Active Transportation and Community Health Impacts of Automated Vehicle Scenarios: An Integration of the San Francisco Bay Area Activity Based Travel Demand Model and the Integrated Transport and Health Impacts Model (ITHIM)

Center for Transportation, Environment, and Community Health
Final Report

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16. Abstract

This study evaluates the potential human health impacts from connected and autonomous vehicles (CAVs) scenarios in the San Francisco, Bay Area. The study concentrates on impacts derived from the effects of CAVs on travel demand, safety, and environmental emissions. The study combines an extensive literature review about the extent of such potential effects, authors informed assessments, as well as results from activity-based travel modeling to quantify the human health impacts of CAVs using the Integrated Transport and Health Impacts Model (ITHIM). Specifically, ITHIM estimates impacts considering changes in travel demand (e.g., vehicle miles traveled) and levels of physical activity. The results show significant opportunities for road traffic injury reductions, as well as the mitigation of environmental emissions. However, reduced physical activity from the mode shift to passenger vehicles (from active travel) could increase negative human health outcomes (e.g., diabetes and lung cancer). Moreover, the paper explores a set of scenarios that could mitigate some of the potential health-related risks associated with CAVs.

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Abstract

This project evaluates the potential human health impacts from connected and autonomous vehicles (CAVs) scenarios in the San Francisco, Bay Area. The study concentrates on impacts derived from the effects of CAVs on travel demand, safety, and environmental emissions. The study combines an extensive literature review about the extent of such potential effects, authors informed assessments, as well as results from activity-based travel modeling to quantify the human health impacts of CAVs using the Integrated Transport and Health Impacts Model (ITHIM). Specifically, ITHIM estimates impacts considering changes in travel demand (e.g., vehicle miles traveled) and levels of physical activity. The results show significant opportunities for road traffic injury reductions, as well as the mitigation of environmental emissions. However, reduced physical activity from the mode shift to passenger vehicles (from active travel) could increase negative human health outcomes (e.g., diabetes and lung cancer). Moreover, the paper explores a set of scenarios that could mitigate some of the potential health-related risks associated with CAVs.

Introduction and Background

Transportation plans and policies affect travel demand, travel frequency, mode choice, route selection, and even the places people choose to live or work. All of these affect the transportation system's externalities, ultimately impacting human health. In 2010, worldwide fatalities caused by motor vehicles exceeded those from dangerous illnesses such as malaria and HIV (Bhalla et al., 2014). In 2016, 1.4 million deaths were recorded due to road crashes and more than 4 million were attributed to air pollution (World Health Organization, 2006, 2018). However, these assessments may underestimate the total health impacts associated with motor vehicles as they only consider traffic injuries and air pollution-related deaths. Transportation-related impacts on human health are numerous, including physical activity levels, accessibility, noise pollution, and mental health.

From an environmental justice or social equity perspective, the distribution of those health impacts in society also matters. In the U.S., federal mandates require that metropolitan planning organizations (MPOs) identify and resolve disproportionately adverse health and environmental impacts of their transportation plans on minority and low-income populations (Singleton and Clifton, 2017). Consequently, there is a need to assess the health impacts of transportation decisions, and to develop long-term transportation plans and policies conducive to a sustainable, and equitable system. At the same time, such plans and policies should also take into consideration other changes in the system brought about by such factors as generational attitudes, new mobility options, and technological developments.

Connected and automated vehicles (CAVs) are a critical new development in the transportation system, and their full impacts are not yet well understood. Optimistic speculation suggests that CAVs will bring enormous health benefits through the prevention of crashes, emission and noise reduction, quality of life improvements (i.e., increased mobility and accessibility), and stress reduction (reduced driving burden) (Pettigrew et al., 2018b). However, other studies have concluded that these potentially safer and more comfortable vehicles will induce more trips, increasing vehicle-miles traveled (VMT) (Clements and Kockelman, 2017) and the associated externalities, including increased traffic congestion, decreased physical activity, and increased road crashes because of higher levels of exposure. Moreover, additional VMT might necessitate the building of more infrastructure, increasing construction emissions and costs, and changing land-use trends.

If appropriate regulations are in place, the health benefits from CAVs could be maximized under full market penetration, and their drawbacks could be minimized. Developing relevant regulations and obtaining public support requires a thorough understanding of CAVs and their system-level impacts (Pettigrew et al., 2018b; Rodier et al., 2018b). Because of their novelty, there is a lack of empirical data on user adoption behavior and vehicle operations across different CAV market penetrations. However, travel demand models, built on travel surveys that record individuals' daily travel activities and capture their willingness to pay for waiting and travel times, offer an alternative for planners, academics, and policymakers (Rodier et al., 2018b) to assess the impacts of CAVs.

In a recent study, the authors explored the impacts of fully CAVs (level 5, according to the National Highway Traffic Safety Administration (2019)) in the San Francisco Bay Area, using the Metropolitan Transportation Commission's activity-based travel model (MTC-ABM). The work

identified plausible scenario parameters for changes in roadway capacity, CAV passenger value of time (VOT), operating costs, and new auto travelers, assuming 100% market penetration (Rodier et al., 2018b). The study is unique in that it articulates the change in travel for a wide range of CAV scenarios and analyzes the variations in daily VMT, vehicle hours of delay (VHD), and mode shares. Building on this previous study, and contributing to the nascent body of literature on CAV's impacts, this paper estimates and presents the direction and magnitude of CAV impacts on human health from regional transportation scenarios in terms of three pathways: physical activity, safety, and emissions, considering changes in travel demand, safety features, and other operational characteristics of these vehicles. The work concentrates on these pathways or metrics as the most salient, given that it is beyond the scope of this research to perform a life cycle analysis of all the potential pathways for transportation and health.

The work begins with a critical literature review to understand CAV's potential impacts on travel demand, travel safety, and emissions. A summary of the lessons learned coupled with expert judgement allow for the characterization and quantification of potential changes in the (occurrence, generation) rates for different safety and emission-related mechanisms associated with CAVs (adjusted as a case study in the San Francisco Bay Area). To estimate CAV impacts on human physical activity, the work relies on the active travel mode share predicted by the travel model for a particular CAV scenario [5]. Next, the estimated travel impacts are evaluated with the Integrated Transport and Health Impact Modelling Tool (ITHIM) to quantify the potential effects on human health considering a wide range of diseases. Finally, the study discusses and assumes a few strategies to mitigate the potential health consequences of CAVs. The outcomes of this study are designed to shed light on the importance of health in the transportation sector, and to incentivize the public sector to contribute more to transportation decisions and regulations. Additionally, the study demonstrates the applicability of ITHIM with travel demand models to include health impacts from new mobility revolutions in future regional transportation plans.

Health Impacts of Connected Autonomous Vehicles

Literature about the impacts of CAVs on human health is scarce (Milakis et al., 2017), although public awareness about their potential benefits could ease their adoption and encourage society to accept relevant regulations (Pettigrew, 2017). Among the few works, (Crayton and Meier, 2017) studied the potential uncertainties associated with CAV impacts and presented an agenda summarizing CAV impact factors, including public health. A recent study by (Sohrabi et al., 2020) resulted in a framework in the form of a conceptual model consisting of a qualitative list of 32 pathways relating to transportation and human health, 24 of which were adverse health impacts that could be controlled by implementing suggested strategies such as electrifying CAVs, regulating urban development, and traffic demand management. The framework is comprehensive and can be used as a reference model for future transportation health impact assessments.

From a positive perspective, these vehicles are capable of minimizing road crashes and reducing fatalities through integrated automation and communication features. (Fleetwood, 2017) nominated CAVs as significant contributors to public health improvements in the 21st century because of possible road injury mitigation. Analyzing US 2012 crash data, (Luttrell et al., 2015) estimated $27 billion savings due to crash reductions with a 90% CAV market penetration. Next to safety, CAVs can contribute to human health and well-being by providing mobility for those individuals with disabilities who would be able to independently access healthcare services and other social opportunities (Bennett et al., 2019). Moreover, these vehicles can mitigate traffic-related stress by relieving congestion and smooth driving (Pettigrew et al., 2018a). Improved energy efficiency in CAVs lowers/eliminates detrimental emissions, leading to a major reduction in air pollution-related diseases (Crayton and Meier, 2017; Hardy and Liu, 2017).

On the other hand, convenient, independent and productive traveling by CAVs could also induce additional trips on the road that might offset the above-mentioned positive outcomes (Lim and Taeihagh, 2018). Additionally, it could encourage auto dependency in communities, hampering active transportation modes as well as public transit usage. This would eventually decrease individuals' physical activity, which would translates into several adverse health consequences (Crayton and Meier, 2017; Van Schalkwyk and Mindell, 2018).

Research studies with a focus on how CAVs influence human health are still rare, and most of are qualitative in nature. This paper contributes to the body of knowledge by conducting a critical study of CAVs' impacts on human health through three pathways (travel demand, safety, and emissions) and by presenting a detailed quantitative analysis of the potential health impacts through a case study.

The following section provides a critical understanding of the fundamentals behind CAV impact mechanisms through each pathway. According to the lessons learned, we estimate the range of impacts per each identified mechanism, adjusted for the case study.

Travel Demand and Physical Activity

Background

Physical activity is vital to maintaining a healthy lifestyle. Regular physical activity helps prevent obesity, reduces cardiovascular and heart diseases, as well as some cancers, and strengthens

bones and muscles, improving mental health, and eventually, contributing to longer living. Walking and biking are among the most accessible and safe means for regular physical activity (Health and Services, 2002). Thus, promoting active transport and multimodal travel can benefit human health by increasing the rate of physical activity in society for all ages. Recent studies analyzed the mechanisms by which CAVs may alter travel demand in the form of increased auto dependency and VMT, as well as decreased traveling by active modes and public transit. *(Childress et al., 2015)* used an activity-based model for the Seattle region to simulate CAV scenarios. When roadway capacity was increased by 30% with and without a 65% reduction in VOT (only for higher-income individuals), VMT increased by 3.5-5%, and average travel delay declined by 14.3-17.6%, respectively. An analysis for the Ann Arbor region in Michigan found a 2-28% increase in VMT when roadway capacity expands by 77%, and VOT reduced by 25% *(Auld et al., 2017)*. *(Levin et al., 2017)* simulated personal CAVs' impacts in the downtown area of Austin (TX) by increasing roadway capacity. The model also considered repositioning for parking and found that 83% of total vehicle trips in the peak period are due to repositioning for low-cost parking. Vehicle trips increased more than four times, and transit trips declined by 63%.

Overall, the simulation approaches for CAVs include increased roadway due to shorter headways and smaller vehicles (Ambühl et al., 2016; Lioris et al., 2017; Shladover et al., 2012); reduced in-vehicle VOT due to the eliminated driving burden (Batley et al., 2010; Ian Wallis Associates Ltd, 2014; Le Vine et al., 2015b); lower operation cost (due to reduced insurance and fuel costs as well as avoided labor costs in taxis) (Kohler, 2018; MacKenzie et al., 2014; Wadud et al., 2016); induced demand (new user groups who were not traveling before because of age (too young or old), disability or lower income) (Brown et al., 2014; Harper et al., 2016; Wadud et al., 2016); and the impacts of automated shared mobility services and parking patterns. The rest of this section elaborates on each approach; a more comprehensive review can be found at (Pettigrew et al., 2018b).

Increased Capacity

The efficient design and smooth driving of CAVs are expected to increase effective roadway capacity by enabling smaller vehicles and shorter headways. Moreover, safety improvements will lead to more efficient road capacity by reducing non-recurrent congestion due to accidents. (Shladover et al., 2012) conducted field tests and microsimulation modeling of CAVs and found increases in the roadway capacity ranging from 5% to 89%, with an increase in market penetration. (Ambühl et al., 2016) implemented reduced headway from two seconds to one half a second for AVs using a mesoscopic simulation model on a gridded network, and reported up to tripled network capacity. (Lioris et al., 2017) applied queuing models to simulate AVs with headways of three-fourths of a second on a small urban network. Results showed a doubling and tripling of roadway capacity and intersections, respectively.

Reduced In-vehicle VOT

Autonomous Vehicles eliminate the burden of driving and provide a more pleasant, comfortable trip due to the potential amenities inside the car. Passengers will be free to use in-vehicle time more productively by engaging in other activities in their vehicles.

There are a few studies to measure the VOT for passengers compared to the one for drivers based on stated preference surveys in different countries and for different travel purposes. One study in the U.K. found that the average ratio for passenger VOT compared to driver VOT is 63% for

commuter travel, 75% for other travel, and 78% for business travel (Wallis et al., 2014). A study in Australia indicated that the VOT for passengers is 75% of drivers, generally (Hensher, 1987). In Denmark, passenger VOT is 67% that of the driver ,and 82% when it was adjusted for the level of income (Fosgerau, 2007). This study did not report any significant differences in VOT by trip purpose. The numbers mentioned above are extrapolated from surveys that may or may not be transferable to the CAV passengers' experience.

Another category of studies examines the rail passenger's VOT while traveling with this public transit line. Only 13% of passengers in the U.K. were engaged in work and study, while 62% to 85% reported doing other non-work activities during their trip with rail transport. Another study by (Batley et al., 2010) in the U.K. found that the train passenger's VOT is more than 10 times that of a car. However, the level of comfort in an automobile (automated/non-automated) cannot equal that found in trains due to cars' greater motion dynamics (Le Vine et al., 2015a).

Induced Demand

CAVs will increase the travel demand as they provide mobility for the disabled, young, elderly, and low-income populations and any other individuals who may not have been able to drive before. This will contribute to more VMT and traffic congestion. Many studies attempted to estimate this increase using the 2009 National Household Travel Survey (NHTS) data. Two other similar studies by (Wadud et al., 2016) and (Harper et al., 2016) estimated the increase in vehicle trips for non-driving seniors (62 to 65 years and older). Both studies assumed the same travel rate for seniors as for younger drivers. (Wadud et al., 2016) estimated a 2% to 10% increase in VMT and (Harper et al., 2016) indicated a 14% increase in annual VMT in the U.S., assuming the same driving rate for working adults (age 19-64) with travel-restrictive medical conditions as for those without. (Schoettle and Sivak, 2015) conducted an online survey of young people (age 18 to 39) without a driver's license and revealed that four of the underlying reasons for not having driver's license would be eliminated in the presence of AVs which would contribute to a 10.6% increase in annual VMT in the U.S. population.

Operating Cost

Safer and potentially low-weight CAVs will tend to reduce the per-mile cost of operation. (Wadud et al., 2016) estimated a 60% to 80% reduction in insurance costs for CAVs due to safety improvements. Moreover, reducing weight for CAVs can reduce fuel consumption by 5.5%, which leads to lower operating costs (MacKenzie et al., 2014).

Shared Mobility Services

Passenger cars are parked 95% of the time, and even during peak hours, only 12% of them are on the road. This indicates that most of the time they are underutilized while occupying a space without providing service (Morris, 2016). New mobility services such as ridesharing and carsharing can change this trend, and yet, there are barriers against their widespread adoption. There are not often enough vehicles accessible to all users, and their marginal per trip-pricing is higher compared to private cars. It is speculated that CAVs can mitigate these barriers by being able to deliver themselves to demand requests and reducing the operation cost. This can boost utilization, reduce parking spaces, and provide almost the same level of mobility for people. (Fagnant and Kockelman, 2014) simulated an automated taxi fleet in an Austin-like city and calculated life-cycle energy and emission impacts, and showed reductions in energy use by 12%,

GHG by 6%, volatile organic compounds (VOC) by 49%, and carbon monoxide (CO) by 34%. However, it must be noted that new shared mobility services potentially increase VMT by attracting new user groups, as well as increasing empty mileage due to vehicle relocation. For a comprehensive literature review, the reader is referred to (Rodier et al., 2018a). The implementation of shared CAVs is outside the scope of this study.

Impact assessment

The San Francisco Bay Area MTC-ABM belongs to the CT-RAMP (Coordinated Travel-Regional Activity Modeling Platform) family of ABMs developed by Parsons Brinkerhoff. The MTC-ABM estimates the activities or day patterns that drive individuals' need to make travel-related choices in time and space, and are based on travel diary surveys (e.g., 2000 Bay Area Travel Behavior Survey, and other recent efforts). In the model, tours are the unit of analysis in a day pattern. A tour represents a closed or half-closed chain of trips starting and ending (in hourly increments) at home or at the workplace, and includes at least one destination and at least two successive trips. The MTC-ABM includes four mandatory tours (work, university, high school, and grade school), and six non-mandatory tours (escort, shop, other maintenance, social/recreational, eat out, and other discretionary). All individuals and their socioeconomic characteristics in the MTC study area are generated through a statistical process known as a population synthesis, which expands survey samples (e.g., 2000 Public Use Microdata Sample and 2010 Census data) of households to represent the entire population. The 2010 zone system includes 1,454 zones. Static network assignment includes the following periods: early off-peak (3 AM to 6 AM), morning peak (6 AM to 10 AM), midday (10 AM to 3 PM), PM Peak (3 PM to 7 PM), and off-peak late (7 PM to 3 AM).

The MTC-ABM runs iteratively and at each iteration, tour and trip lists are generated for all individuals within the sample. The selection of choices at each stage of the model depends on the individual's socioeconomic characteristics and the relative attractiveness of the choice. The generated individual trips are aggregated at the zonal origin and destination matrices and assigned to the network by mode (drive alone, shared rides, bike, walk, walk-transit, and drive-transit) and by period. After the assignment, the updated network variables such as traffic volume and speeds and later, travel times are calculated and stored as average loaded network files to be used for the next iteration. These new network values are used to derive zonal skims (e.g. in-vehicle travel time and wait time), which are subsequently input to the following model components: (1) trip generation by zonal accessibility log sums, (2) mode choice by the utility function, (3) trip distribution by mode choice log sum parameters, and (4) traffic assignment by the general cost function.

This study builds on the previous work that explored the travel demand impacts of CAV scenarios using the MTC-ABM (Rodier et al., 2018b). Based on the literature, and expert judgments, the scenarios included doubled roadway capacity; 25% reduction of in-vehicle value of time; 20% reduction in vehicle operating cost per mile; induced demand from people that could not drive before because of age restrictions or vehicle accessibility. See (Rodier et al., 2018b) for a detailed description of the scenarios, their implementation, rationale, analysis, and limitations. TABLE 1 shows the results of a scenario combining the aforementioned assumptions and is used as the basis of the current study. The results represent the base-case scenario, where all travel and network parameters are set to default values representing the transportation system in the year

2010. The results show that VMT increases by 10% along with a noticeable decrease in VHT and delay. The trip mode share shows an increase in the single-occupancy vehicles (SOV) mode with decreases in all others. This is because the travel opportunities and potential perceived benefits of CAVs make travelers more inclined to travel alone than to share rides, take public transit, or pursue active transportation. The research team then integrated these outputs with the ITHIM model to assess the health impacts of CAVs.

TABLE 1. CAV Combined Scenario Results

Measure	Value	Base Case	CAV Scenario
VMT (vehicle-mile)	Total Daily	186,680,784	204,827,275
	Change (%)	-----	10%
VHT (vehicle-hour)	Total Daily	5,141,012	4,914,833
	Change (%)	-----	-4%
Delay (vehicle-hour)	Total Daily	862,505	300,990
	Change (%)	-----	-65%
Mode share	SOV	11,616,115 (48%)	12,607,211 (52%)
	Change (%)	-----	9%
	Shared Ride	8,789,456 (36%)	8,550,862 (35%)
	Change (%)	-----	-3%
	Transit	1,176,641 (5%)	944,931 (4%)
	Change (%)	-----	-20%
	Walk\Bike	2,624,613 (11%)	2,324,475 (9%)
	Change (%)	-----	-11%
	Total Trips	24,206,825	24,427,479
	Change (%)	-----	1%

Travel Safety

Background

The WHO estimates more than 1.3 million deaths globally each year are due to road crashes, as well as 20-50 million injuries and disabilities. These rates are expected to double by 2030 without any responsive actions. More than half of all road traffic deaths happen among vulnerable road users: pedestrians, cyclists, and motorcyclists (World Health Organization, 2020). Serious non-fatal injuries can have a major impact on the survivors and their dependents' quality of life, and also pose a burden to society. Physical disability caused by road injuries limits individuals' activities and social participation. This brings psychological and economic consequences to the victim, and to others that might persist in the long-term (Weijermars et al., 2017).

Several innovations in vehicles such as seatbelts, airbags, and automated brake systems have reduced the number and severity of injuries; however, morbidity and mortality tend to increase with vehicle usage (Crayton and Meier, 2017). Many studies conclude that the proximal cause of over 90% of motor vehicle crashes is human error (Atiyeh, 2012; Barth and Boriboonsomsin, 2009b; Berry, 2010). Generally, human error is mediated through the PIJR (perception (P), interpretation (I), judgment (J) and reaction (R)) process. The National Motor Vehicle Crash Causation Survey (NMVCCS 2005-2007) derives the critical reasons behind human errors in driving by studying more than two million crashes nationwide (He et al., 2012; Matsumoto et al.,

2014). Descriptions of these reasons, along with the estimated proportion of crashes nationwide (Noy et al., 2018) are presented in FIGURE 1. It is also important to recognize that there are potential biases within the crash data, i.e., a major concern with police-reported traffic injuries is that of under-estimation of collisions.

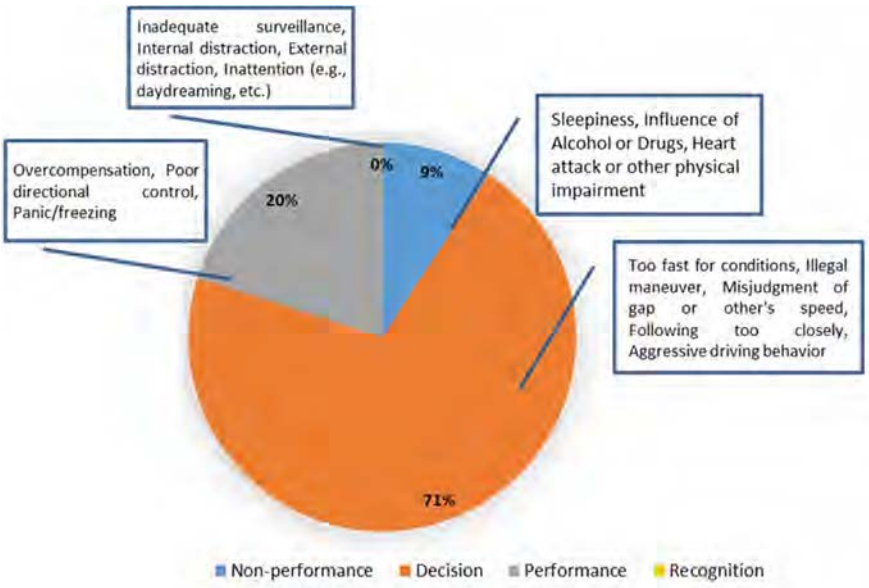


FIGURE 1. Critical driver-related reasons for road crashes in San Francisco Bay Area

In general, automated driving could reduce fatality rates to zero (Liu et al., 2017), but there are uncertainties associated with this claim and its underlying assumptions (Mensing et al., 2013):

1. **Human error is the result of misperception, misjudgment, or inappropriate behavior.** There may be other factors involved in the crashes labeled as human error such as poor roadway design and visual obstructions that induce human errors. Additionally, crashes can happen as a result of the human driver taking control of the autonomous vehicle. Approximately, 45% of the mileage driven by Google cars was in manual mode (i.e., with driver), and two crashes were reported (Jeong et al., 2017). Furthermore, 12% of crashes occur due to false assumptions about other drivers' behavior.
2. **Technology is error-free.** Software failures could exist with more catastrophic results than those that may occur on a desktop computer. There are no algorithms so far that cover all types of crashes that might happen with a CAV, as the current safety rules are defined based on human driver behavior, as there is not enough data or evidence on the CAV side. Moreover, object recognition on the road is more challenging for CAVs than for human drivers. Today, weather conditions and levels of light impact CAV detection and operations quality (Zhang et al., 2010).

As a result, fatality rate reductions may happen gradually as CAV technology progresses when vehicle manufacturers and software developers learn from previous experiences to enhance the system logics. New types of crashes might emerge, such as software failures, for which the prediction of occurrence rate will not be possible within the near future.

There are a few studies that measure the safety impacts of CAVs. (Jeong et al., 2017) evaluated the (cooperative) adaptive cruise control and the automatic emergency braking system for rear-end crash risk reduction by simulating both the vehicle and traffic stream maneuvering. Results indicated that increased market penetration leads to a significant reduction in rear-end crashes. In another study, (Xia et al., 2013) evaluated the effectiveness of the sensing capabilities of AVs in pedestrian fatality reduction. Results showed that CAVs can reduce pedestrian crashes via more expensive combinations of technologies, while the most affordable detection technology, cameras, is unlikely to be effective.

Impact assessment

Under a best-case scenario based on the literature review, the analyses consider that all human error crashes would be eliminated through vehicle automation and connection, which is equivalent to a 90% reduction of total crashes. In this case, the study assumed the technology to be error-free, and that any human error would be entirely the result of misperception, misjudgment, or inappropriate behavior. However, there are many exceptions to these assumptions, as discussed before, such as manual control by the human diver, misjudgment of other road participants' actions, and hardware and software failures. Nevertheless, in a full market penetration and the highest level of autonomy, all of the vehicles are expected to be connected and fully controlled by an automated system in all driving aspects. The analyses also assume that hardware failures are included in the remaining non-human error 10% crash rate. However, for software failure, it is expected that the impact on driving performance would be similar to non-performance crash causes, such as sleepiness, intoxication, heart attack or other sudden physical impairment, representing 9% of total human error crashes in the case study region (FIGURE 1). Accordingly, a 70% crash reduction rate is estimated as a lower bound safety effect, including software failure crashes.

Transport Emissions

Background

Vehicle emissions are an important source of air pollution, which causes several pollution-related human diseases, including respiratory infections, heart disease, stroke, and lung cancer. Air pollutants emitted into the atmosphere by vehicle combustion engines include CO_2, CO, NO_x, volatile organic compounds (VOCs) and particulate matters (PM), among others.

CO_2 has been described as the leading pollutant, making up roughly 99% of the total GHGs emitted from the tailpipe. A typical passenger vehicle emits about 4.6 metric tons of CO_2 each year. Asthma and Allergy Foundation of America states that CO_2 plays a catalyzer role in the process behind human allergies and symptoms. Moreover, ragweed, a flowering plant and an important source of allergens, grows faster and in larger volumes when CO_2 levels are high. As a GHG, it contributes to a warmer environment suitable for allergenic plant growth and climate change, which expands allergy season (Staudt et al., 2010). In an intense case, it can trigger asthma attacks as well (DerSarkissian, 2019). Overexposure to CO_2 by inhalation, particularly inside a vehicle or a closed space, causes adverse health impacts starting with dizziness, headaches, breathing difficulty, vomiting, vision problems and might end by heart attack, coma,

and death. CO_2 inhalation during long-distance vehicular travel impacts driving skills and decision-making, which might cause road crashes and injuries.

Particulate matters (PM)s are tiny solid or liquid particles suspended in a gas. Because of the size of the particles, they can penetrate the deepest part of the lungs and cause human diseases such as asthma, respiratory symptoms, chronic diseases, lung cancer, cardiovascular diseases, and premature deaths, particularly for children and elderly populations having preexisting heart or lung diseases (Babadjouni et al., 2017; Brook, 2008; California Air Resource Board, 2020; Kurt et al., 2016). In the U.S, transportation is responsible for less than 10% of $PM_{2.5}$ emissions (Environmental Protection Agency, 2012). There are two main sources of $PM_{2.5}$ emission in transportation: exhaust emissions and non-exhaust emissions. Exhaust emission is the result of engine-related processes, and emitted directly from the tailpipes of on-road vehicles. On the other hand, non-exhaust emissions include tire wear, brake wear (created by abrasion, corrosion, and turbulence) and suspension/resuspension of road dust. In addition to these two main sources, $PM_{2.5}$ is created by chemical reactions formed by precursor emissions such as SO_2, NO_x, VOCs, and NH_3, exiting through the exhaust stream of on-road vehicles (Mendoza-Dominguez and Russell, 2001). Measuring $PM_{2.5}$ emission from the latter source is difficult because the chemical process behind the formation of second-hand $PM_{2.5}$ depends on environmental conditions which vary regionally and seasonally, and many of the resulted products can fluctuate between particulate and vapor states, depending on the condition (Hodan and Barnard, 2004).

Exhaust emissions can be mitigated by employing eco-friendly technologies and alternative fuels (e.g. electricity, hydrogen fuel cell or compressed natural gas) in vehicles, however, brake and tire wear emissions depend on the building materials inside tires and brakes, as well as the road surface. It is estimated that non-exhaust emissions rise as vehicles depreciate, or as their weight increases. Besides, re-entrained fugitive dust from old unpaved roads contributes more to $PM_{2.5}$ formations due to the friction between vehicle tires and the road surface (Hodan and Barnard, 2004). Producing tires and brakes with eco-friendly materials, installing alternative electric brakes, improving the road pavements and maintenance, mitigating stop-and-go driving, and decreasing vehicle weights are among suggested strategies to reduce non-exhaust $PM_{2.5}$ emission from the transportation sector.

CAVs manufacturing and operational characteristics impact the amount of emission they generate compared to traditional cars. This work is only concerned with the operational phase of the vehicles, and does not include manufacturing, fuels and energy production, and end-of-life. The mechanisms enabled by CAVs impacting travel emission are summarized below:

Traffic congestion

Automation coupled with vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communications could improve traffic congestion and reduce fuel consumption/emission. Real-time route guidance or eco-routing could reduce system-level GHGs emissions by 5-10% (Rios-Torres and Malikopoulos, 2017), and energy consumption by 5% (for a plug-in electric vehicle) (MacKenzie, 2013). The previously discussed safety benefits of CAVs could also reduce congestion by 13%, considering that 25% of congestion is attributable to traffic incidents, around half of which are crashes (Robinson et al., 2010). Recent studies have estimated some of these impacts. (Duan et al., 2007) assumed a 75% congestion reduction (60% on the freeway, and 15% on arterials), which is equivalent to a 25% fuel consumption reduction due to better route choice,

lower road-train drag, and more optimal drive cycle in a 90% market penetration. (Barth and Boriboonsomsin, 2009b) estimated an increase in fuel economy and congested speeds within a range of 23–39% and 8-13%, respectively, for all vehicles on the freeway. (Schoettle and Sivak, 2015) assumed a 4% fuel consumption reduction by CAVs in 2050.

Eco-driving

Eco-driving is a driving approach where speed, acceleration, and braking are governed by fuel efficiency. Empirical studies show that eco-driving could reduce fuel consumption by an average of 10% to 20% for real-world and simulation experiments, respectively (Schito, 2012). Another study indicated a 35%-50% energy saving under an optimal driving cycle in heavily congested conditions (Berry, 2010; He et al., 2012). However, depending on the presence of other vehicles on the road, eco-driving could increase headway distance (Matsumoto et al., 2014), and the benefits would only be 15% (Mensing et al., 2013). (Wadud et al., 2016) also discusses that possible impacts depend on the eco-driving algorithms embedded into CAVs.

(Liu et al., 2017) simulated the emission impacts of CAVs and recorded emission reductions of CO_2 and $PM_{2.5}$ of 2-3% and 2-11%, respectively, for gasoline vehicles. For diesel cars, they estimated 2% and 10% reduction of CO_2 and $PM_{2.5}$, respectively. (Barth and Boriboonsomsin, 2009a) conducted a real-world experiment on a congested highway, resulting in a 13% fuel consumption and 12% CO_2 emission reductions. With the information from the road and infrastructure, the vehicles' predictive powertrain control functions could carefully select available gears (Vahidi and Sciarretta, 2018). (Zhang et al., 2010) estimated a 3-6% energy efficiency gain for a hybrid electric vehicle driving on hilly roads of California. CAVs could also improve efficiency by improving operations at the intersections with information about signal phase and timing (SPaT). Simulation studies reported a 6-25% network-wide energy efficiency gain under various conditions (Kamalanathsharma et al., 2015; Wang et al., 2016; Xia et al., 2013). Lastly, lane change and merging are complex driving decisions; microscopic simulation studies estimated 8 to 14% efficiency gain in lane selection (Dollar and Vahidi, 2018; Kamal et al., 2016), and 48% gain from yielding and merging (Rios-Torres and Malikopoulos, 2017).

Engine performance

Today's vehicles are capable of accelerating very rapidly, but at the expense of fuel efficiency. However, considering the connected system, CAVs may not need to experience this acceleration to improve energy efficiency. Assuming that acceleration rates stabilize at the current rate of 7.8 seconds (0 to 60 mph), (MacKenzie, 2013) estimated a 5% energy intensity reduction in the future. Moreover, they showed that dropping acceleration to 8.8 seconds (1982 levels) would lead to fuel consumption reductions of up to 23%.

Platooning

Platooning reduces fuel consumption and emissions through the reduction of aerodynamic resistance when multiple vehicles are closely following each other. Platooning benefits are realized significantly in tight formations which is unsafe without automation due to human drivers' longer reaction time to the speed changes of vehicles ahead. (Robinson et al., 2010) conducted simulations on three trucks following each other at a speed of 80 km and a distance of 4 meters in Japan, and found an average of 15% fuel consumption reduction. Another study, in Europe, considered the case where two trucks were followed by three passenger cars traveling

at 56 mph, at a distance of 4 meters. They found an average of 8% fuel consumption reduction for the leading vehicle, and 16% for the followers. In a longer platoon stream (five vehicles or more, separated by 0.5-1 vehicle length) 45-55% of average drag reductions have been reported (Duan et al., 2007; Schito, 2012). In the U.S., (Wadud et al., 2016) calculated an average energy saving of between 3-25% on U.S. highways for light-duty vehicles when platooning.

Travel speeds

Automation and cooperation allow CAVs to drive close to any posted speed limit regulated on the roads. On the other hand, faster and more efficient navigation and reaction times of CAVs make it possible for them to drive safely at higher speeds as well, thus they can provide the opportunity to increase the speed limit. Assuming drivers increase their speed until the marginal value of saved time equals the marginal cost of increased fuel consumption, (Wadud et al., 2016) calculated an increase in energy intensity within the range of 7-22% on highways for light-duty vehicles.

Vehicle size and weight

CAVs are expected to be smaller and lighter mainly due to the elimination of safety features (e.g. airbags, structural steel, and roll cages) as they become safer. (MacKenzie et al., 2014) predicted that this could reduce fuel consumption by 5.5%. On the other hand, additional installed features such as sensors and cameras or user convenience tools will add to both vehicle weight and size. Using the car weight increase rates from 1980 to 2010, (MacKenzie et al., 2014) estimated an 11% increase in fuel consumption in 2050, with a net impact of around 5.5%. Moreover, considering that around 98% of trips are single passenger vehicles in the U.S. there is an opportunity to right-size the fleet (though it is expected that CAVs will also foster shared mobility). Using current travel patterns, (Wadud et al., 2016) estimated the impact of right-sizing vehicle. If all private vehicle trips with 1–2, 3-4 and 5-7 travelers were met with compact cars, midsize cars, and minivans, respectively, energy intensity would decrease by 21%. Using smaller vehicles for single-occupancy trips reduces energy by 45%.

Fuel type

Alternative fuels, particularly electricity, hydrogen fuel cell or compressed natural gas, provide another opportunity to decrease energy intensity and emissions from the transportation sector. Although electrification, for instance, is not a requirement for CAVs, it could potentially be a sustainable pathway. Charging times and charging detours (distance to reach charging locations/stations) could potentially affect the efficiency and availability of the vehicles.

Parking

According to (Mitchell, 2007), half of the fuel consumed by cars in urban areas is due to cruising for parking. Additionally, parking has consumed vast amounts of land and resources in American cities to accommodate the billion parking spots across the United States (Litman, 2018; Plumer, 2016). CAVs are expected to revolutionize parking structures and needs. Shared CAVs also contribute to parking space reductions, particularly up to 67% in central business districts (CBDs) (Zhang and Guhathakurta, 2017). These erase the high expenditure and emissions associated with parking construction. V2I features in CAVs can intelligently direct cars to the closest available spot, thus, cruising for parking would be reduced. However, because of the increased travel

mileage to relocate for parking, the net effect might not significantly impact emissions and fuel consumption. Studies estimate the relocation share of total VMT to be 10-90% for personal AVs, and 10-20% for shared AVs (Rodier et al., 2018b).

Impact assessment

Here, we estimate final rates for emissions due to CAV features per each mechanism studied in the previous section. The majority of the rates derived by reviewed studies are in terms of fuel/energy consumption, however, according to (Barth, 2000; Barth and Boriboonsomsin, 2009b), CO_2 and fuel are linearly related. Thus, the same rate can be approximated to CO_2 emission as well. For $PM_{2.5}$, no particular trend was found to relate it directly to vehicle fuel/energy consumption. This is because there are other sources for $PM_{2.5}$, particularly tire and brake wear, in addition to operational fuel consumption. To estimate the change in $PM_{2.5}$, we made several assumptions. We assume that a change in CO_2 emissions is proportional to the change in VMT. To derive the change in $PM_{2.5}$ from CO_2, we used a linear relationship model between car VMT and air shed levels of $PM_{2.5}$ developed for the San Francisco Bay Area (**Eq. 1**) (Maizlish, 2016b):

$$PM_{2.5\,scenario} = PM_{2.5\,baseline} - (3.17 * \Delta VMT + 0.23)/1000 \quad (1)$$

Assuming a linear relationship between VMT and CO_2 emission, we replaced change in VMT with change in CO_2 emission estimated for each mechanism considering 9.3 μg/m^3 as the baseline value of the emission, according to ITHIM calibration database for the case study.

For the initial analysis in this study, all vehicles are assumed to be of gasoline type, wherever appropriate. According to the EMFAC database, 99% of LDVs on the roads will be gasoline in 2040.

Traffic congestion

For traffic congestion, 5-10% of system-wide fuel consumption reduction was estimated by (Rios-Torres and Malikopoulos, 2017) because of real-time routing. The elimination of total road crashes also contributes to congestion reduction by 13% (Robinson et al., 2010). According to prior 70-90% estimated crash reduction by CAVs, congestion reduces by approximately 11% in our scenario. Assuming a linear relation between congestion and travel speed (Barth et al., 1999), this leads to a 5.5% decrease in CO_2 emission based on emission–speed curves developed by (Atiyeh, 2012). The average travel speed (weighted by VMT) equals 23.5 mph for our travel model scenario.

Eco-driving

(Liu et al., 2017) estimated emission reductions of 2-3% and 2-11% for CO_2 and $PM_{2.5}$ considering smooth driving in gasoline cars for different types of facilities. In our scenario, 72% and 28% of VMTs are on highways and urban roads, respectively. Accordingly, a reduction of 2% and 4.5% in CO_2 and $PM_{2.5}$ were estimated considering smooth driving. We assume an additional 3-6% emission reduction due to road grade anticipation and speed adjustment at the top of these numbers. Due to V2I communication at the intersection, there is an opportunity for 6-25% emission savings referring to several studies on energy efficiency gained by accessing signal phase and timing information (Vahidi and Sciarretta, 2018). All of these together lead to an emission

reduction of 11-33% for CO_2 and 5-5.5% for $PM_{2.5}$. Here, the analyses assume that the impact of improved lane changes and merging strategies on energy consumption is negligible compared to their effects on road capacity, which is already included in the travel model.

Engine performance

For engine performance, a 5-23% emission reduction is estimated when boundaries correspond to stabilizing acceleration/deceleration rates at the current value and when reducing it to the level of 1980s vehicles.

Platooning

For platooning, we based our estimate on the fraction of energy wasted to overcome aerodynamic drag. This can be eliminated by AV driving. As we are considering full market penetration, the formation of longer platoons is possible. From the literature, we know that 45-60% of drag is reduced on highways through long platoon formation. In our case study, 70% of total VMT is on freeway facilities, and 85% on freeways and major arterials. (Kasseris, 2006) indicates that 50% and 75% of tractive energy is consumed to overcome drag on the U.S. Highway Fuel Economy Test cycle (up to 60 mph) and steady-speed travel at more typical highway speeds respectively (up to 75 mph). As we aim to increase travel speed on highways to 80 mph, we will increase the tractive energy consumption rate from 75% to 80%. Combining all of these, we suggest a fuel consumption reduction of 16- 41%. However, longer platoons may block/pause on/off-ramp traffic, causing traffic congestion and increasing emission/energy consumption in return. To take this into account, we reduce the already obtained absolute values by 50% (Yelchuru et al., 2014) to update the platoon reduction rate to 8-20% instead.

*Travel speed*s

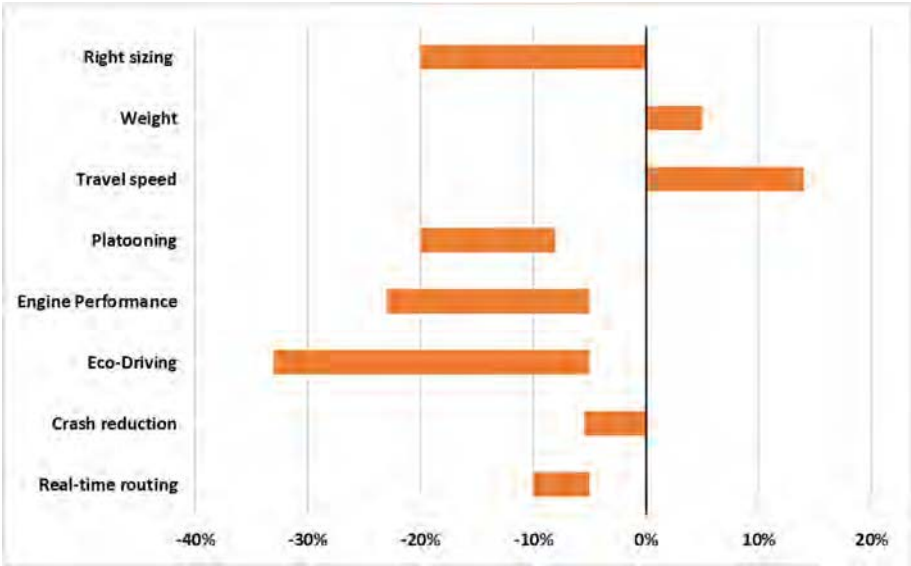
For the speed limit, an increase to 80 mph on highways is set in our scenario. This is equivalent to a 20% increase in vehicular emission. In the travel model scenario, 70% of VMT is on highways, thus emissions increase by 14%.

Vehicle size and weight

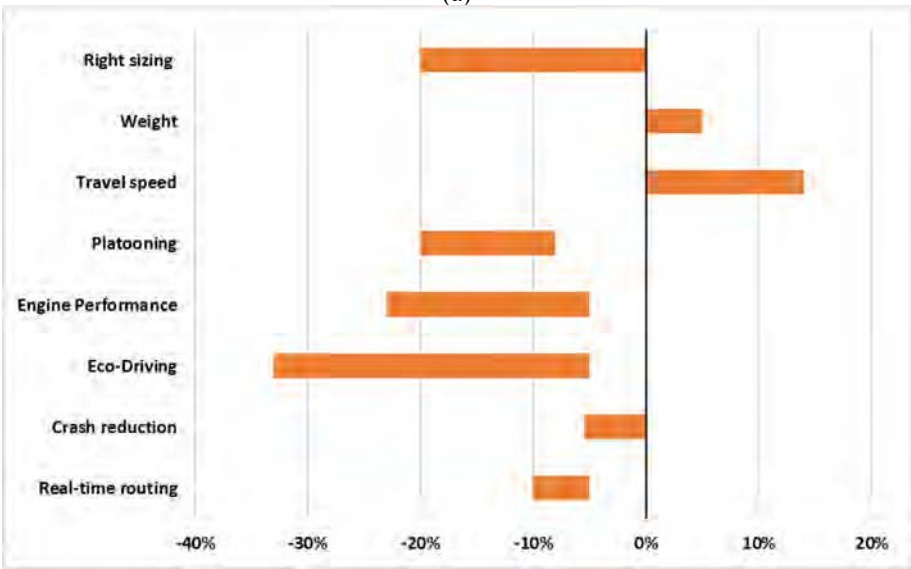
Combining additional convenience features and eliminating safety features leads to a net increase of 5.5% in vehicle weight. Assuming a linear relationship between vehicle weight and fuel consumption (Bandivadekar et al., 2008), this is equivalent to the same rate of increase in emission. In our travel model, 87% of total trips are by passenger cars. Hence, the final rate of increase in emissions is 0-5%. For right-sizing, all single and two passenger car trips are assumed to be replaced by two-seat cars, which are 29% lighter than an average car (compared to a Smart car). In our travel model, 70% of total trips are by single and two passenger cars. Then, the reduction rate in vehicle weight, as well as fuel/emissions, equals 20%. The study does not consider one-seat cars or transition to compact cars, as in our scenario all of the auto trips are made by personal vehicles, and safety is not the only factor impacting households' auto purchase decisions.

This study did not consider mobility services such as taxis, ride-sourcing, and carsharing, as well as cruising for parking. The authors conducted additional scenarios to analyze the impact of electrification of CAVs. The summary of the range of change rate in emission types per

mechanism is illustrated in FIGURE 2. The reader is referred to Appendix A for a summary of assumptions behind the potential impacts for each mechanism.



(a)



(a)

FIGURE 2. Summary of estimated ranges of operational emission impacts of vehicle automation through different mechanisms in the San Francisco Bay Area: (a) CO2; (b) PM.

Integrated Transport and Health Impact Model (ITHIM)

ITHIM, conceived in 2010, is an open-source tool that reflects the peer-reviewed science with a web-accessible engine capable of inputting calibration and scenario data to generate quantitative estimates of health impacts (Maizlish, 2016a; Maizlish and Siegel, 2012; Maizlish et al., 2013; Whitfield et al., 2017; Woodcock et al., 2009; Woodcock et al., 2013). The model has been used by large MPOs in California and has accurately predicted the health co-benefits of greenhouse gas mitigation strategies in their transportation sectors (Mueller et al., 2015). ITHIM considers physical activity, air pollution and road injuries in its assessments ,which are recognized as the main factors through which transportation can impact human health (Mindell et al., 2016). Specifically, ITHIM is based on comparative risk assessment methods, where a change in the disease burden, DB, as a result of a shift in the exposure distribution from a baseline scenario to an alternative scenario, is expressed by (Eq. 2):

$$\Delta DB = \frac{\int_{x_{min}}^{x_{max}} RR(x)P(x)dx - \int_{x_{min}}^{x_{max}} RR(x)Q(x)dx}{\int_{x_{min}}^{x_{max}} RR(x)P(x)dx} \times DB_{Baselines} \quad (2)$$

RR(x) is the relative risk at exposure level *x*, weighted by population distribution *P(x)* and *Q(x)* associated with baseline and alternative scenarios, respectively. DB represents the burden of disease measured in the unit of Disability-Adjusted Life Years (DALYs), which is a sum of Years of Life Lost due to premature death (Triantaphyllou) and Years of Living with Disability (YLD). For the baseline scenario, the DALYs were obtained from the Global Burden of Disease database for the U.S. in 2010 (Murray, 2013), and scaled to the Bay Area population-adjusted in age-gender strata by the ratio of the San Francisco Bay Area to US mortality for specific chronic diseases and road traffic injuries. ITHIM characterizes physical activity in quintiles of a lognormal distribution of per capita mean weekly active transport and non-transport time and its standard deviation. The active travel times for walking and cycling are weighted by metabolic-equivalent task hours to incorporate energy expenditures. To model exposure to air pollution, ITHIM uses population-weighted average airborne fine particulate matter $PM_{2.5}$ based on outputs from automobile emissions and air shed models calibrated for the Bay Area. *RR* of $PM_{2.5}$ is represented by the change in risk per microgram per cubic meter of $PM_{2.5}$. To estimate vehicular carbon emissions, ITHIM takes emission rates from the EMFAC database and multiplies by per capita car VMT and the scenario population. EMFAC emission rate is aggregated from cars and light trucks, estimated for each California region for a typical year. The EMFAC model takes into account the characteristics of the vehicle fleet, fuel type (gasoline, diesel, and electric), and operating conditions (Maizlish et al., 2013). In this study, we consider the year 2010 and 2040 as the base and AV scenario years, respectively.

Systematic reviews identified causes of mortality and morbidity that show strong evidence of an *RR*-exposure gradient for physical activity and air pollution. The causes impacted by physical activity include diabetes, dementia, depression, colon cancer, and breast cancer. Similarly, those impacted by air pollution include lung cancer, respiratory diseases and infections and inflammatory heart diseases. Three other causes are related to both physical activity and air pollution: stroke, hypertensive heart disease and ischemic heart disease (Maizlish et al., 2013).

ITHIM models road traffic injuries (RTI) in the baseline scenario as a rate for each pair of victim mode *i* and striking object mode *j* which can be a bicycle, pedestrian, motorcycle, car, bus, and truck. The injury rate, *R*, is the formulation (Eq. 3):

$$R = \frac{\sum Injuries_{0i}}{\sqrt{\sum Victim\ Mode\ Miles \times Striking\ Mode\ Miles}} \quad (3)$$

Where, R_0 is calculated in terms of injury per mile of travel for each possible pair of modes and segmented into different road facility and severity types. For both fatal and serious injuries, facility types are categorized as local, arterial, or highway. Baseline injury numbers were compiled from the Statewide Integrated Traffic Reporting System (SWITRS), 2006-2010. The predicted number of injuries for an alternative scenario is obtained by multiplying the baseline rate by the square root of the change in distances traveled by victims and striking vehicles on the roadway type. The square root is a central estimate of 'safety-in-numbers,' which describes the empirical observation that injury rates to pedestrians and cyclists decrease non-linearly as their mode share increases (Elvik and Bjørnskau, 2017; Jacobsen, 2015).

This study uses the California version of the ITHIM model implemented as spreadsheets in Excel. This model poses features that enable users to specify different calibration data sources (survey or travel models), developing and running various scenarios by altering independently the model variables and taking advantage of plotting tools and tables to summarize health outcomes.

CAVs impact travel demand, travel safety and travel emissions in a wide spectrum of ways, as noted in the previous section. These impacts affect human health through various diseases and disabilities as illustrated in FIGURE 3. The contribution of each transportation pathway to the majority of diseases is captured by ITHIM, however, there is a gap in modeling the potential health consequences of CO_2, such as allergies and eye diseases. This is a limitation for this study, and a potential direction for future work.

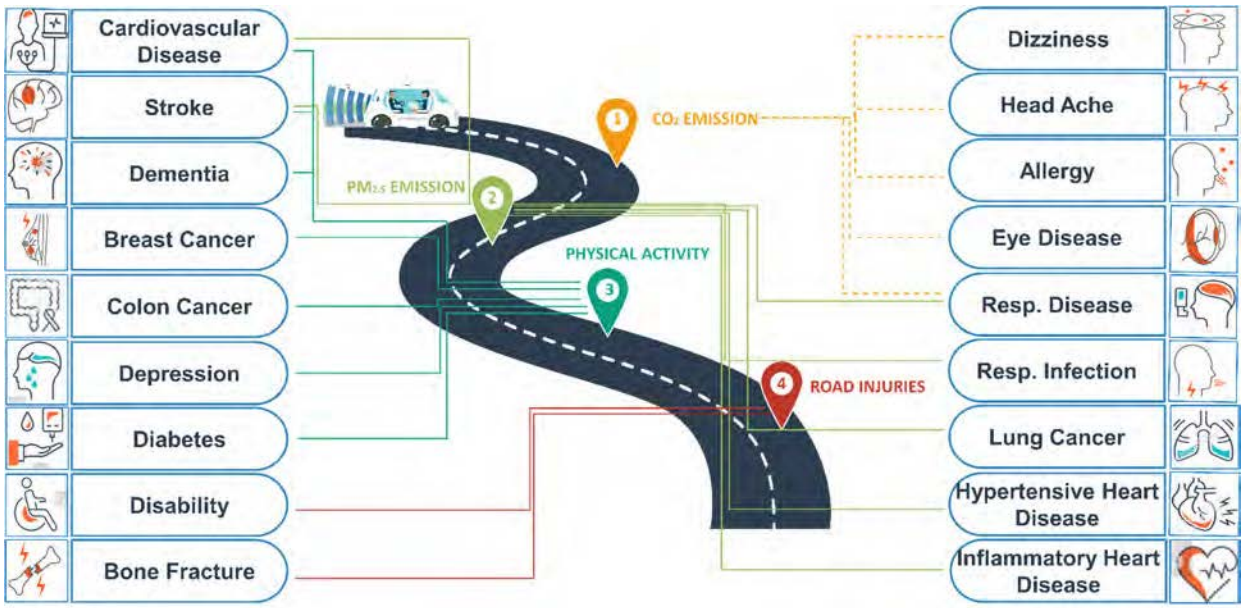


FIGURE 3. Projecting AV health effects on human diseases considering major transportation pathways: emission, physical activity, and safety

Health Impact Assessment: Empirical Results

To implement health impact assessments in ITHIM for a CAV scenario, we customized the model to our case study (San Francisco Bay Area) and estimated the impacts across three levels: travel demand, travel safety and travel emissions, referring to the findings from the previous section. We prepared ITHIM inputs by extracting travel times and distances per facility type and mode from the AV scenario. To this aim, several code scripts in R, Python, and Cube language were written and executed over trip lists and loaded network files from the travel model. Coupled with these, several scenarios were developed implementing estimated safety and emission impacts on car safety risk ratios and emission calculations, respectively. The reader is referred to Appendix B for a description of the files and processes to integrate the results from the MTC-ABM model into ITHIM.

TABLE 2 shows the results for the various scenarios considering midpoints of the estimated range of change in emissions. Daily physical activity time for walking and bicycling decreased from the median of 8.2 and 0.4 minutes in the baseline to 7.2 and 0.3 minutes in the CAV scenario. On the other hand, daily travel time for the car driver and passenger individuals increased from 28.4 and 9.1 minutes to 32.2 and 9.5 minutes, respectively. The results also show significant reductions in CO_2 emissions brought about by CAV technology, whereas $PM_{2.5}$ emissions remain constant. This is because the change estimated for this emission type was negligible, and an increase in car VMT offsets the potential benefits from CAV operations.

TABLE 2. Predicted Emission and Per Capita Daily Travel Times by Travel Mode and Scenario

	Travel time (minute per day)					
Scenario	Walk	Bike	Bus	Train	Car (Driver)	Car (Passenger)
Baseline	8.2	0.4	1.7	1.6	28.4	9.1
AV	7.2	0.3	1.4	1.4	32.2	9.5
AV+50% AT	9.2	1.7	1.4	1.4	31.4	9.5
AV+10% AT	7.6	0.6	1.4	1.4	32.1	9.5
	CO_2				**$PM_{2.5}$**	
	Aggregate *(MMT/Y)*[1]		Per Capita *(MMT/Y)*		Mean per week *($\mu g/m^3$)*[2]	
Baseline	16.1		2.3		9.30	
AV	3.8		0.6		9.32	
AV+50% AT	3.7		0.7		9.30	
AV+10% AT	3.7		0.6		9.31	
EAV	0.0		0.0		9.34	

FIGURE 4 thru FIGURE 7 show estimated changes in DB as a function of change in physical activity and $PM_{2.5}$ emission levels for various scenarios. Compared with the baseline, decreased physical activity in the AV scenario could generate an additional 37 premature deaths and 773 DALY per year, particularly for diabetes and dementia (FIGURE 4). Together with $PM_{2.5}$ emissions, DALY increases by more than 900 with cardiovascular disease (CVD) and lung cancer representing a large portion of it (FIGURE 5 and FIGURE 6). Moreover, the burden resulting from road traffic injuries decreases significantly, avoiding 270-320 premature deaths and gaining more than 12-14 thousand DALY per year (FIGURE 7), primarily as a result of a decrease in car-car and car-pedestrian crashes on local roads.

Active transport (AT) increase scenarios

The results show that the substitution of active transportation by passenger cars due to CAV's travel advantages could lower physical activity levels, possibly leading to premature deaths and disabilities. Thus, future policies should focus on promoting active transport mode shares (e.g. pedestrian and bicycle facility improvement), and auto-alternative strategies (e.g. congestion pricing or tolls for cars) to counteract the health consequences in the era of automation. These policies could be leveraged by the fact that the perception of a safer and more environmentally friendly transportation system as a result of CAVs would encourage more walking and biking trips in the future. Two categories of policy implications can be considered. First category is by promoting active transportation:

1. Improving pedestrian and bicyclist facilities (e.g. providing protected bike lanes and bike parking racks) to encourage people to walk/bike for short distance trips and consider exercise as a daily routine.
2. Improving public transportation as many public transit riders are multimodal and access/egress the service on foot.
3. Developing partnership with new mobility services companies to provide bikes and scooters options in connection with transit or wherever is appropriate.
4. Supporting mixed land use pattern development wherever it is appropriate. This enables several key destinations to be within walking/biking distance from each other.

Second category is referred to auto shedding strategies:

1. Incentivizing city and region developers to reduce the size of parking spaces and impose appropriate pricing rates for storing cars in public and private parking structures.
2. Implementing congestion pricing or tolls on specific bridges and highways as well as zones.
3. Implementing high occupancy restrictions on specific facilities or zones.

To simulate the effects of active transport (AT) policies, we identified short SOV trips that could be made by walking (under 1.5 miles), and biking (between 1.5 and 5 miles). From these trips, a certain percentage (i.e., 10, and 50%) were replaced by active modes and reassigned to the network in the travel model to update VMT and VHT parameters.

The results of AT policy simulations showed the enormous potential of active modes in generating health benefits compared to the CAV scenario. An increase in active mode by a 50% rate saves DALYs and premature deaths, which entirely compensate for the generated DB caused by AV presence (FIGURE 4-FIGURE 6).

However, there is only a slight decrease in $PM_{2.5}$ caused DBs (FIGURE 5) because of walkers and bikers' higher respiration rate, which can offset the benefits from eliminated car trips. From a safety perspective, injuries and fatalities are increased, compared to the AV scenario (FIGURE 7). This is because pedestrians and bicyclists are increased in these scenarios, and have higher exposure to road crashes as vulnerable users.

FIGURE 4. Predicted annual change in the burden of disease from physical activity compared with baseline scenario, by cause of death and disability: San Francisco Bay Area

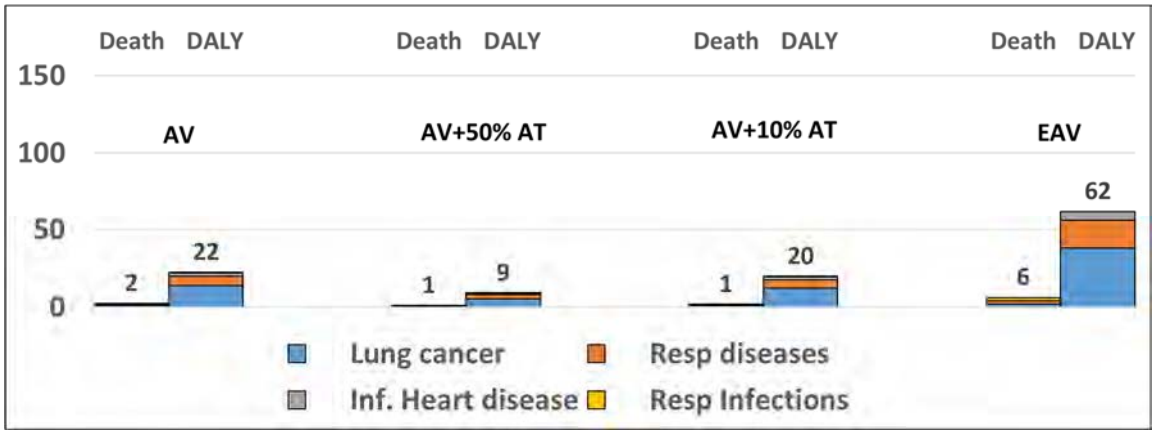


FIGURE 5. Predicted annual change in the burden of disease from PM2.5 compared with baseline scenario, by cause of death and disability: San Francisco Bay Area

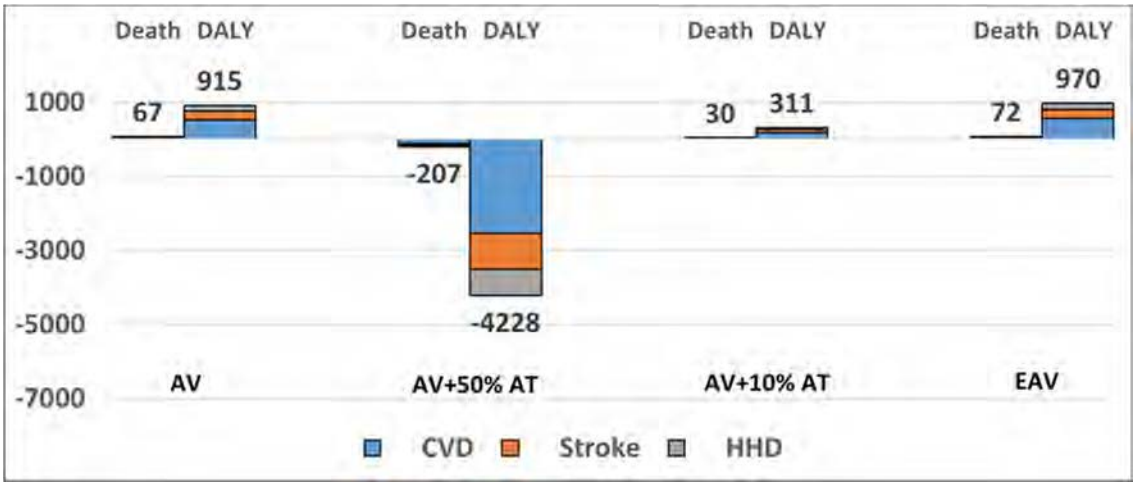


FIGURE 6. Predicted annual change in disease burden from physical activity and PM2.5 by scenario and cause of death and disability: San Francisco Bay Area

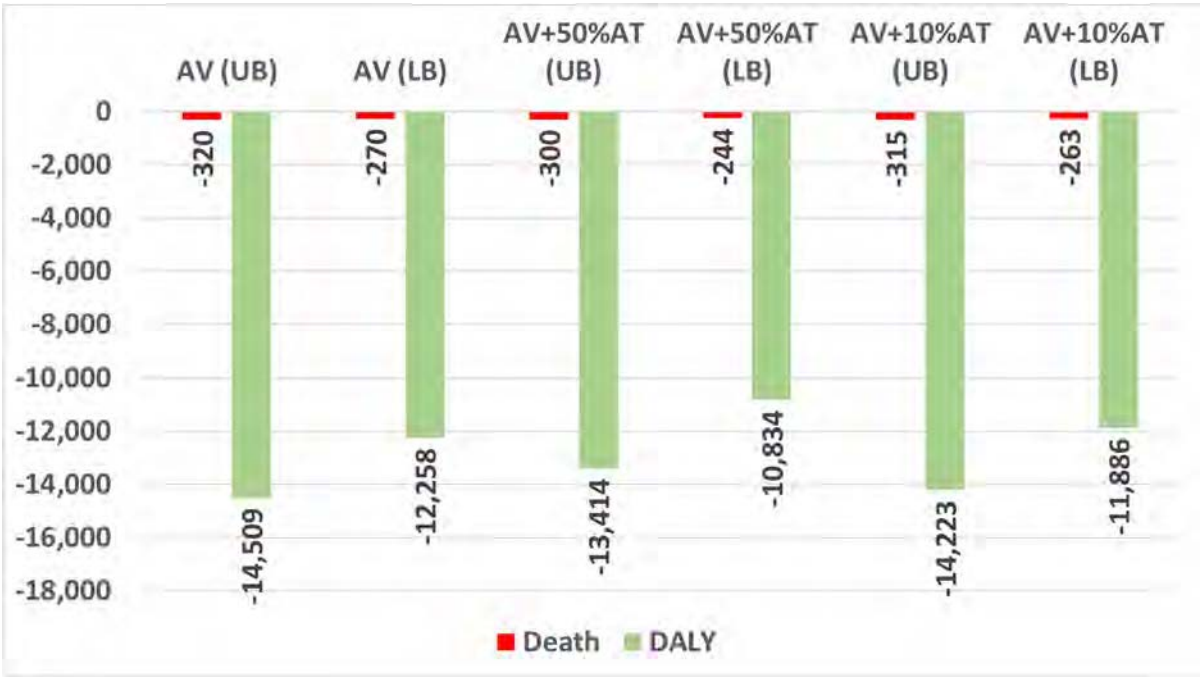


FIGURE 7. Predicted annual change in disease burden from road traffic injuries by scenario: San Francisco Bay Area

The reader is referred to Appendix C for additional active transport scenarios and results.

Electrifying AV scenario

Although we only considered gasoline vehicles in this study so far, the electrification of CAVs is indispensable due to the potential power budget issues these vehicles face in operation. Higher-voltage electrical architectures embedded in electric vehicles (EVs) can accommodate CAV power requirements to run their sensors, actuators, and computers (Offer, 2015). It is also speculated that AVs travel longer than conventional cars, which increases their fuel consumption in return. More efficient operation by electrification can also decrease maintenance costs (Murray, 2019). To simulate the impact of electrification in CAVs, we designed another scenario where all CAVs are assumed to be electric (EAV). EVs significantly eliminate exhaust tailpipe emissions (Office of Energy Efficiency & Renewable Energy 2020), and so we considered zero tailpipe emission rates for both CO_2 and $PM_{2.5}$. Among non-exhaust emission causes of $PM_{2.5}$, those attributed to fugitive dust from the road surface and secondary chemical reactions are not modeled in this study as there are several environmental and regional factors involved in their formation, making their measurement uncertain. Referring to EMFAC inventory (California Air Resource Board, 2017), in our case study about 74% and 10% of total daily $PM_{2.5}$ emissions from gasoline vehicles are due to brake and tire wear, respectively. Both of these are affected by vehicle weight (Bai, 2015). According to our estimates, AVs are 14% heavier (considering both vehicle weight and rightsizing effects). Also, the extra weight of the battery, fuel-cells, storage tanks, associated with electrification, increases the weight of a vehicle up to 20%, compared to a conventional vehicle (easyelectriccars, 2019). Eco-driving impacts brake wear as well, by allowing smooth driving and stop-and-go prevention. For eco-driving, we previously estimated a 5% reduction in $PM_{2.5}$ which impacts the emission from tire and brake wear in EAVs. Figures 5 and 6 show an increase in the

number of deaths and DALY from EAVs, which is particularly evident in lung cancer and respiratory diseases. This is due to the increased level of $PM_{2.5}$ emission (Table 2) in this particular scenario, where the $PM_{2.5}$ emission is risen from the considered non-exhaust sources as a function of the increased weight of EVs.

Generally, CAVs have the potential to significantly reduce CO_2 emission as well as road injuries. Although they increase DBs associated with lower physical activity and higher $PM_{2.5}$ compared to the baseline scenario, the health co-benefits of reduced road injuries appear to far exceed those harms. Excluding the safety impacts of AVs, increasing physical activity by replacing 50% of short SOV trips with walking and biking erases the AV-generated harms, and saves additional DALYs, despite a slight increase in $PM_{2.5}$-caused diseases. On the other hand, electrifying AVs significantly eliminates tailpipe emissions, while generating additional non-exhaust $PM_{2.5}$ due to heavier EVs on the road. This would triggers negative health consequences through increased rates in respiratory diseases and lung cancer.

Limitations

In this study, we used MTC-ABM to predict future travel behavior and network performance by customizing vehicle characteristics (e.g. operating cost and speed) and individual driver's choice preferences (e.g. the value of time) or restrictions (e.g. driver age). However, there are certain limits associated with this model and our estimates. The model: does not include new mobility services (e.g. ride-sourcing services, carsharing, and bike-sharing); active mode trips are underrepresented and their impacts on physical activity might be underestimated, as is the case with many travel models,; has limited parameters to represent induced demand by CAVs into individuals' choice decisions; and it cannot model empty trips by CAVs, which are speculated to be a major cause of traffic externalities in the era of automation. Understanding the potential effects of CAVs on the transportation system is challenging, as there is no observed data on their adoption, and no feedback from users of other transportation system stakeholders. Despite these limitations, travel models still provide insights, given that they are based on travel survey data, they can capture individuals' travel activities, their willingness to pay, and their willingness to endure waiting and travel times.

ITHIM is based on aggregated region-level travel data that relates the results of travel model scenarios (in terms of travel demand, mode share, VMT) into health outcomes. While ITHIM is appropriately matched to the purpose of this study, a more sophisticated version of the model is under development that is designed to overcome its limitations. The current model does not allow potential spatial variability analysis. While it provides insights on transportation's relation to human health, ITHIM requires more options to incorporate the various emission and safety features of vehicles. The model does not include CO_2-caused diseases or those related to other emission types, such as NOx. Moreover, changes in travel- related physical activity are not adjusted with respect to potential variations in non-transport physical activity. An ITHIM impact assessment is focused on safety, physical activity, and emissions, while transportation impacts human health on a much broader scale, including several other measures such as noise pollution and accessibility.

Estimated rates of change in travel demand, emissions, and safety in the presence of CAvs are only conducted for full market penetration at the highest level of autonomy. Several assumptions were made to develop estimates for emissions and safety, such as linearity between vehicle emission and energy consumption. Finally, a life cycle assessment of vehicle emissions is not considered in this work, and recommended for future work.

Discussion and Conclusions

This study investigates the potential human health impacts of CAVs concentrating on changes in travel demand, safety, and emissions with full penetration of CAVs in the San Francisco Bay Area. Different mechanisms of change were considered, and ranges of changes were estimated for each pathway through literature review and expert judgment. The estimated impacts were then implemented into MTC-ABM and ITHIM models. Several scenarios were also developed to contend with the large uncertainties surrounding CAV deployment and operations.

Overall, the results show potential for CAVs to benefit human health through road traffic injury reduction and emission , particularly CO_2, mitigation, However, experientially, the convenience of travel with CAVs would shift current active travel to these vehicles. Accordingly, a shift of 11% walk/bike trips to SOV would generate annual 773 DALYs for physical activity-related diseases (more importantly for diabetes and dementia), and average 915 DALYs in combination with $PM_{2.5}$ effects (mostly for CVD).

Additional scenarios considering an increase in active travel at the system level show that a 50% increase in active modes (shifted from car trips) could offset the negative impacts from CAVs. However, they could also slightly increase road traffic injuries, as well as air pollution. Electrifying AVs in the latter scenario demonstrated high potential for a decrease in exhaust emissions, but an increase in non-exhaust $PM_{2.5}$ emissions due to heavier EVs.

To simplify analyses, we assumed that scenarios and their health outcomes were implemented and achieved equilibrium in the baseline year of 2010. Based on previous modeling (Maizlish et al., 2017), selecting a future year that anticipates both demographic changes and reductions in disease rates does not materially alter the health outcomes. However, the phasing in of safety improvements that overlap between CAVs and traditional vehicles could mitigate our results.

Still, there is much uncertainty about the impacts of CAVs, and while this study has limitations, it provides insight into the human health impacts, under various scenarios. Moreover, the work shows how planners could enhance their travel demand modeling capabilities to conduct health assessment impacts with a tool such as ITHIM. ITHIM uses the outputs from demand models to estimate a wide range of disease burdens and road injury rates based on the resulting travel activity by the different modes.

The authors expect to update this study in future work to: 1) measure safety impacts from CAVs using microsimulation and incorporating available crash data for the case study; (2) estimate emission impacts following macrosimulation approaches for the case study; (3) incorporate additional health measures such as noise reduction and accessibility improvements from CAVs; and, (4) model CAVs' operations in the context of new mobility services (e.g., TNC), as well as parking patterns and behaviors.

References

Ambühl, L., Ciari, F., Menendez, M., 2016. What about space?: A simulation based assessment of AVs impact on road space in urban areas, *16th Swiss Transport Research Conference (STRC 2016)*. STRC.

Atiyeh, C., 2012. Predicting traffic patterns, one Honda at a time. MSN Auto.

Auld, J., Karbowskia, D., Sokolova, V., 2017. Assessing the regional energy impact of connected vehicle deployment. *Transportation Research Procedia. Retrieved from http://polaris. es. anl. gov/pdf/WCTR_CAV_paper_v2. pdf*.

Babadjouni, R.M., Hodis, D.M., Radwanski, R., Durazo, R., Patel, A., Liu, Q., Mack, W.J., 2017. Clinical effects of air pollution on the central nervous system; a review. *Journal of Clinical Neuroscience* 43, 16-24.

Bai, S., Du, Y., and Reid, S., 2015. Contributions of Tire Wear and Brake Wear to Particulate Matter Emissions Inventories for On-Road Mobile Sources *International Emission Inventory Conference* San Diego, California.

Bandivadekar, A., Bodek, K., Cheah, L., Evans, C., Groode, T., Heywood, J., Kasseris, E., Kromer, M., Weiss, M., 2008. On The Road in 2035: Reducing Transportation's Petroleum Consumption and GHG Emissions (Massachusetts Institute of Technology) Report No. LFEE.

Barth, M., 2000. An emissions and energy comparison between a simulated automated highway system and current traffic conditions, *Proceedings of the 2000 IEEE Intelligent Transportation Systems Conference,* , Dearborn, MI.

Barth, M., Boriboonsomsin, K., 2009a. Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D: Transport and Environment* 14(6), 400-410.

Barth, M., Boriboonsomsin, K., 2009b. Traffic congestion and greenhouse gases.

Barth, M., Scora, G., Younglove, T., 1999. Estimating emissions and fuel consumption for different levels of freeway congestion. *Transportation Research Record* 1664(1), 47-57.

Batley, R., Mackie, P., Bates, J., Fowkes, T., Hess, S., de Jong, G., Wardman, M., Fosgerau, M., 2010. Updating Appraisal Values for Travel Time Savings. *Report to the Department for Transport, UK*.

Bennett, R., Vijaygopal, R., Kottasz, R., 2019. Willingness of people with mental health disabilities to travel in driverless vehicles. *Journal of Transport & Health* 12, 1-12.

Berry, I.M., 2010. The effects of driving style and vehicle performance on the real-world fuel consumption of US light-duty vehicles. Massachusetts Institute of Technology.

Bhalla, K., Shotten, M., Cohen, A., Brauer, M., Shahraz, S., Burnett, R., Leach-Kemon, K., Freedman, G., Murray, C., 2014. *Transport for health: the global burden of disease from motorized road transport*.

Brook, R.D., 2008. Cardiovascular effects of air pollution. *Clinical science* 115(6), 175-187.

Brown, A., Gonder, J., Repac, B., 2014. An analysis of possible energy impacts of automated vehicles, *Road vehicle automation*. Springer, pp. 137-153.

California Air Resource Board, 2017. EMFAC2017 Web Database.

California Air Resource Board, 2020. Inhalable Particulate Matter and Health (PM2.5 and PM10).

Childress, S., Nichols, B., Charlton, B., Coe, S., 2015. Using an activity-based model to explore the potential impacts of automated vehicles. *Transportation Research Record* 2493(1), 99-106.

Clements, L.M., Kockelman, K.M., 2017. Economic effects of automated vehicles. *Transportation Research Record: Journal of the Transportation Research Board*(2606), 106-114.

Crayton, T.J., Meier, B.M., 2017. Autonomous vehicles: Developing a public health research agenda to frame the future of transportation policy. *Journal of Transport & Health* 6, 245-252.

DerSarkissian, C., 2019. Ragweed Allergy. WebMD.

Dollar, R.A., Vahidi, A., 2018. Predictively Coordinated Vehicle Acceleration and Lane Selection Using Mixed Integer Programming, *ASME 2018 Dynamic Systems and Control Conference*. American Society of Mechanical Engineers, pp. V001T009A006-V001T009A006.

Duan, K., McDaniel, C., Muller, A., Yokota, B., Kleissl, J., 2007. Effects of Highway Slipstreaming on California Gas Consumption. June.

easyelectriccars, 2019. How Much Do Electric Cars Weigh (with 10 examples).

Elvik, R., Bjørnskau, T., 2017. Safety-in-numbers: a systematic review and meta-analysis of evidence. *Safety science* 92, 274-282.

Environmental Protection Agency, 2012. Fast Facts: U.S. Transportation Sector Greenhouse Gas Emissions.

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies* 40, 1-13.

Fleetwood, J., 2017. Public health, ethics, and autonomous vehicles. *American journal of public health* 107(4), 532-537.

Fosgerau, M., 2007. Using nonparametrics to specify a model to measure the value of travel time. *Transportation Research Part A: Policy and Practice* 41(9), 842-856.

Hardy, J., Liu, L., 2017. Available Forward Road Capacity Detection Algorithms to Reduce Urban Traffic Congestion, *2017 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)*. IEEE, pp. 110-119.

Harper, C.D., Hendrickson, C.T., Mangones, S., Samaras, C., 2016. Estimating potential increases in travel with autonomous vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. *Transportation research part C: emerging technologies* 72, 1-9.

He, Y., Rios, J., Chowdhury, M., Pisu, P., Bhavsar, P., 2012. Forward power-train energy management modeling for assessing benefits of integrating predictive traffic data into plug-in-hybrid electric vehicles. *Transportation Research Part D: Transport and Environment* 17(3), 201-207.

Health, U.D.o., Services, H., 2002. Physical activity fundamental to preventing disease. *US Department of Health and Human Services, Office of the Assistant Secretary for Planning and Evaluation* 2002.

Hensher, D.A., 1987. Productive efficiency and ownership of urban bus services. *Transportation* 14(3), 209-225.

Hodan, W.M., Barnard, W.R., 2004. Evaluating the contribution of PM2. 5 precursor gases and re-entrained road emissions to mobile source PM2. 5 particulate matter emissions. *MACTEC Federal Programs, Research Triangle Park, NC*.

Ian Wallis Associates Ltd, W., 2014. Car passenger valuations of quantity and quality of time savings. NZ Transport Agency.

Jacobsen, P.L., 2015. Safety in numbers: more walkers and bicyclists, safer walking and bicycling. *Injury prevention* 21(4), 271-275.

Jeong, E., Oh, C., Lee, S., 2017. Is vehicle automation enough to prevent crashes? Role of traffic operations in automated driving environments for traffic safety. *Accid Anal Prev* 104, 115-124.

Kamal, M.A.S., Taguchi, S., Yoshimura, T., 2016. Efficient driving on multilane roads under a connected vehicle environment. *IEEE Transactions on Intelligent Transportation Systems* 17(9), 2541-2551.

Kamalanathsharma, R.K., Rakha, H.A., Yang, H., 2015. Network-wide impacts of vehicle eco-speed control in the vicinity of traffic signalized intersections, *Transportation Research Board 94th Annual Meeting*.

Kasseris, E.P., 2006. Comparative analysis of automotive powertrain choices for the near to mid-term future. Massachusetts Institute of Technology.

Kohler, C., 2018. This Woman Makes $17.50 an Hour Grocery Shopping in Her Free Time.

Kurt, O.K., Zhang, J., Pinkerton, K.E., 2016. Pulmonary health effects of air pollution. *Current opinion in pulmonary medicine* 22(2), 138.

Le Vine, S., Zolfaghari, A., Polak, J., 2015a. Autonomous cars: The tension between occupant experience and intersection capacity. *Transportation Research Part C: Emerging Technologies* 52, 1-14.

Le Vine, S., Zolfaghari, A., Polak, J., 2015b. The tension between autonomous cars' impacts on intersection level-of-service and their occupants' use of travel time for leisurely or economically-productive activities, *Proceedings of the 94th Annual Meeting of the Transportation Research Board, January 2015*.

Levin, M.W., Kockelman, K.M., Boyles, S.D., Li, T., 2017. A general framework for modeling shared autonomous vehicles with dynamic network-loading and dynamic ride-sharing application. *Computers, Environment and Urban Systems* 64, 373-383.

Lim, H.S.M., Taeihagh, A., 2018. Autonomous vehicles for smart and sustainable cities: An in-depth exploration of privacy and cybersecurity implications. *Energies* 11(5), 1062.

Lioris, J., Pedarsani, R., Tascikaraoglu, F.Y., Varaiya, P., 2017. Platoons of connected vehicles can double throughput in urban roads. *Transportation Research Part C: Emerging Technologies* 77, 292-305.

Litman, T., 2018. *Parking management best practices*. Routledge.

Liu, J., Kockelman, K., Nichols, A., 2017. Anticipating the emissions impacts of smoother driving by connected and autonomous vehicles, using the MOVES model, *Transportation Research Board 96th Annual Meeting*.

Luttrell, K., Weaver, M., Harris, M., 2015. The effect of autonomous vehicles on trauma and health care. *Journal of Trauma and Acute Care Surgery* 79(4), 678-682.

MacKenzie, D., Zoepf, S., Heywood, J., 2014. Determinants of US passenger car weight. *International Journal of Vehicle Design* 65(1), 73-93.

MacKenzie, D.W., 2013. Fuel economy regulations and efficiency technology improvements in US cars since 1975. Massachusetts Institute of Technology.

Maizlish, N., 2016a. Increasing Walking, Cycling, and Transit: Improving Californians' Health, Saving Costs, and Reducing Greenhouse Gases, *California Department of Public Health*.

Maizlish, N., 2016b. Integrated Transport and Health Impact Model (ITHIM): A Guide to Operation, Calibration and Integration with Travel Demand Models.

Maizlish, N., Linesch, N.J., Woodcock, J., 2017. Health and greenhouse gas mitigation benefits of ambitious expansion of cycling, walking, and transit in California. *Journal of transport & health* 6, 490-500.

Maizlish, N., Siegel, Z., 2012. Monetizing Health Co-benefits from Transportation Strategies that Reduce Greenhouse Gas Emissions in the San Francisco Bay Area, *Annual Meeting of the American Public Health, San Francisco*.

Maizlish, N., Woodcock, J., Co, S., Ostro, B., Fanai, A., Fairley, D., 2013. Health cobenefits and transportation-related reductions in greenhouse gas emissions in the San Francisco Bay area. *American journal of public health* 103(4), 703-709.

Matsumoto, S., Park, T., Kawashima, H., 2014. A comparative study on fuel consumption reduction effects of eco-driving instructions strategies. *International Journal of Intelligent Transportation Systems Research* 12(1), 1-8.

Mendoza-Dominguez, A., Russell, A.G., 2001. Emission strength validation using four-dimensional data assimilation: Application to primary aerosol and precursors to ozone and secondary aerosol. *Journal of the Air & Waste Management Association* 51(11), 1538-1550.

Mensing, F., Bideaux, E., Trigui, R., Tattegrain, H., 2013. Trajectory optimization for eco-driving taking into account traffic constraints. *Transportation Research Part D: Transport and Environment* 18, 55-61.

Milakis, D., Van Arem, B., Van Wee, B., 2017. Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems* 21(4), 324-348.

Mindell, J., Rutter, H., Watkins, S., 2016. Urban Transportation and Human Health. *Reference Module in Earth Systems and Environmental Sciences*, 578-589.

Mitchell, W., 2007. Smart Cities: Concept Car Project. Massachusetts Institute of Technology (MIT) Media Lab.

Morris, D.Z., 2016. Today's Cars Are Parked 95% of the Time. Fortune.

Mueller, N., Rojas-Rueda, D., Cole-Hunter, T., de Nazelle, A., Dons, E., Gerike, R., Goetschi, T., Panis, L.I., Kahlmeier, S., Nieuwenhuijsen, M., 2015. Health impact assessment of active transportation: a systematic review. *Preventive medicine* 76, 103-114.

Murray, C., 2013. The global burden of disease: Generating evidence, guiding policy. *Seattle, Washington: Institute for Health Metrics and Evaluation*.

Murray, C., 2019. Here's Why Autonomous Vehicles Will Need to Be Electrified. Designnews.

National Highway Safety Administration, 2019. Automated Vehicles for Safety. National Highway Safety Administration.

Noy, I.Y., Shinar, D., Horrey, W.J., 2018. Automated driving: Safety blind spots. *Safety Science* 102, 68-78.

Offer, G.J., 2015. Automated vehicles and electrification of transport. *Energy & Environmental Science* 8(1), 26-30.

Office of Energy Efficiency & Renewable Energy 2020. Reducing pollution with electric vehicles.

Pettigrew, S., 2017. Why public health should embrace the autonomous car. *Australian and New Zealand journal of public health* 41, 1-3.

Pettigrew, S., Fritschi, L., Norman, R., 2018a. The potential implications of autonomous vehicles in and around the workplace. *International journal of environmental research and public health* 15(9), 1876.

Pettigrew, S., Talati, Z., Norman, R., 2018b. The health benefits of autonomous vehicles: public awareness and receptivity in Australia. *Aust N Z J Public Health* 42(5), 480-483.

Plumer, B., 2016. Cars take up way too much space in cities. New technology could change that., *The new new economy*. Vox.com.

Rios-Torres, J., Malikopoulos, A.A., 2017. Automated and cooperative vehicle merging at highway on-ramps. *IEEE Transactions on Intelligent Transportation Systems* 18(4), 780-789.

Robinson, T., Chan, E., Coelingh, E., 2010. Operating platoons on public motorways: An introduction to the sartre platooning programme, *17th world congress on intelligent transport systems*, p. 12.

Rodier, C., Jaller, M., Pourrahmani, E., Bischoff, J., Freedman, J., Pahwa, A., 2018a. Automated vehicle scenarios: Simulation of system-level travel effects using agent-based demand and supply models in the San Francisco Bay area. National Center for Sustainable Transportation.

Rodier, C., Jaller, M., Pourrahmani, E., Bischoff, J., Freedman, J., Pahwa, A., 2018b. Automated Vehicle Scenarios: Simulation of System-Level Travel Effects Using Agent-Based Demand and Supply Models in the San Francisco Bay Area.

Schito, P., 2012. Numerical and experimental investigation on vehicles in platoon. *SAE International Journal of Commercial Vehicles* 5(2012-01-0175), 63-71.

Schoettle, B., Sivak, M., 2015. Potential impact of self-driving vehicles on household vehicle demand and usage.

Shladover, S.E., Su, D., Lu, X.-Y., 2012. Impacts of cooperative adaptive cruise control on freeway traffic flow. *Transportation Research Record* 2324(1), 63-70.

Singleton, P.A., Clifton, K.J., 2017. Considering health in US metropolitan long-range transportation plans: A review of guidance statements and performance measures. *Transport Policy* 57, 79-89.

Sohrabi, S., Khreis, H., Lord, D., 2020. Autonomous Vehicles and Public Health: A Conceptual Model and Policy Recommendation.

Staudt, A., Glick, P., Mizejewski, D., Inkley, D., 2010. Extreme allergies and global warming. *Reston: National Wildlife Federation*.

Triantaphyllou, E., 2000. Multi-criteria decision making methods, *Multi-criteria decision making methods: A comparative study*. Springer, pp. 5-21.

Vahidi, A., Sciarretta, A., 2018. Energy saving potentials of connected and automated vehicles. *Transportation Research Part C: Emerging Technologies*.

Van Schalkwyk, M., Mindell, J., 2018. Current issues in the impacts of transport on health. *British medical bulletin* 125(1), 67-77.

Wadud, Z., MacKenzie, D., Leiby, P., 2016. Help or hindrance? The travel, energy and carbon impacts of highly automated vehicles. *Transportation Research Part A: Policy and Practice* 86, 1-18.

Wallis, I., Ballantyne, J., Lawrence, A.J., Lupton, D., Weir, D., 2014. *Economic benefits of park and ride*. NZ Transport Agency.

Wang, Y., Zhang, D., Liu, Q., Shen, F., Lee, L.H., 2016. Towards enhancing the last-mile delivery: An effective crowd-tasking model with scalable solutions. *Transportation Research Part E: Logistics and Transportation Review* 93, 279-293.

Weijermars, W., Bos, N., Wijlhuizen, G.J., Meunier, J., Nuyttens, N., Dupont, E., Barnes, J., Brown, L., Quigley, C., Filtness, A., 2017. Physical and psychological consequences of serious road traffic injuries, Deliverable 7.2 of the H2020 project SafetyCube.

Whitfield, G.P., Meehan, L.A., Maizlish, N., Wendel, A.M., 2017. The integrated transport and health impact modeling tool in Nashville, Tennessee, USA: Implementation steps and lessons learned. *Journal of transport & health* 5, 172-181.

Woodcock, J., Edwards, P., Tonne, C., Armstrong, B.G., Ashiru, O., Banister, D., Beevers, S., Chalabi, Z., Chowdhury, Z., Cohen, A., 2009. Public health benefits of strategies to reduce greenhouse-gas emissions: urban land transport. *The Lancet* 374(9705), 1930-1943.

Woodcock, J., Givoni, M., Morgan, A.S., 2013. Health impact modelling of active travel visions for England and Wales using an Integrated Transport and Health Impact Modelling Tool (ITHIM). *PLoS One* 8(1), e51462.

World Health Organization, 2006. Night Noise Guidelines for Europe. WHO Regional Office for Europe, Copenhagen.

World Health Organization, 2018. Fact sheet: Ambient (outdoor) air quality and health.

World Health Organization, 2020. Road traffic injuries.

Xia, H., Boriboonsomsin, K., Barth, M., 2013. Dynamic eco-driving for signalized arterial corridors and its indirect network-wide energy/emissions benefits. *Journal of Intelligent Transportation Systems* 17(1), 31-41.

Yelchuru, B., Fitzgerel, S., Murari, S., Barth, M., Wu, G., Kari, D., Xia, H., Singuluri, S., Boriboonsomsin, K., Hamilton, B.A., 2014. AERIS-applications for the environment: real-time information synthesis: eco-lanes operational scenario modeling report. United States. Department of Transportation. Intelligent Transportation ….

Zhang, C., Vahidi, A., Pisu, P., Li, X., Tennant, K., 2010. Role of terrain preview in energy management of hybrid electric vehicles. *IEEE transactions on Vehicular Technology* 59(3), 1139-1147.

Zhang, W., Guhathakurta, S., 2017. Parking spaces in the age of shared autonomous vehicles: How much parking will we need and where? *Transportation Research Record* 2651(1), 80-91.

Appendix A. Summary of Impact Assumptions

TABLE 3. Summary of Estimated Safety and Emission Impacts from CAVs in San Francisco, Bay Area

Category		Lower Bound	Upper Bound
Safety	Crash	-70%	-90%
	Comments	All human error crash elimination, except non- performance category crashes as a representative of software failure in AVs *9% of crashes in Bay area are of non-performance category	All human error crash elimination
Real-time routing (eco-routing)	CO_2	-5%	-10%
	$PM_{2.5}$	-0.2%	-0.3%
	Comments	$PM_{2.5}$ calculated replacing VMT change by CO_2 emission change inside ITHIM $PM_{2.5}$ equation provided for Bay Area	
Crash reduction	CO_2	0	-5.5%
	$PM_{2.5}$	0	-0.2%
	Comments	1. 13% of congestion is due crashes. 2. AVs reduce crashes. This reduces congestion by average 11% considering safety improvement rates estimated before. 3. It is assumed that congestion reduction linearly increases travel speed 4. VMT weighted average speed of MTC CAV scenario network equals 23.5 mph, equivalent to 370 gr/mile CO_2 emission, following the emission-speed curves developed by (Barth and Boriboonsomsin, 2009b) 5. 11% increase in travel speed leads to 26 mph average speed equivalent to 350 gr/mile CO_2 (Barth and Boriboonsomsin, 2009b), in other words, 5.5% decrease in emission.	
Eco-driving	CO_2	-5%	-33%
	$PM_{2.5}$	-4.7%	-5.6%
	Comments	1. According to EMFAC database, 99% of LDVs on the roads are gasoline in 2040, thus we only consider gasoline fuel vehicle estimates from (Liu et al., 2017): 2. Urban drive cycle (CO2: -3%, PM2.5: -11%), Highway (CO2: -2%, PM2.5: -2%) 3. In MTC CAV scenario, VMT share on urban roads and highways equal 28%and 72%, respectively. 4. CO2: 0.72*0.02 + 0.28*0.03=-2%, PM2.5: -4.5% 5. 3-6% energy efficiency gain due grade anticipation (Vahidi and Sciarretta, 2018) 6. 6-25% energy efficiency gain due SPaT *(Vahidi and Sciarretta, 2018)*	
Engine performance	CO_2	-5%	-23%
	$PM_{2.5}$	-0.2%	-0.8%
	Comments	Fuel consumption reduction due to maintaining acceleration rate at current rates 7.8 second (MacKenzie, 2013)	Fuel consumption reduction due to maintaining acceleration rate at 1982 rates 8.8 second (MacKenzie, 2013)
Platooning	CO_2	-8%	-20%
	$PM_{2.5}$	-0.3%	-0.7%
	Comments	1. Considering full market penetration, long platoon formation by CAVs is highly possible. 45-60% of drag reduces on highways through long platoon formation. 2. 50% and 75% of tractive energy is consumed to overcome drag on the U.S. Highway Fuel Economy Test cycle (up to 60 mph) and steady-speed travel at more typical highway speeds (up to 75 mph), respectively. Assuming an increase in speed on highways to 80 mph requires an increase of tractive energy consumption rate from 75% to 80%. 3. In MTC CAV scenario, 70% of total VMT is on freeway facilities and 85% on freeways and major arterials: 4. LB: (0.45*0.7*0.5) = 0.16 UB: (0.60*0.85*0.80) = 0.40 5. Long platoons on real road highways may block/pause ramp traffic causing congestion, which in turn may increase emission. In order to consider this impact, we reduce the absolute values by 50% to update the platoon reduction rate to 8-20% instead.	
Travel speed	CO_2	0	14%
	$PM_{2.5}$	0	0.5%

	Comments	1. Increased speed limit (up to 80 mph on highways) is equivalent to 20% increase in fuel consumption 2. Here, we assume an increase of 20% on freeways and expressways; 3. In MTC AV scenario, 70% of total VMT is on freeway facilities 4. UB: 0.2*0.7 = 0.14	
Vehicle weight	CO_2	0%	5%
	$PM_{2.5}$	0%	0.2%
	Comments	1. There is 5.5% net increase in weight of passenger car (combination of additional convenience features and elimination of safety features) 2. In MTC AV scenario, 87% of total trips are by passenger car (DA, SR2 and SR3). 3. UB: 0.055*0.87 = 0.05 4. Fuel consumption is linearly related to vehicle mass *FC = 0.004m + 2.993	
Right Sizing	CO_2	0	-20%
	$PM_{2.5}$	0	-0.7%
	Comments	1. It is assumed that single and two passenger vehicle trips are replaced by a two-seat car as an upper bound impact 2. A two-seat car is 29% lighter than an average car (comparing to a smart car) 3. In MTC CAV scenario, 70% of VMT are single and two passenger car trips 4. UB: 0.7*0.29 = 0.20	

Appendix B. Integrating MTC-ABM Results into ITHIM

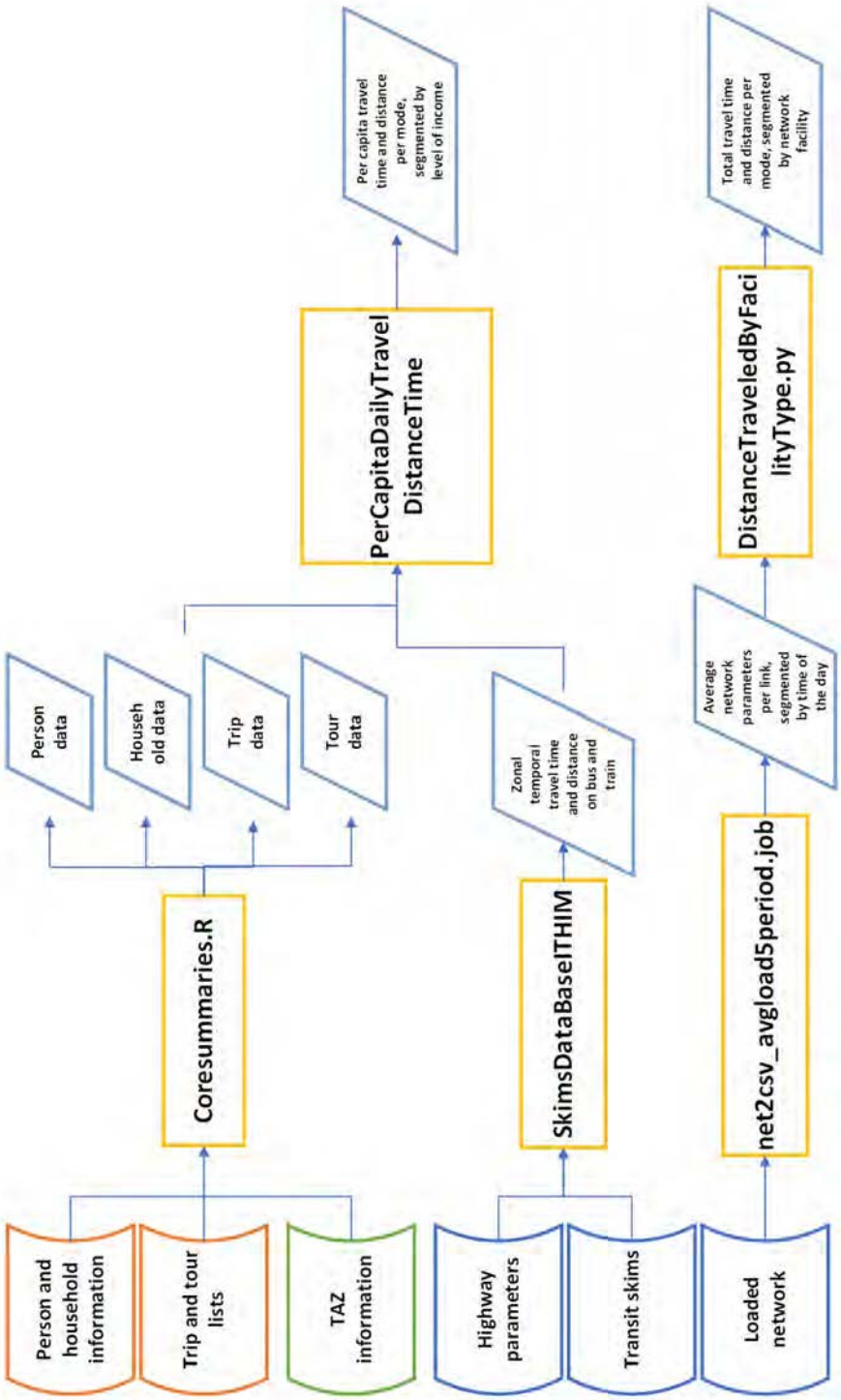


FIGURE 8. Integrating MTC-ABM Results into ITHIM

1. **Selecting and processing MTC-ABM data**

Person and household information: there are two files named by personData and householdData including attributes such as age, gender, employment type, and value of time per person in personData, and household size, auto ownership, and number of workers per household in householdData.
In MTC-travel model the files are in \main folder.
Trip and tour lists: there are individual and joint trip and tour files per iteration of travel model. These include information about travel time, purpose, mode, etc. per trip/tour including persons' IDs involving in the travel activity.
In MTC-travel model the files are in \main folder.
TAZ information: this is a unique file for case study including information about land use type, area, population, average parking cost, etc. per TAZ.
In MTC-travel model the files are in \INPUT\landuse folder.
Highway parameters: this is a unique file for case study including basic parameter values such as operation cost per mile for autos and trucks as well as average bike/walk speed.
In MTC-travel model the files are in \CTRAMP\scripts\block folder.
Transit skims: these files output the zonal transit travel parameters such as in vehicle travel time, distance, waiting time, transfer time, etc. for each daytime period, for various transit line types, combined with walk/drive access/egress, included in travel model.
In MTC-travel model the files are in \trn folder.
Loaded network: this is the output spatial network file from travel model assignment task including traffic volume, VMT, congested speed, etc. per link.
In MTC-travel model the files are in \hwy\iter folder.

2. **Creating ITHIM scenarios.**

After all the completion of the process illustrated in Figure 1, users must create a scenario in ITHIM, sheet 'Scenario Data' using outputs created by the process:

1. Scenario name_1_mode: per capita mean daily travel time for each mode in minutes
2. Scenario name_3_mode: per capita mean daily travel distance for each mode in miles
3. Scenario name_18: population forecast
4. Scenario name_18_mode_facilitytype: proportions of VMT per mode and facility type

For more information, it is referred to ITHIM documentation.

Appendix C. Additional Active Transport Scenarios

In addition to the combined CAV scenarios from MTC-ABM, and the potential estimated lower and upper bounds of each mechanism, a number of scenarios were designed considering an increase in the level of active transport.

TABLE 4 (expanding results from TABLE 2) shows the results for the additional scenarios.

TABLE 4. Predicted Emission and Per Capita Daily Travel Times by Travel Mode and Scenario

Scenario	**Travel time** (minute per day)					
	Walk	Bike	Bus	Train	Car(Driver)	Car(Passenger)
Baseline	8.2	0.4	1.7	1.6	28.4	9.1
AV scenario	7.2	0.3	1.4	1.4	32.2	9.5
AV scenario+50% AT	9.2	1.7	1.4	1.4	31.4	9.5
AV scenario+40% AT	8.8	1.4	1.4	1.4	31.6	9.5
AV scenario+30% AT	8.4	1.2	1.4	1.4	31.7	9.5
AV scenario+20% AT	8.0	0.9	1.4	1.4	31.9	9.5
AV scenario+10% AT	7.6	0.6	1.4	1.4	32.1	9.5

	CO_2		**$PM_{2.5}$**
	Aggregate *(MMT/Y)*[1]	Per Capita *(MMT/Y)*	Mean per week *($\mu g/m^3$)*[2]
Baseline	16.1	2.3	9.30
AV (UB)	2.1	0.3	9.31
AV (LB)	5.5	0.8	9.32
AV+50% AT (UB)	2	0.3	9.30
AV+50% AT (LB)	5.4	0.8	9.31
AV+40% AT (UB)	2	0.3	9.30
AV+40% AT (LB)	5.4	0.8	9.31
AV+30% AT (UB)	2	0.3	9.30
AV+30% AT (LB)	5.4	0.8	9.31
AV+20% AT (UB)	2	0.3	9.31
AV+20% AT (LB)	5.4	0.8	9.31
AV+10% AT (UB)	2	0.3	9.31
AV+10% AT (LB)	5.4	0.8	9.31

FIGURE 9 thru FIGURE 13 show the results of changes in annual disease burden for all active transport scenarios.

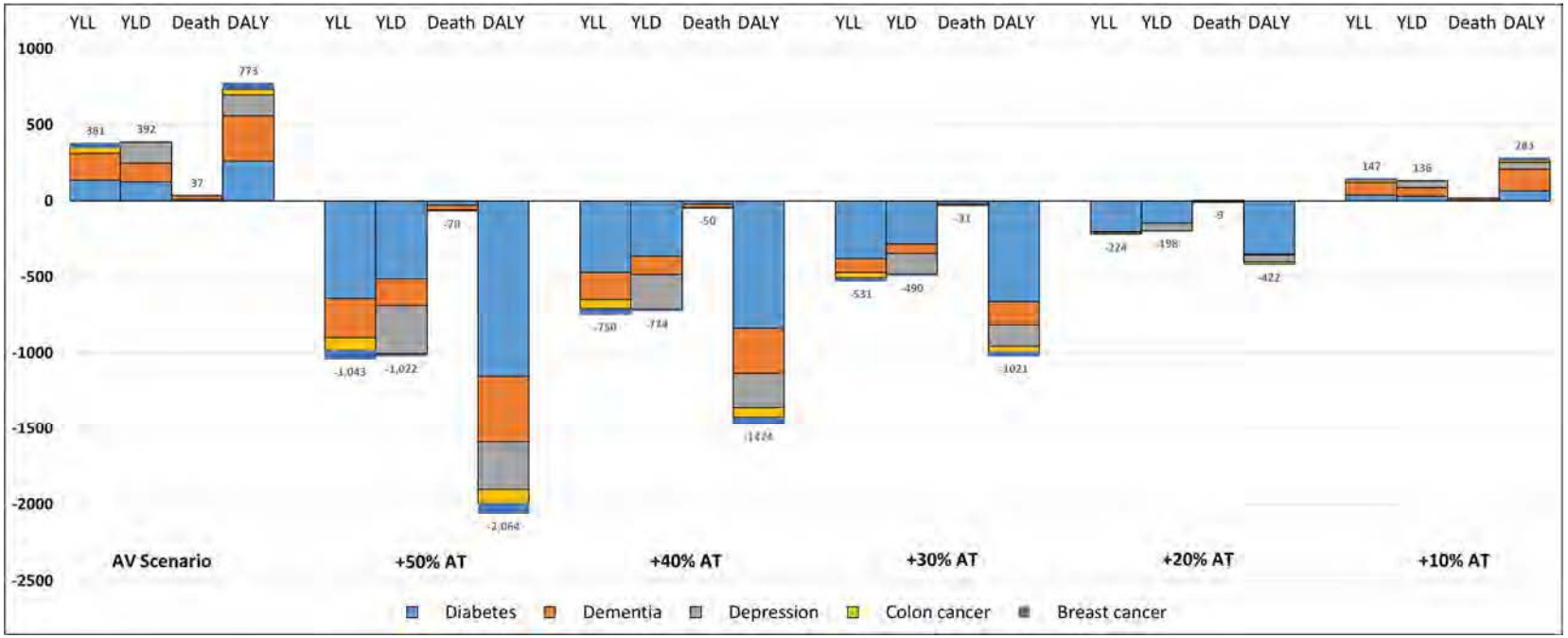
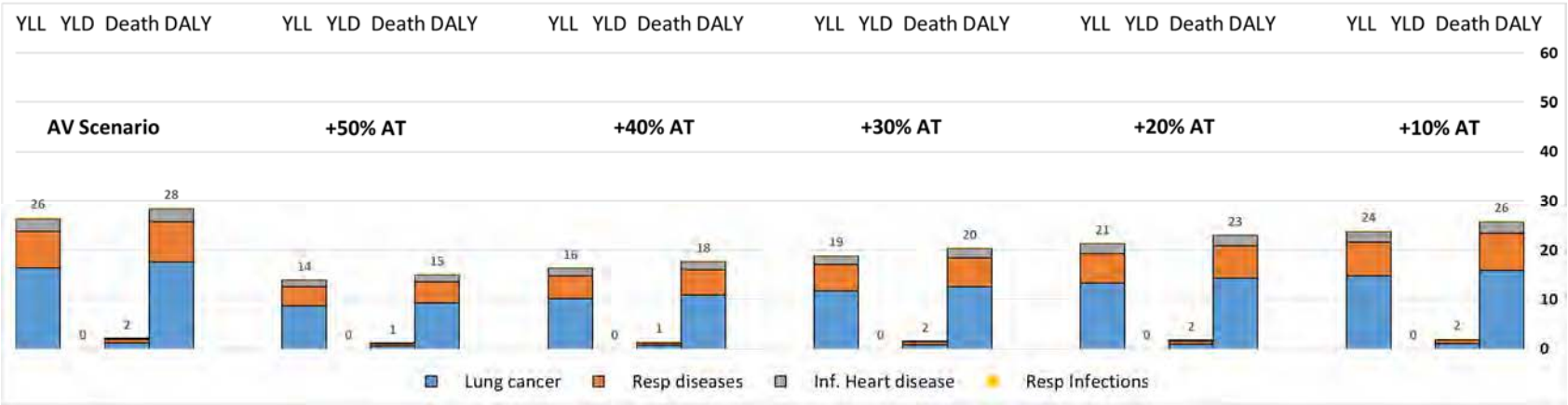
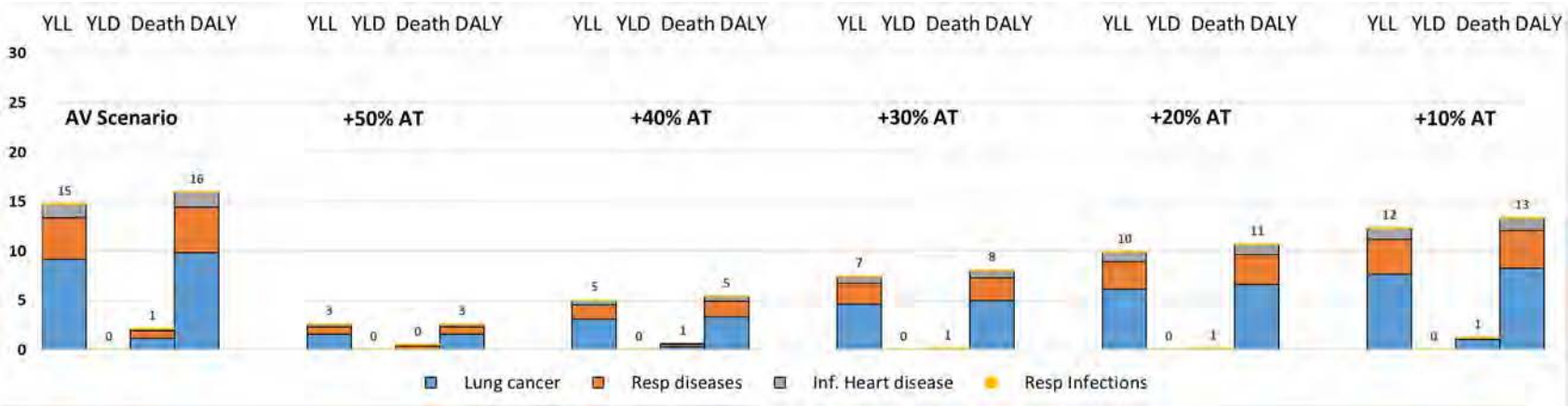


FIGURE 9. Predicted Annual Change in Burden of Disease from Physical Activity Compared with Baseline by Scenario and by Cause of Death and Disability: San Francisco Bay Area, CA

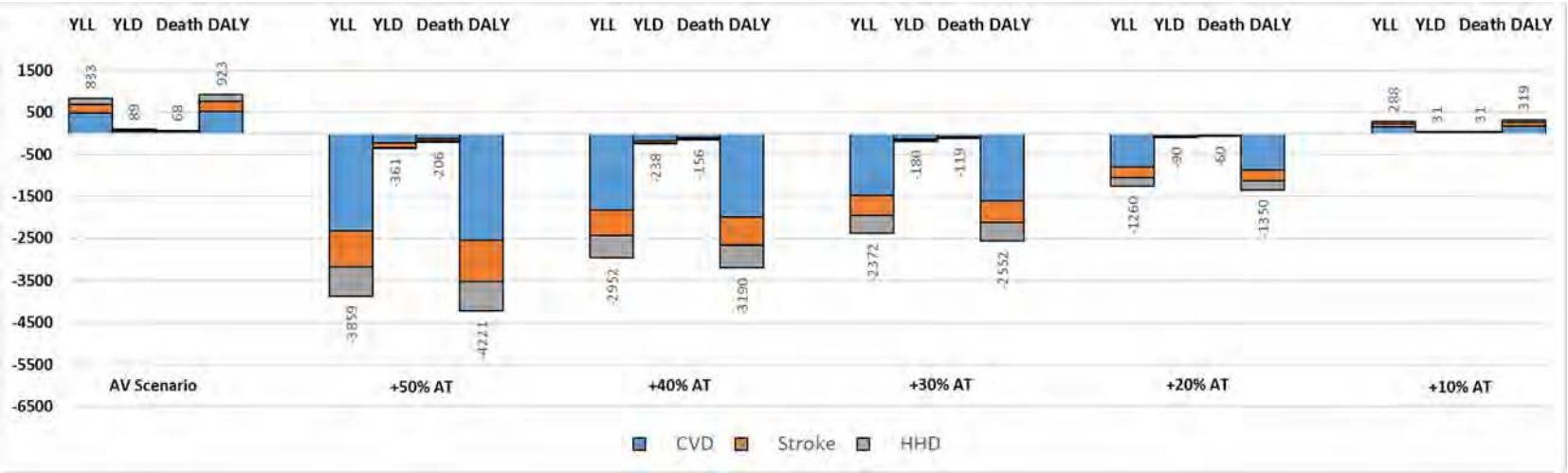


(a)

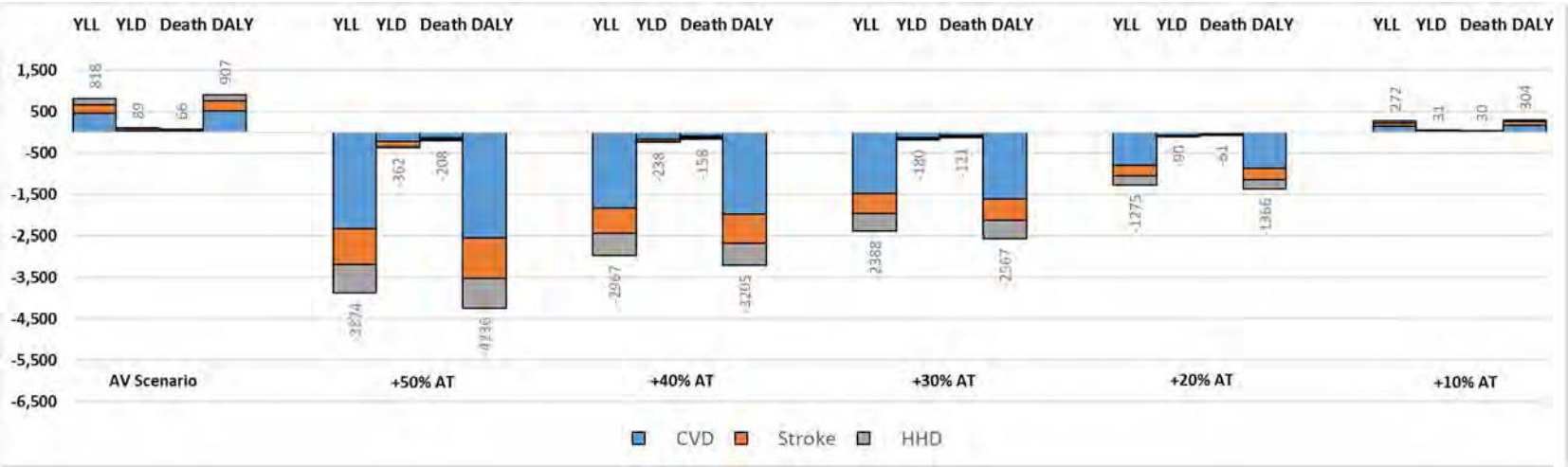


(b)

FIGURE 10. Predicted Annual Change in Burden of Disease from PM2.5 Compared with Baseline by Scenario and by Cause of Death and Disability: San Francisco Bay Area, CA, (a) Lower Bound Impact (b) Upper Bound Impact

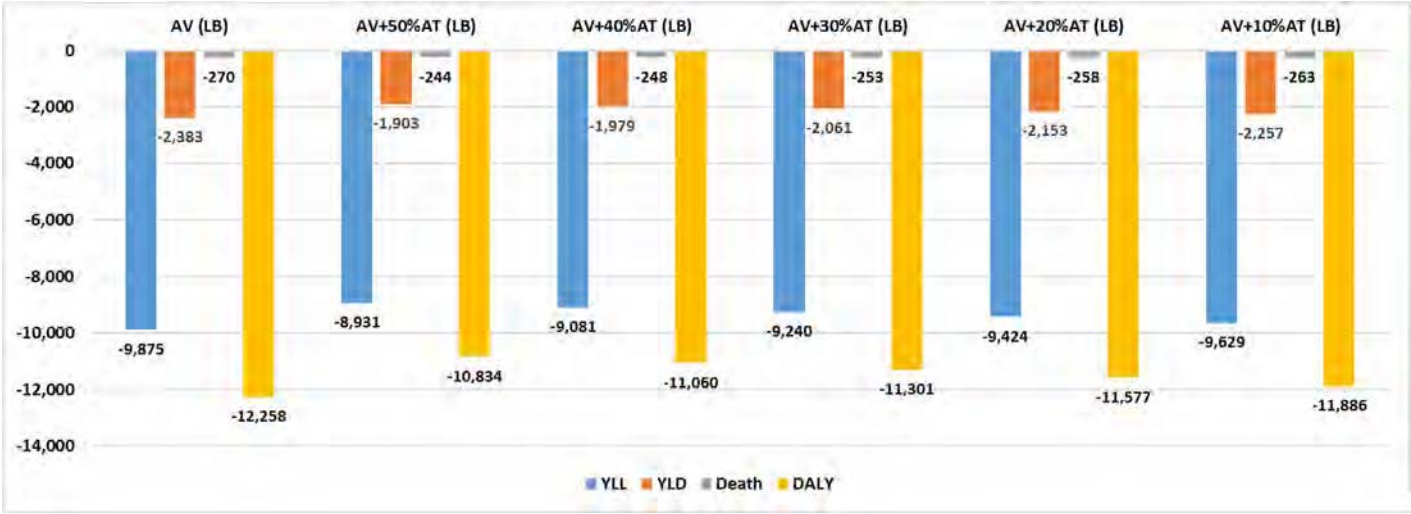


(a)

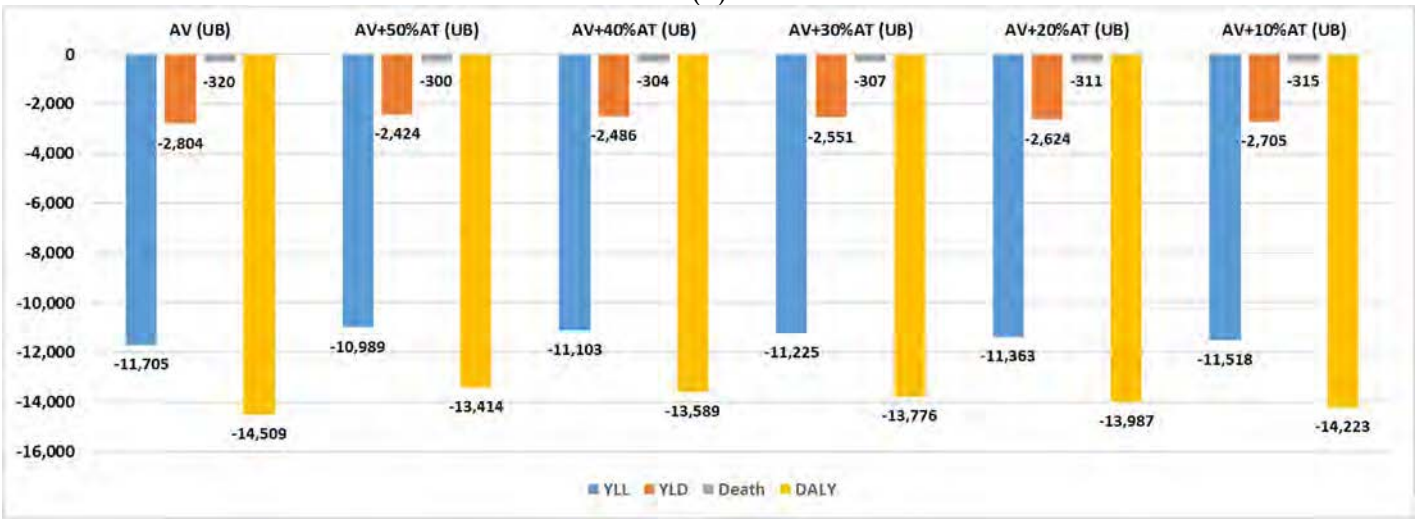


(b)

FIGURE 11. Predicted Annual Change in Disease Burden from Physical Activity and PM2.5 by Scenario and Cause of Death and Disability: (a) Lower Bound Impact; (b) Upper Bound Impact



(a)



(b)

FIGURE 12. Predicted Annual Change in Disease Burden from Road Traffic Injuries by Scenario, (a) Lower Bound Impact; (b) Upper Bound Impact

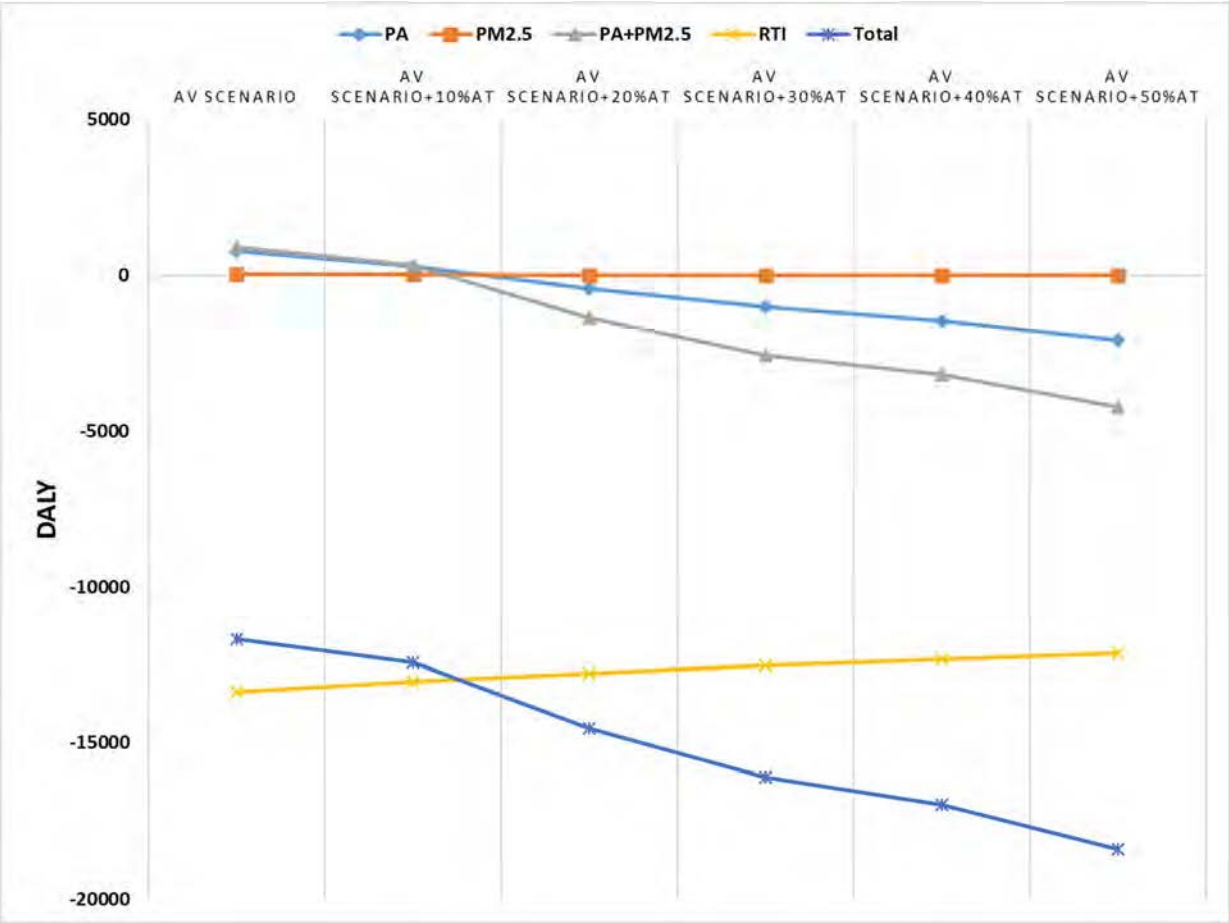


FIGURE 13. Predicted Annual Change in Burden of Disease Compared with Baseline by Scenario and by Cause of Death and Disability: San Francisco Bay Area, CA