUMMARY AND CONCLUSIONS

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, the equity assessment of AVs' 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 AVs' operation, including AVs' technology safety effectiveness, system failure risk, and the potential risk of disengagement from an automated system to manual driving. The proposed framework uses more robust estimations of AVs' safety implications and provides insights into the potential safety impacts of AVs. We defined an empirical study and examined the proposed framework using the crash data from the Dallas-Fort Worth area. The comparison between the safety implications of AV's technologies and levels of automation showed the contribution of each technology and the variation in their impacts. The analysis of AVs' 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 the 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 uncertainty 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 AVs' safety implications and communities' socioeconomic characteristics in terms of consumer purchase power. Although the preliminary findings of this study indicate that the underserved and ethnically diverse communities may benefit the most from AV deployment, however, we do not account for the consumer purchase power. The discussion about the equity implications of AVs is not limited to their safety impacts but also their potential in providing an independent mode of transportation for individuals with mental or physical disabilities and unlicensed (Sohrabi et al., 2020). Future work is needed to identify pathways through which AVs can affect equity and quantify their extent of impacts

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