Quantifying the Health and Health Equity Impacts of Autonomous Vehicles: A Conceptual Framework and Literature Review

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ABSTRACT

Every year, 1.4 million people die in roadway crashes, in addition to a huge mortality and morbidity toll of traffic through traffic-related air pollution, heat, stress, and noise, which affect the low-income communities and ethnic minorities disproportionately. Automated vehicle (AV) technologies are one of the most highly disruptive transportation technologies that have the potential to transform the existing transportation systems and the associated impacts on public health and health equity. There have been numerous attempts to recognize and frame the consequences of AVs on public health; however, the discussion around this topic is still in its infancy, while studies quantifying these impacts are non-existent. In this study, we propose a conceptual framework for estimating AVs' health impacts at the system level by estimating the changes in transportation and subsequent changes in roadway crashes and traffic-related air pollution. To develop this framework, we first assess the mechanisms through which AVs impact health and equity and then review the existing literature on the quantification of AVs' impacts on public health. The proposed framework aims to provide researchers with a full-chain impact assessment framework for quantifying the health and equity impacts of AVs at the system level and identify the methodological gaps for future research.

Keywords: *Automated vehicles; public health; health equity; travel demand; crashes; air quality.*

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1. Introduction

1.1. Background

Beyond the primary role of transportation systems in providing mobility, transportation can dramatically impact public health in cities (Khreis et al., 2016a). A significant number of preventable deaths are attributable to transportation. According to the World Health Organization (WHO), in 2016, 1.4 million deaths were due to motor vehicle crashes globally (WHO, 2018b). In 2016, 4.2 million deaths were attributable to ambient air pollution (WHO, 2018a), and traffic-related air pollution in particular was responsible for one-fifth of deaths in the United Kingdom, United States, and Germany (Lelieveld et al., 2015). The death rate from transportation noise is comparable to death rates from motor vehicle crashes in cities (Sohrabi and Khreis, 2020). Contaminants from traffic (Burant et al., 2018), traffic-related stress (Wei, 2015), lack of active travel and physical inactivity (Reiner et al., 2013), and greenhouse gases (Woodcock et al., 2009) are a few of the other detrimental exposures related to transportation which lead to worse health, as manifested in increased morbidity and premature mortality. The inequity in the health impacts related to transportation has also been shown in the literature where low-income communities and ethnic minorities have a higher exposure to roadway crash risk and traffic-related air pollution (Sohrabi and Khreis, 2020, Sohrabi et al., 2020, Mueller et al., 2018). This is mostly because these population groups are located near high-capacity roadways (i.e., interstates and freeways). Low-income communities also have poor infrastructure design, which again increases the roadway crash risk (Huang et al., 2010, Noland and Laham, 2018, Barajas, 2018).

Automated vehicle (AV) technologies are expected to be one of the most disruptive transportation technologies, with extensive potential impacts on public health and health equity. Identifying these impacts and their extent is required to govern AVs and prevent the unintended negative consequences of this technology, both on public health and health equity. Crayton and Meier (2017), produced a research agenda highlighting areas where AVSs may impact public health, which include changes in roadway safety, air pollution, greenhouse gases (GHG), aging populations, non-communicable disease, land use, and labor markets. Dean et al. (2019) reviewed the impacts of AVs on public health, focusing on changes in five thematic areas: road safety, social equity, environment, lifestyle, and the built environment. Sohrabi et al. (2019) proposed a conceptual model to identify the impacts of AVs on public health and found that changes in transportation after AVs' implementations can affect public health through 32 pathways. This study showed that AVs' potential contribution to job losses, transportation demand and modal shift, vehicle miles traveled in the system, electromagnetic fields, and changes in required infrastructure could have negative impacts on a wide variety of health outcomes (Sohrabi et al., 2019). On the other hand, providing accessibility for individuals with disabilities and unlicensed transportation users, and improving traffic safety can promote public health and health equity. Nevertheless, it is yet unclear how AVs could affect health in low-income and ethnic minority communities. It is likely that the cost of AVs will be high (at least in the short term), and if so, 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 further health inequities in low-income and ethnic minority communities.

1.2. Problem Statement

The existing literature on AVs' health impacts is comprised of commentaries and speculations, which draw conclusions upon the authors' opinion and perspective—as opposed to data-driven quantitative approaches. Given the limitations in the availability and operation of AVs, AV's impacts cannot be estimated by empirical studies yet because they are not operating freely on public roads. Besides, the extent and nature of AVs' impacts carry considerable uncertainty. Although the existence of uncertainty in AVs implementation and associated health impacts was acknowledged in many studies (Milakis et al., 2017, Crayton and Meier, 2017, van Schalkwyk and Mindell, 2018), quantification of these impacts is required to investigate the extent and nature of these uncertainties. In this study, we address existing gaps in the literature by proposing a conceptual framework for estimating the impact of AVs on public health at the system level through changes in motor vehicle crashes and traffic-related air pollution (TRAP). We selected motor vehicle crashes and TRAP, among other transportation-related risk factors, because of the dominant discussion around these two risk factors both in the AVs impacts literature (Milakis et al., 2017) and transportation health impacts assessment literature (Khreis et al., 2016b). The proposed framework is developed as a result of an overview of the existing knowledge regarding AVs impacts and quantification methodologies for capturing the extent of these impacts as well as health impact assessments (HIA) of transportation projects and policies.

1.3. The mechanism of AVs impacts on public health and health equity

The mechanisms by which AVs can impact health and health equity are very complex, and quantifying them requires an interdisciplinary effort. Figure 1 represents a simplified scheme of AVs' health and health equity impacts. The manner and extent of changes in transportations rely on the vehicles' automation level and the intent of using this new technology. Changes in transportation can be captured by evaluating several possible scenarios for AVs implementation against transportation system performance indicators, using travel demand models. Travel demand models can then be used as tools for exploring potential future changes in transportation. These changes may then be translated into health outcomes through transportation-related health risk factors. The health equity outcomes of AVs' implementations can be explored by stratifying the estimated health outcomes based on socioeconomic, sociodemographic, and geographic factors.

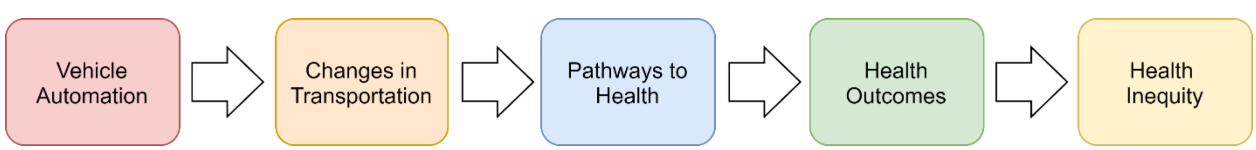

Figure 1. A scheme of the mechanism of AVs' impacts on health and health equity

2. Methodology

In the "Introduction," we set the context of this paper and discussed the mechanism of AVs' impacts on public health and health equity, focusing on two transportation-related risk factors: motor vehicle crashes and TRAP. In light of the mechanisms through which AV's deployment can affect health and health equity, and considering knowledge gained from the literature, we propose a conceptual framework for AVs' full-chain health and health equity impact assessment.

Given that several review studies exist on AVs' impacts, we overview the available review studies in this paper (listed in Table 1) to uncover the potential impacts of AVs on transportation—as opposed to conducting a comprehensive review. With the same rationale, we overview the recent review studies on transportation HIA and health equity assessment (Waheed et al., 2018, Cole et al., 2019). Next, we discuss the approaches and methodologies used in the literature for quantifying AVs' impacts on public health and transportation HIA studies that have the potential to be employed in the proposed framework. We explore the identified literature by the most recent review papers and include the studies that fit within the scope and context of the proposed framework. Since the objective of this study is to investigate the AVs' impacts at the system level, the proposed framework and the discussion about quantification methods aim to fulfill this objective. Therefore, macro-level studies are covered in the review. Since this study concerns about the health impacts of AVs, as opposed to connected vehicles, we focus on the methodologies for quantifying AVs impacts. However, we include some of the connected and autonomous vehicles' (CAVs) literature to cover applicable quantification methods that can be used in the proposed framework.

In the "Results" section, the conceptual framework is proposed and discussed. Then, each component of the proposed framework is discussed, and the potential quantification methodologies are introduced. Finally, in the "Discussion and Conclusion" section, we discuss our findings, critically investigate the literature, and identify methodological gaps.

Tables 1. Recent review studies on the impacts of AVs

Study	Review type	Studied AV's impacts
Wang et al. (2020)	Systematic review—Meta-analysis	Traffic safety
Kopelias et al. (2020)	Narrative review	Energy, emission, air pollution, and noise
Rojas-Rueda et al. (2020)	Narrative review	Public health
Soteropoulos et al. (2019)	Systematic review	Travel behavior and demand
Dean et al. (2019)	Systematic review—Scoping review	Public health
Faisal et al. (2019)	Systematic review	Car ownership, energy, transport infrastructure, car ownership, land use, safety, and public health
Taiebat et al. (2018)	Narrative review	Energy, emission and air pollution
Duarte and Ratti (2018)	Narrative review	Travel demand, parking, urban area, and transport infrastructure
Martinez-Diaz and Soriguera (2018)	Narrative review	Traffic flow, travel demand, safety
Montanaro et al. (2018)	Narrative review	Traffic flow and energy
Milakis et al. (2017)	Systematic review	Travel cost, travel time, value of time, travel comfort, road and intersection capacity, travel choice, vehicle ownership, land use, transport infrastructure, fuel and energy efficiency, emission and air pollution, safety, social equity, economy, and public health
Sousa et al. (2017)	Narrative review	Urban area, congestion, car ownership, driver behavior, emission and energy, safety and lower insurance costs, traffic flow, equity and unemployment
Baglooee et al. (2016)	Narrative review	Safety, congestion, emission and energy, car ownership, road congestion, value of time, land use, travel demand, and vehicle routing

Fagnant and Kockelman (2015)	Narrative review	Safety, traffic flow, congestion, travel behavior, car ownership, economic, travel demand, parking and freight transportation
Hoogendoorn et al. (2014)	Narrative review	Traffic flow and road capacity

3. Results

3.1. Conceptual Framework for Full-Chain Health and Equity Impacts Assessment of AVs

Figure 2 shows the proposed framework and its linkages to the mechanism of AV's impacts on public health and health equity. The extent of changes in transportation is measured through changes in travel behavior, driving behavior, land use and infrastructure, and the interaction effect between them. These changes depend on vehicle automation, which can be characterized by the level of automation and the level of deployment (i.e., intent to use, adoption rate, market penetration). The AV scenarios need to be developed based on assumptions regarding vehicle automation to capture the changes in transportation. Then, travel demand models can be employed to explore the extent of the changes in transportation in each scenario. The changes in transportation will then affect public health and, subsequently, equity through two pathways: motor vehicle crashes and TRAP. Emission and dispersion models based on the changes in traffic flow, speed, and vehicle type (cars, trucks, and buses) are required to estimate the changes in TRAP for each scenario. AVs' impact on motor vehicle crashes can be captured by incorporating the changes in traffic flow—aka exposure in road safety performance functions (Lord et al., 2005)—and the AVs' safety functions regarding the level of automation. Employing standard HIA methodologies, the health outcomes—e.g., mortality, morbidity, and injury—associated with each pathway can be quantified at the desired spatial level. Quantifications at the finer spatial resolution can facilitate health equity impact assessments where stratifications based on socioeconomic, sociodemographic, and geographic factors can be conducted with higher precision.

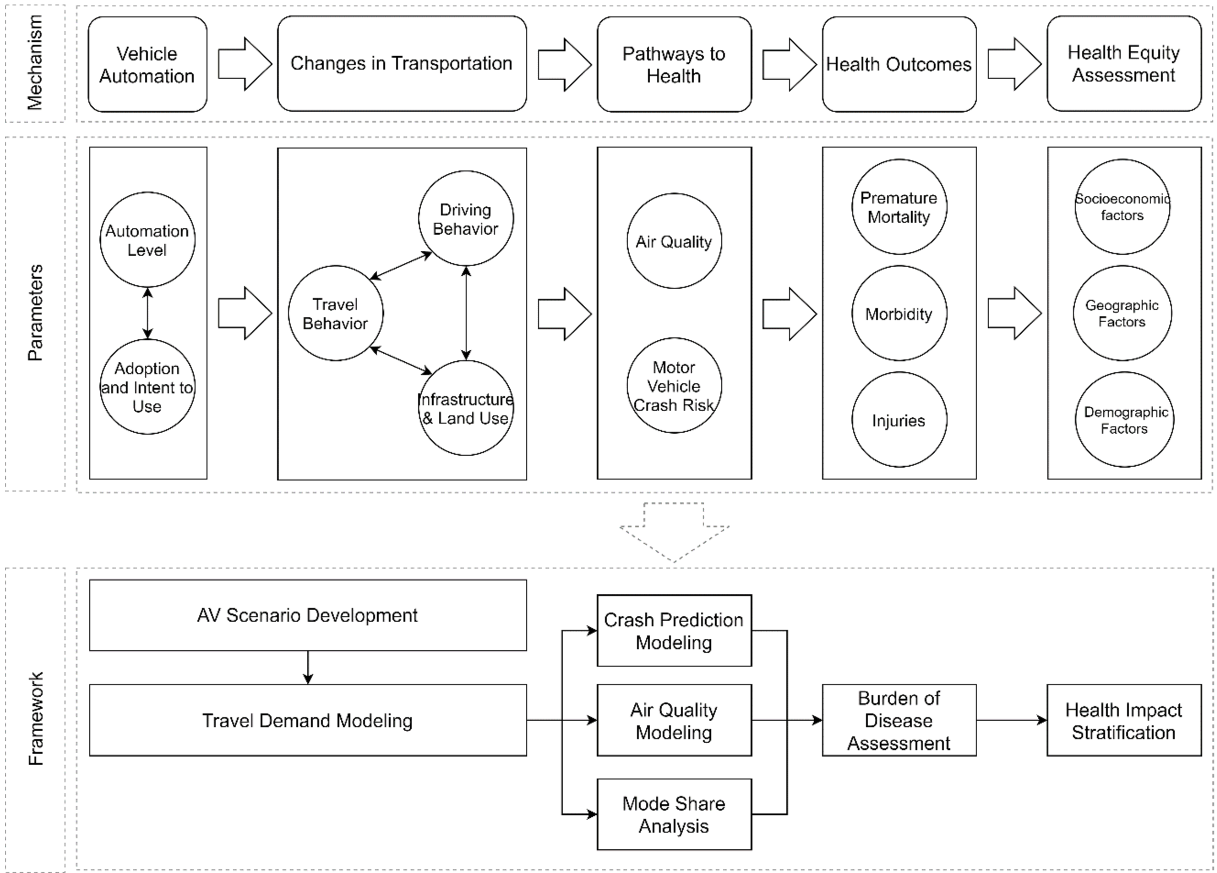

Figure 2. The proposed conceptual framework for full-chain health impact and equity assessment of AVs implementation

3.2. Vehicle Automation Levels and Adoption

AVs are vehicles that have at least some aspects of the vehicle's control function (e.g., steering, throttle, or braking) occurring without direct driver input (NHTSA, 2013). The Society of Automobile Engineers (SAE) categorized automated driving systems into six categories based on the extent of input required from the human driving and driving assistant system capabilities, ranging from no automation to fully automated vehicles (SAE, 2018). The higher levels of automation require less input from the driver. The extent of driver input for each level of automation is shown in **Error! Reference source not found.**. We expect different impacts, both in magnitude and direction, for the different levels of automation, given the functionality of AVs at different levels.

Table 2. AVs Levels of Automation

Automation Level	SAE Definition	Human Drivers' Responsibilities
Level 0	No automation	The human driver is controlling the vehicle and must constantly supervise the driving assistant features
Level 1	Driver assistant of either steering or acceleration/deceleration	
Level 2	Partial automation of both steering or acceleration/deceleration	
Level 3	Conditional automation of all aspects of dynamic driving tasks	Driver intervention upon request of the system
Level 4	High automation of all aspects of dynamic driving tasks even if the driver does not respond appropriately to a request to intervene	No driver input
Level 5	Full automation (highly automated)	

In addition to the automation level, the deployment and usage of AVs are other factors that define vehicle automation in the proposed framework. The extent of AVs' impacts is assumed to be different depending on the levels of deployment; thus, accounting for it while estimating the AVs' impacts can lead to more accurate results. AVs' usage was investigated in the literature in the form of adoption rate (Bansal and Kockelman, 2017, Lavieri et al., 2017, Fagnant and Kockelman, 2014, Lee et al., 2019, Haboucha et al., 2017), market penetration (Lavasani et al., 2016, Litman, 2017), and intent to use (Sener et al., 2019, Zmud and Sener, 2017). The predictions regarding AVs' deployment are mainly based on survey studies (Bansal and Kockelman, 2017, Zmud and Sener, 2017, Sener et al., 2019, Haboucha et al., 2017) or the experience from other technology adoptions (e.g., electric vehicles, airbag, cruise control, etc.) (Litman, 2017, Lavasani et al., 2016).

Several factors were showed to influence AVs' deployment. In the majority of the literature, AVs' costs, including, purchase cost, operation cost and maintenance cost, and consumers' willingness to pay (WTP) were introduced as key factors that affect AV's deployment (Lavasani et al., 2016, Fagnant and Kockelman, 2015, Litman, 2017, Bansal and Kockelman, 2017, Lee et al., 2019, Haboucha et al., 2017). The impacts of individual demographics and socioeconomic characteristics (Zmud and Sener, 2017, Sener et al., 2019, Haboucha et al., 2017, Lee et al., 2019), travel behavior characteristics (Sener et al., 2019), interest in technology (Zmud and Sener, 2017, Sener et al., 2019, Haboucha et al., 2017, Lee et al., 2019), culture and lifestyle preferences (e.g., green lifestyle) (Lee et al., 2019, Lavasani et al., 2016), safety concerns (Zmud and Sener, 2017, Sener et al., 2019), and social influence (Sener et al., 2019, Fagnant and Kockelman, 2015) are other factors that discussed in the literature. Given the variety in the approaches and contributing factors—and the assumptions behind it—used for predicting AVs' deployment, the results of the previous studies were inconsistent and incomparable.

3.3. Changes in Transportation

In this section, we first summarized AVs' potential impacts on driving behavior, travel behavior, and infrastructure and land use and then discussed the methodological approaches to measure these impacts.

3.2.1 AV Impacts on Driver Behavior, Travel Behavior, and infrastructure and Land Use

One of the most significant advantages of automated driving is eliminating human error and improving **driving behavior**, which leads to safer trips as well as more efficient roadway operations in terms of the roadways' throughput (Haboucha et al., 2017). In a fully automated system, the gap between vehicles can be remarkably reduced, which contributes to vehicle platooning (Hoogendoorn et al., 2014). AVs are equipped with multiple sensors that provide a large amount of information from other vehicles' maneuvers, deceleration/acceleration, and lane-changing intent, which allows the vehicles to choose the optimum course of action to maintain traffic efficiency and safety. This can result in significant fuel savings along with lower levels of detrimental emissions (Igliński and Babiak, 2017), a reduction in traffic congestion, and an increase in average speed (Hoogendoorn et al., 2014). Furthermore, the capacity of the transportation infrastructure could be increased in an automated system (Talebpour and Mahmassani, 2016).

Travel behavior can change after the implementation of AVs due to changes in travel time, the value of travel time (VOT), comfort, parking costs, and fares (both for freight and passenger vehicles), as well as the opportunity of independent traveling for previously dependent users. Specifically, AVs have the potential to reduce travel time with more efficient driving (Fagnant and Kockelman, 2015). Steck et al. (2018) showed that VOT could be reduced by 31 percent for users of automated private cars and 10 percent for users of shared automated cars compared to conventional cars, using a stated-choice experiment. However, research has shown that AVs' impact on VOT is not consistent for different income groups (Kolarova et al., 2018). In addition, AVs will impact traveling comfort mainly because of the loss in human control of the vehicle (Elbanhawi et al., 2015). Parking costs will change simply because the parking needs will change after the implementation of AVs (Zhang et al., 2015, Fagnant and Kockelman, 2015). Finally, AVs may provide the possibility of independent traveling for more individuals with physical and mental disabilities as well as unlicensed travelers (Fagnant and Kockelman, 2015, Bennett et al., 2019). These changes will influence travelers' choice of trip, mode, and route. Offering a safer, cheaper, and more comfortable traveling option for individuals with disabilities after the implementation of AVs may induce additional transportation demand and encourage longer trips. AVs are expected to make cars a more favorable mode of transportation after changes in traveling costs (VOT and fare) as well as comfort and encourage shifting from public transit and active transportation (walking and cycling) to private cars (Fagnant and Kockelman, 2015).

Based on the changes in travel behavior, AVs have the potential to change the **transportation infrastructure and land use** substantially. Transportation and land use are tightly linked in urban areas (Rodrigue et al., 2016). Providing a more affordable and comfortable traveling option with AVs can increase the willingness to travel longer distances, which may ultimately result in urban sprawl (migrating to areas with lower density and consequently spreading cities) (Milakis et al., 2017). There is evidence that urban sprawl results in increased vehicle miles traveled (VMT) and negatively influences accessibility in an urban area (Milakis et al., 2017). The changes in parking demand and AVs' ability to operate with no passenger for a higher level of automation affect the need for parking facilities in terms of size and location (Zhang et al., 2015). In other words, parking facilities after AV implementations can be relocated to farther locations, which may enable cities to densify urban areas (Millard-Ball, 2019). Living in areas with higher density, greater connectivity, and more land-use mix has been associated with higher rates of active transportation (Saelens et al., 2003).

3.2.4 Travel Demand Model

A systematic review by Soteropoulos et al. (2019) identified 37 studies that quantified AVs' impacts on travel behavior and land-use. Five published studies employed travel demand models for the quantification of AVs' impacts in cities (Childress et al., 2015, Wang et al., 2018, Zhao and Kockelman, 2018, Friedrich et al., 2019, Auld et al., 2017, Zhang et al., 2018). These studies employed either activity-based demand models (Wang et al., 2018, Childress et al., 2015, Auld et al., 2017, Kim et al., 2015) or four-step travel demand models (Zhao and Kockelman, 2018).

Different scenarios were defined, based on assumptions regarding AVs' implications, and examined to uncover AVs' impacts on the system by comparing with the base scenario: no vehicle automation. Childress et al. (2015) defined AVs' implementation scenarios in terms of roadway capacity, user VOT, and parking costs. Four scenarios were defined to explore AVs impacts: (1) increase in capacity (30 percent); (2) increase in capacity and changes in VOT (65 percent decrease in VOT for households with high VOT); (3) increase in capacity, changes in VOT, and reduction in parking cost (50 percent parking cost reduction); and (4) per-mile auto cost changes. Wang et al. (2018) considered changes in capacity (assuming 50 percent and 10 percent less space occupied by AVs), and a 65 percent decrease in VOT. Zhao and Kockelman (2018) examined the impacts of changes in the operating cost of vehicles, VOT, parking cost, and toll cost on VMT and system average speed after the implementation of AVs and shared AVs in Austin, Texas. A number of scenarios were defined to evaluate the sensitivity of VMT and speed to the changes. Kim et al. (2015) considered potential reduction in AVs operation cost and increases in capacity to define AVs' implementation scenarios. Auld et al. (2017) assumed changes in the base model in terms of VOT, road capacity, and intersection automation (no traffic signal).

The AVs' level of deployment and its distribution across travelers was considered in most of the previous studies. In the most simplified case, Childress et al. (2015) assumed a 100 percent adaptation rate of AVs. Auld et al. (2017) assumed different levels of AVs penetration rates and assigned vehicles to travelers randomly. Wang et al. (2018) assigned AVs to travelers based on trip, demographic and economic characteristics. This study assumed that households with an $80,000 or higher income, at least one child, one private car that could be replaced by an AV, and a daily commute equal to or greater than 20 km would adopt AVs.

The results of analyzing AVs' impacts on modal split and VMT were consistent in the previous studies where AVs implementation was shown to increase VMT and prompt a shift from public transit to AVs, the extent of which varies according to the study's assumption (Childress et al., 2015, Wang et al., 2018, Zhao and Kockelman, 2018, Friedrich et al., 2019, Auld et al., 2017, Zhang et al., 2018). On the other hand, inconsistent results regarding the changes in the total travel time in the system (vehicle hour traveled) were reported. This implies the sensitivity of travel demand model results to the assumption of AVs' implementation.

3.3. Pathways to Health

3.3.1 Motor vehicle crash risk

AVs' safety concerns are by far one of the most studied issues in the AV literature. AVs are equipped with automated driving assistance systems (ADASs) that can prevent crash fatalities and injuries. ADASs include but are not limited to collision avoidance (Naranjo et al., 2017), lane-keeping (Lee et al., 2014) and lane-change assistance (Luo et al., 2016), longitudinal speed assistance (Martinez and

Canudas-de-Wit, 2007), and intersection assistance (Liebner et al., 2013). In optimistic views, eliminating human error through an automated system is expected to reduce roadway crashes by 94 percent (NHTSA, 2018). Typical reasons include, in descending order, eliminating errors of recognition (e.g., inattention), decision (e.g., driving aggressively), performance (e.g., improper directional control), and non-performance (e.g., sleep). The potential safety benefits of AVs can be quantified in this context by addressing the potential impacts of ADAS technologies in eliminating driver error. Although traffic crashes with driver responsibility are anticipated to be prevented after the deployment of AVs, other safety issues may emerge (Kockelman et al., 2016, Litman, 2017, Yang et al., 2017). System operation failure (Koopman and Wagner, 2016), mixed-traffic safety issues (Virdi et al., 2019), overconfidence, and cybersecurity (Lee, 2017, Taeihagh and Lim, 2018) are some examples of the potential safety concerns of AV operations. We grouped the studies that quantified the impacts of AVs on roadway crashes at the system level into four categories based on the employed approach: target crash population, AV crash analysis, AV failure risk, and safety effectiveness of AVs. A large portion of the literature about AVs' safety impacts employed microsimulations for quantifications, which does not fit in the scale of the proposed framework and therefore these studies are not covered in this section.

Target Crash Population

AVs equipped with ADAS technologies have the potential to improve traffic safety and reduce a certain type of motor vehicle crashes (i.e., target crash population) based on the primary function of the AV technology. Rau et al. (2015) and Yanagisawa et al. (2017) proposed estimating the number of potentially preventable crashes by ADAS using three steps:

1. identify AVs' ADAS functions, automation levels, and operational characteristics;
2. breakdown the ADAS function into five layers of crash information, including crash location, pre-crash scenario, driving conditions, travel speed, and driver condition;
3. query the General Estimates System (GES) and Fatality Analysis Reporting System (FARS) crash databases from National Highway Traffic Safety Administration (NHTSA) and identify the preventable crashes.

Following these steps, Yanagisawa et al. (2017) showed that the total number of 8,676 fatal crashes in 2013 could be prevented by Level 4 (NHTSA definition (NHTSA, 2013)) AVs, while 2,792, 1,127, and 1,212 crashes could be prevented by Level 0 and 1, Level 2, and Level 3 AVs, respectively. This finding means that $197,801 million could have been saved from crashes in 2013 with Level 4 AVs.

Similarly, the AAA Foundation of Traffic Safety conducted research to find the potential safety benefits of selected ADAS and provide new estimates of the numbers of crashes, injuries, and deaths that such systems could potentially prevent based on characteristics of crashes that occurred on United States roads in 2016 (Benson et al., 2018). Three sets of ADAS technologies examined in this study were (a) forward collision warning (FCW) and automatic emergency braking (AEB), (b) lane departure warning (LDW), and lane-keeping assistance (LKA), and (c) blind-spot warning (BSW). The estimation results showed that 4,738, 4,654, and 274 deaths could have been potentially prevented by FCW or AEB systems, LDW or LKA, and BSW, respectively. These results represent the benefits that could be observed if all vehicles were equipped with ADAS technologies (i.e., 100 percent adoption rate), the systems functioned properly 100 percent of the time, and drivers were to take timely and proper action in response to warnings 100 percent of the time. All crashes were deemed “likely preventable” in the study and actually did occur under conditions in which the system had the ability and opportunity to act.

AV Crash Analysis

Due to limited market penetration, there are very few AV crashes; thus, very few studies have attempted to analyze crashes involving AVs. Favarò et al. (2017) analyzed the AV-involved crash reports in California. The crashes from September 2014 to March 2017 were used to assess the AV crash dynamics related to the most frequent types of collisions and impacts, crash frequencies, and other contributing factors. Based on the distribution of crashes locations, AV crashes occurred at intersections with more traffic conflicts. In addition, this study proposed that a statistically significant correlation exists between the number of miles AVs drive and the number of crashes.

Kalra and Paddok (2016) estimated the number of miles of driving that would be needed to provide clear statistical evidence of autonomous vehicle safety. They calculated the reliability of AVs (the probability of not having a failure) using a binomial distribution. They found that AVs would have to be driven hundreds of millions of miles and sometimes hundreds of billions of miles to demonstrate their reliability in terms of fatal and injury crashes. For example, it is expected that one fatal AV crash occurs after driving 275 million miles. Assuming a test drive of 24 hours a day, 365 days a year at an average speed of 25 miles per hour, 275 million miles would take about 12.5 years of driving. Therefore, test-driving alone cannot provide sufficient evidence for demonstrating autonomous vehicle safety.

AV Failure Risk

Before AVs find their way onto roads, the vehicle needs to be tested thoroughly to prevent any safety risks. System operation failure is one probable risk that AVs are encountering (Koopman and Wagner, 2016). Malfunctioning sensors, cameras, and computers can jeopardize the reliability of AVs and cause serious safety consequences in an automated environment (Bila et al., 2017). The failure rate of each component of AVs is synthesized in a study by Bhavsar et al. (2017). Failure probability of an AV involved in a crash with a non-autonomous vehicle (NAV) can be calculated by multiplying the risk of failure of AVs and the crash probability of NAVs. For example, lidar technology has a 10 percent failure risk based on a simulation study (Bhavsar et al., 2017). The failure of lidar technology would result in laser malfunction, minor motor malfunction, position encoder failure, overvoltage, short-circuit, and optical receiver damages that could be translated to the risk of crashes.

AV Safety Effectiveness

AVs may negatively influence a driver’s behavior when using conventional vehicles in mixed traffic situations by making them adopt unsafe time headways. Given the limitations of AVs on-road experiments and, consequently, scarcity of AV crash data, microsimulations are employed to capture the impacts of AVs on road safety. In this regard, surrogate safety measures (e.g., traffic conflicts and time to collision) have been used in the literature (Virdi et al., 2019, Papadoulis et al., 2019, Li et al., 2016). Wang et al. (2020) synthesized previous micro simulations and field experiments to find the effectiveness of various ADASs that can be used in connected vehicles (CV) and AVs, including intersection movement assist (IMA), curve speed warning (CSW), forward collision warning (FCW), adaptive cruise control system (ACC), automated emergency braking (AEB), lane departure warning (LDW), electronic stability control (ESC), blind-spot warning (BSW), lane change warning (LCW), pedestrian collision and mitigate (PCAM), left turn assist (LTA), and cooperation adaptive cruise control (CACC). The safety effectiveness of each technology was estimated using a meta-analysis on 89 studies. The safety effectiveness is presented in the form of the ratio of crashes that can be prevented with each ADAS technology and the total number of crashes. The authors designed a comprehensive assessment study to quantify the potential impacts of CV and AV on different crash types in using the estimated safety effectiveness. The result of their analyses showed that 3.4 million crashes could be prevented representing a significant reduction in crashes in each country, in descending order India (54.24%), Australia (51.55%), USA (48.07%), New Zealand(45.36%), Canada (44.71%), and the UK (40.95%).

3.3.2 Air Pollution and Emissions

Milakis et al. (2017) reviewed the potential impacts of AVs on air pollution and emissions. This study found that the potential reduction in traffic congestion and vehicle idling, more homogeneous traffic flows, reduced air resistance, changes in vehicle size and weight, increase in empty cruising to search for parking, and potential increases in travel demand and VMT after AVs' implementation are the key factors that can change TRAP levels after the implementation of AVs. According to this study, more efficient traffic flow will result in less traffic congestion and, consequently, less idle time of vehicles. The possibility of reducing headways between traffic flow will result in a reduction in air resistance of vehicles, thereby reducing energy consumption and emissions (Milakis et al., 2017). Also, given the improvements in safety, the vehicles can be manufactured in lighter weights, which would reduce vehicle emissions (Milakis et al., 2017). On the contrary, more and longer vehicle trips increase the VMT in the system, and thus vehicle emissions.

Taiebat et al. (2018) reviewed the literature on the potential environmental impacts of AVs as well as the interactions between AVs and the environment for four levels: vehicle, transportation system, urban system, and society. At the vehicle level, the review of the literature found that AV technology can reduce vehicle emissions by higher energy efficiency (as a result of less idling, fewer speed fluctuations, and self-parking), reduction in vehicle weights, and platooning. On the other hand, emissions can be increased after AV implementation, mainly because of higher speeds and potential aerodynamic shape changes. At the transportation system level, AVs' role in reducing congestion, promoting shared mobility, and decreasing crash and crash-related congestion can reduce vehicle emissions, while the potential increase in VMT, shift from transit, and unoccupied trips can increase vehicle emissions. At the urban system level, AVs have the potential to change land-use patterns and parking needs, which will impact emissions. Finally, society-level impacts of AVs refer to the impacts of AVs on the workforce by changing jobs and consequently travel patterns. For example, participating in activities while traveling can eliminate some trips and so reduce the VMT and emission in the system.

Based on Milakis et al. (2017) and Taiebat et al. (2018), we identified, reviewed, and summarized four relevant studies that quantified the impacts of AVs on air pollution and emissions. The quantifications of AVs' impacts on air pollution were conducted through various approaches; however, in all cases, estimations were based on the changes in transportation after AVs' implementation—i.e., traffic flow at the micro-level and VMT at the macro-level.

Stogios et al. (2019) used microsimulation to estimate AVs' impacts on greenhouse gas (GHG) emissions in terms of CO_{2eq}[†] in two sites in Toronto. Three different driving behavior scenarios were

[†] *CO_{2eq}: Equivalent unit carbon dioxide (CO_2) based on the global warming potential of different greenhouse gases.*

defined in the study—aggressive, default, and cautious—each with different micro-level driving behavior characteristics, including car-following and acceleration/deceleration parameters. These scenarios were then simulated using PTV's VISSIM micro-simulator software. The results showed that in a fully automated system, the aggressive driving scenario could reduce GHGs by 26 percent. However, cautiously programmed AVs to have the potential to increase GHGs by 35 percent.

Wang et al. (2018) conducted a macroscale chain modeling exercise consisting of activity-based travel demand modeling and modal split, traffic assignment, and emission modeling using MOtor Vehicle Emission Simulator (MOVES) to quantify the impacts of AVs and vehicle electrification on nitrogen oxides (NO_x), particulate matter with a diameter less than 2.5 ($PM_{2.5}$), and black carbon (BC) emissions. The study considered well-to-pump emissions for passenger cars in addition to pump-to-wheels emissions. The changes in travel demand and modal split were captured by taking into account the changes in the value of time (assumed 65 percent of conventional cars) and efficiency of vehicles, which was defined as the percentage of roadway occupied by AVs. Different scenarios for AVs with and without electrification were defined and examined considering the efficiency of AVs, fuel type, and their sources in the Greater Toronto and Hamilton area. Results showed that 4 percent more passenger car trips and 6 percent fewer transit trips were expected after AV implementation, assuming 50 percent of roadway capacity would be used by AVs compared to regular cars. Also, the vehicle kilometers traveled from private cars increased by 3.6 percent. As a result, the emissions from all air pollutants were estimated to increase in the AV scenarios compared to the base scenario. Specifically, NO_x emissions were estimated to increase by 8.6 percent and 6.8 percent, $PM_{2.5}$ emissions were estimated to increase by 9.5 percent and 8.1 percent, and BC emissions were estimated to increase by 9.5 percent and 8.1 percent, in the 50 percent and 90 percent efficiency scenarios (using 50 percent and 10 percent of road capacity), respectively.

Liu et al. (2017) investigated the impact of smoother driving of CAVs on volatile organic compounds (VOCs), carbon monoxide (CO), NO_x, sulfur dioxide (SO_2), and CO_2, and $PM_{2.5}$ emissions compared to conventional cars. In this context, the average driving cycles for different road classifications and traffic conditions proposed by the Environmental Protection Agency (EPA) were used to characterize the driving behavior of vehicles. It was assumed that the CAV driving cycles would be smoother, with less noise, due to fewer driving events. Therefore, the study used the spline method to smooth the driving cycles of conventional vehicles and simulating AV emission impacts. Next, vehicle emissions were estimated using MOVES considering the changes in speed that were extracted from driving cycles. As a result, smoothing of the federal test procedure cycle resulted in 5 percent reduction in VOC, 11.4 percent less $PM_{2.5}$, 6.4 percent less CO, 13.5 percent less NO_x, and 3 percent reduction in SO_2 and CO_2.

Using Austin link-based driver cycles (extracting them from the database of Texas-specific vehicle activity profiles), average reductions were 10.9 percent for VOC, 19.1 percent for $PM_{2.5}$, 13.2 percent for CO, 15.5 percent for NO_x, and 6.6 percent for SO_2 and CO_2 (Greenblatt and Saxena, 2015). Greenblatt and Saxena (2015) estimated the reductions in GHG emissions after autonomous taxi implementation. The assumed autonomous taxis were highly automated shared AVs with electric engines. The authors considered the potential future decrease in electricity GHG emissions, changes in vehicle size, and potential increases in VMT. They employed GHG intensity data from the National Academy of Science, vehicle occupancy per VMT from the Federal Highway Administration, right-sizing based on Nissan LEAF parameters, and annual VMT from the Energy Information

Administration. The GHG data were available for gasoline, gas, and electricity in terms of CO_{2eq}. The authors estimated that GHG emissions per mile in 2030 for an autonomous taxi would reduce by 87–94 percent compared to regular cars in the United States.

3.1 Public Health Impacts

Milakis et al. (2017) and Dean et al. (2019) conducted systematic reviews on AVs' impacts on public health. According to these reviews, no quantification studies exist in the context of AVs' health impacts, and rather, the nature of the previous discussions is speculative. In the following, a summary of the AVs impacts on public health is presented, and then the methodologies for quantifying the transportation health impacts are discussed.

Fleetwood (2017) introduced AVs as one of the most critical advancements in improving public health in the 21st century by highlighting AVs' contribution to preventing road causalities. AVs have the potential to promote public health by reducing crashes through eliminating driver error (Kelley, 2017), leading to safer driving behavior via technologies (Subit et al., 2017), or enforcing limits on driving violations (e.g., speeding and sudden lane changing) more efficiently by autonomous vehicle police (Al Suwaidi et al., 2018). A study on the United States crashes in 2012 showed that $27 billion in healthcare costs were attributable to roadway crashes, which may be saved with a 90 percent market penetration of AVs (Luttrell et al., 2015). Freedman et al. (2018) compared projected vehicle costs and safety benefits of private and taxi AVs in the form of saved quality-adjusted life-years based on microsimulations. The authors demonstrated the cost-effectiveness of AVs compared to regular cars. AVs may contribute to public health by mitigating congestion and improving the energy efficiency of traveling, which leads to less air pollution and associated diseases, although no quantification of these benefits currently exists (Hardy and Liu, 2017, Crayton and Meier, 2017). On the other hand, the induced transportation demand after AV implementation can be associated with adverse public health impacts by increasing air pollution and congestion through the potential increases in VMT (Lim and Taeihagh, 2018).

Although no study has quantified AVs impacts on public health, the health impacts of motor vehicle crashes (Briggs et al., 2016, Sohrabi and Khreis, 2020) and transportation-related air pollution (Khreis et al., 2016a, Mueller et al., 2018, Tainio, 2015) were estimated. Previous studies share similar methods for quantifying the health impact of air pollution, where the standard burden of disease assessment framework is used in the literature (e.g., (Mueller et al., 2016, Mueller et al., 2017, Mueller et al., 2018, Sohrabi et al., 2020, Tainio, 2015)). For air pollution, the inputs to the burden of disease assessment models include TRAP exposure levels, as well as the baseline mortality or disease rate in the studied region. Next, the relative risk (RR) of mortality or disease in association with the difference between current TRAP levels and the counterfactual TRAP exposure level is estimated using exposure-response function sourced from the best available and most relevant epidemiological or meta-analysis studies. Then, the attributable population fraction can be calculated based on the exposure level and RR. The burden of disease from crashes is, however, directly extracted from the road crash datasets (Briggs et al., 2015, Götschi et al., 2015). In previous studies, the burden of disease from transportation-related exposures was measured as the number of mortalities (Tobías et al., 2015), premature mortalities (Mueller et al., 2016), or morbidity in the form of disability-adjusted life year (DALY) (Götschi et al., 2015, Mueller et al., 2017, Mueller et al., 2018), as well as health care costs saved (Ling-Yun and Lu-Yi, 2016).

3.4. Health Equity

No quantification could be found in the literature regarding AVs' impacts on health equity. To evaluate the health equity implications of AVs, we first have to understand the health inequity created by transportation. The transportation impacts on health equity can be investigated by focusing on (1) the role of transportation to provide access for vulnerable users, and (2) the various health implications of transportation systems and infrastructure (see (Khreis et al., 2019a, Khreis and Nieuwenhuijsen, 2019)).

Transportation systems provide access and enable the movement of vulnerable user groups such as the elderly and young population and people with different disabilities, and help them access employment, goods and services, recreation, and healthcare, thus improving health equity. In this regard, AVs' impact on health equity is expected to be positive since they will have the potential to enable social inclusion by providing access to healthy food and medical care for people with different physical disabilities (Brooks et al., 2018, Pettigrew et al., 2018a, Pettigrew et al., 2018b). AVs will have the potential to provide mobility independence to people with both physical and intellectual disabilities (Bennett et al., 2019), prolong the independent living of elderly people, and consequently improve their health and well-being (McLoughlin et al., 2018). Reports by Shaheen et al. (2019), Ricci et al. (2019), and Zmud and Reed (2019) have discussed the aforementioned aspects of the relationship between AV and health equity in detail.

Transportation infrastructure, on the other hand, affects larger user groups and communities; thus, it may have a more prominent impact on the health outcomes discussed earlier (i.e., fatality and injury from crashes, premature mortality, and morbidity from air-quality-related diseases). Studies have long shown that low-income and ethnically diverse communities have a higher exposure to roadway risk and TRAP (Sohrabi and Khreis, 2020, Khreis and Nieuwenhuijsen, 2019). This effect can be attributed to several factors. First, low-income communities and ethnic minorities are located near high-capacity roadways (i.e., interstates and freeways). This is not a coincidence; in fact, the very purpose of highways in the 1950s and 1960s was to segregate the low-income and black communities. This promise has since held true; as the result of this urban policy, major cities were carved up, and low-income and ethnically diverse communities ended up being located near interstates and highways. As high-capacity roadways, interstates and highways experience higher volumes of traffic, thus increasing the probability of crashes and TRAP exposures. Being near this type of infrastructure increases the health inequity of low-income and ethnically diverse communities. For example, the ongoing study by Khreis et al. (2019b) found that the number of school children with asthma was much higher in low-income areas. Low-income communities also have poor roadway infrastructure, which again increases the roadway risk (Huang et al., 2010, Noland and Laham, 2018, Barajas, 2018). In this regard, it is not clear how AVs will affect health equity in low-income communities; this factor can only be speculated at this stage. In the travel demand review, we observed that AVs have the potential of increasing VMT in the system, which is probably not good news for low-income communities, considering that a lot of these trips will be taken through the high-capacity roadways near these communities. On the other hand, based on the review of literature on pathways to health, we observed that the implementation of AVs might help to decrease the number of crashes and TRAP; however, most of these studies have not accounted for the disproportionate impacts of these changes. In fact, low-income communities may not have the means to reap these benefits of AVs. 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 adverse health impacts to low-income and ethnic minority communities.

4. Discussion and Conclusions

4.1. Key Findings from the Literature Review and Discussion

In this study, we proposed a conceptual framework for estimating AVs' impacts on health and health equity based on the existing knowledge from the literature. To this end, we did an overview of the existing review paper on AVs' impacts and transportation HIA. The proposed framework translates the impacts of AVs on the transportation system into health outcomes through TRAP, and motor vehicle crashes at the system level. In essence, the changes in transportation after AVs deployment with defined adoption rates are measured using travel demand models. Then, the results will be used for quantifying the changes in TRAP and motor vehicle crashes. Finally, the health impacts associated with changes in motor vehicle crashes and TRAP after AVs implementation can be estimated using standard HIA methodologies. Stratification of the estimated health outcomes based on sociodemographic, economic, and geographic characteristics would give insights into health inequities in AVs' impacts.

The literature review effort showed that although the direction of AVs' effects on travel demand, mode share, and VMT is consistent across studies, the order of impact varies based on the assumptions of the travel demand models. Highly automated AVs [Levels 4 and 5 based on SAE (SAE, 2018)] are mainly considered for travel demand quantifications. AV impacts are quantified by incorporating a number of assumptions regarding VOT, operating cost, parking cost, adoption rate, capacity, and toll price based on AVs' potential impacts. Regarding the forecasting horizon of the previous studies, AV impacts are quantified either in the near future or by considering the existing system. Higher levels of uncertainties are expected for long-term predictions (Zmud et al., 2018). AV impacts are evaluated by transportation change scenarios to either model the transportation system of a city with AVs or quantify the sensitivity of transportation systems to AV impacts. Generally speaking, a more rigorous effort is required to define scenarios based on more accurate assumptions. Given the findings from the literature, we expect an inconsistent adoption rate in households with different demographics, travel behavior, knowledge of AVs, and interest in technology. This expectation implies the necessity of considering the AV adoption rate before attempting to quantify the impacts.

The literature quantifying AV impacts on two health risk factors was reviewed: motor vehicle crashes and TRAP. The previous quantifications of AVs' impact on motor vehicle crashes are suffering from the availability of empirical data. In other words, AVs have not been driven enough, so there is insufficient data for evaluating their safety impacts. Estimating AVs' target population of crashes is introduced as a practical approach for evaluating AVs' impacts on motor vehicle crashes. This approach can estimate the optimistic safety impacts of AVs and does not consider the potential factors that may impact the risk of crashes, namely safety issues in mixed-traffic (interaction between AVs and human-driven vehicles), changes in VMT (exposure to the risk of crashes) and location-specific characteristics (e.g., road geometry and intersection characteristics). The AVs' safety effectiveness based on a meta-analysis of the microsimulations showed more accurate estimations regarding the AVs' health impacts, which accounts for the AVs' operational characteristics (e.g., in mix-traffic conditions). In addition, the AV operation pertains to the accuracy of the sensor. A sensor malfunction can be seen as a factor that can increase the risk of crashes and the uncertainties in AV safety impacts.

Previous studies have quantified the vehicle emission impacts of AV adoption across a range of GHG emissions and air quality pollutants. However, most of the previous studies were based on microsimulations of a limited roadway network. To be able to capture the transportation system and urban system-level impacts of AVs, macro-level simulations are required. Previous macro-level studies lacked travel demand modeling of AVs and so the changes in traveling behavior and VMT. Given that changes in VMT can affect TRAP, estimating the emission impacts of AVs on the basis of travel demand modeling will result in more realistic system-level estimations. In addition, no study has translated estimated changes in vehicle emissions into changes in TRAP and associated health outcomes—a significant gap in the literature. To be able to conduct such a health impact assessment, the emissions and their dispersion into ambient air pollution concentrations need to be quantified across the studied area. Air pollution dispersion models could be used for this purpose and would enable estimating the spatial distribution of air pollutant concentration, and consequently, exposure, attributable health outcomes, and health equity.

The review of literature on AVs' impacts on health outcomes and health equity showed that very few studies had assessed these impacts, and those that do are speculative. Given the uncertainties in AVs' health and equity impacts, a comprehensive analysis of AV impacts on travel demand, safety, and air pollution is required to quantify the benefits and harms of automated vehicles on public health and health equity.

4.2. Conclusions and Future Research

Despite speculations regarding the AVs' impacts on public health and health equity, no study has formally quantified these impacts. This study proposed a full-chain health impact assessment framework to address this remarkable gap in the literature. To this end, we first investigated the mechanism of AVs' impact on public health and equity and proposed a conceptual framework for reviewing the relevant literature. Full-chain health and equity impacts assessment of AVs is a tool for quantifying the health and health equity impacts of AVs with an application in policy evaluations.

The proposed framework for AVs' health impact assessment through the changes in transportation at the system level has certain limitations. First, the focus of the proposed framework changes in transportation after AVs implementation, and so does not cover other potential impacts of AVs such as impacts on substance use in a vehicle (Rojas-Rueda et al., 2020). Second, the health impacts of AVs can be estimated through two pathways, motor vehicle crashes, and air pollution, among others (Sohrabi et al., 2019), which we do not address in this work. These pathways include noise, social exclusion, community severance, electromagnetic fields, jobs, stress, physical inactivity, contamination, greenhouse gases, and green area (Sohrabi et al., 2019). Third, we explored the changes in transportation at the system level, which means the proposed framework is designed to capture the macro-level changes in transportation. Therefore, the health impacts of micro-level changes in driving behavior and traffic flow cannot be quantified within this framework. Fourth, the intention of the proposed framework is not quantifying the equity impacts of AVs, but the health inequity caused by socioeconomic and sociodemographic factors. Fourth, the travel or driving behaver changes might be relatively short-term, while land use and infrastructure will be long-term changes. Long-term estimations by the proposed framework are required to capture the health impact of AVs through the changes in land-use and transportation infrastructure. Fifth, we discussed the critical importance of the model assumption in the results when quantifying AVs' impacts on motor vehicle crashes, TRAP and associated health outcomes. Similarly, the accuracy and validity of the estimation using the proposed model heavily depend on the assumptions and availability of data.

Quantifying the health impacts of AVs could be used for making more informed decisions about AVs supporting policies, increasing the public awareness of health impacts of AVs, and incentivizing the health and transportation sectors to intervene and contribute to policymaking and investments regarding AVs. The results can also be used to uncover the uncertainties in AVs' harms or benefits. Here are some of the potential benefits of the proposed framework, and results of the ensuing literature review:

1. a practical mechanism of AVs' health impacts which can be used as a research agenda for future studies,
2. a full-chain health impacts assessment framework for quantifying the health impacts of AVs at the system level, and
3. a review of the state of the art methods required for quantifying the AVs impacts.

There is a need for future research for implementing the proposed framework to assess the potential health and equity impacts of AVs. Also, Future studies can promote this framework by:

1. capturing broader impacts of AVs (e.g., on society) and translate it to publish health impacts,
2. extending the framework by incorporating other pathways through which transportation has impacts on public health, and
3. quantifying the health impacts of AVs at the micro-level.

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