Travel Effects and Associated Greenhouse Gas Emissions of Automated Vehicles

April 2018

A White Paper from the National Center for Sustainable Transportation

Caroline Rodier, University of California, Davis

National Center for Sustainable Transportation

UC DAVIS INSTITUTE of TRANSPORTATION STUDIES

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EXECUTIVE SUMMARY

In much the same way that the automobile disrupted horse and cart transportation in the 20th century, automated vehicles hold the potential to disrupt our current system of transportation and the fabric of our built environment in the 21st century. Experts predict that vehicles could be fully automated by as early as 2025 or as late as 2035 (Underwood, 2015). The public sector is just beginning to understand automated vehicle technology and to grapple with how to accommodate it in our current transportation system.

Research on automated vehicles is extremely important because automated vehicles may significantly disrupt our transportation system with potentially profound effects, both positive and negative, on our society and our environment. However, this research is very hard to do because fully automated vehicles have yet to travel on our roads. As a result, automated vehicle research is largely conducted by extrapolating effects from current observed behavior and drawing on theory and models. Both the magnitude of the mechanism of change and secondary effects are often uncertain.

Moreover, the potential for improved safety in automated vehicles drive the mechanisms by which vehicle miles traveled (VMT), energy, and greenhouse gas (GHG) emissions may change. We really don't know whether automated vehicles will achieve the level of safety that will allow for completely driverless cars, very short headways, smaller vehicles, lower fuel use, and/or reduce insurance cost. We don't know whether automated vehicle fleets will be harmonized to reduce energy and GHG emissions.

In this white paper, the available evidence on the travel and environmental effects of automated vehicles is critically reviewed to understand the potential magnitude and likelihood of estimated effects. We outline the mechanisms by which automated vehicles may change travel demand and review the available evidence on their significance and size. These mechanisms include increased roadway capacity, reduced travel time burden, change in monetary costs, parking and relocation travel, induced travel demand, new traveler groups, and energy effects. We then describe the results of scenario modeling studies. Scenarios commonly include fleets of personal automated vehicles and automated taxis with and without sharing. Travel and/or land use models are used to simulate the cumulative effects of scenarios. These models typically use travel activity data and detailed transportation networks to replicate current and predict future land use, traffic behavior, and/or vehicle activity in a real or hypothetical city or region. The findings from this white paper are summarized in the text and in Table A below.

- **Road Capacity**: Safety improvements from automated vehicles could significantly reduce headways on roadways and the results could be an almost doubling or tripling of capacity. These findings are based on a limited number of microsimulation studies that draw on traffic flow theory. Only one study uses field data. However, there is a relatively strong body of literature on the induced travel effects of roadway capacity on VMT. This literature suggests that the elasticity of VMT with respect to road capacity is 0.3 to 0.6 (short run) and 0.6 to 1.0 (long run). Thus, if roadway capacity increases by 10% then VMT may increase by 3% to 6% in the short run and 6% to 10% in the long run.
- **Time Costs**: The ability to engage in other activities while traveling in an automated vehicle may reduce the time burden of travel. Potential reductions in the value of travel time from automated vehicles are largely extrapolated from the results of stated preference surveys of car passengers and rail passengers, which may or may not be transferable to the experience of automated vehicle passengers. The results of these studies vary widely, but 75% to 82% of current driver values of time may be reasonable. Studies also indicate that working may not be a common use of time for those traveling in automated vehicles.
- **Monetary Costs**: Safety improvements in automated vehicles may lower vehicle insurance costs. Reductions in fuel costs could be enabled from lighter vehicles, lower time costs of refueling electric vehicles, and harmonization of vehicle flows. Avoided labor cost could enable fleets of automated taxis and shared taxi with user costs lower than personal vehicles. The magnitude of cost reductions is largely speculative, and few peer reviewed studies evaluate these effects. Reduced monetary costs of vehicle travel would tend to increase VMT. The body of literature on the effect of gas prices, which is the largest component of variable cost for conventional vehicles, on VMT is relatively strong. Elasticity of VMT with respect to gas price is -0.03 to -0.10 (short run) and -0.13 to -0.30 (long run). Thus, if gas price is reduced by 10% then VMT may increase by 0.3% to 1% in the short run and 1.3% to 3% in the long run. Only one study in New York City estimates the elasticity of taxi trips with respect to fares at -0.22, which may be applicable to automated taxi fleets (i.e., if fares increased by 10% then taxi trips would be reduced by 2.2%).
- **Mode Choice**: Available research suggests that automated vehicles would reduce transit and non-motorized mode shares and increase car mode shares. The limited available research on this subject confirms expected direction change, but magnitude is highly uncertain due to study quality.
- **Empty Vehicle Relocation Travel**: Automated vehicles may travel while empty to pick up passengers and to avoid parking where it is scarce or costs are high. The limited research on this topic shows that empty relocation travel is positively correlated with distance from the urban core, the price of parking, and per mile user costs, and is

inversely correlated with ride-sharing and transit. Empty relocation travel may contribute significantly to VMT effects of automated vehicles; however, studies do not fully represent induced travel effects and thus may overestimate the relative importance of this effect. U.S. studies are simulated only in Austin (TX).

- **Parking**: There are very few studies that evaluate the effect of automated vehicles on parking. Three simulation studies (one in the U.S. and two in the E.U.) suggested that automated taxis may reduce parking demand by about 90%.
- **New Travelers**: Automated vehicles may allow many people to engage in car travel who cannot now drive a vehicle because of young-age and/or medical disabilities. Also, if shared automated taxis provide travel at a cost lower than current costs, then many lower income people who do not have access to a reliable car may also begin traveling more by car. Only a few studies evaluate the potential magnitude of this effect by extrapolating from 2009 NHTS Household Travel Survey data. Most studies estimate an increase in VMT on the order of 10% to 14%. However, the magnitude of effects is based largely on study assumptions.

Table A. Summary of White Paper Findings and Quality of Evidence

Mechanisms	Summary of Findings	Quality of Evidence
Road Capacity	Reduced headways could almost double or triple roadway capacity. Elasticity of VMT with respect to road capacity increase is 0.3 to 0.6 (short run) and 0.6 to 1.0 (long run).	Limited research largely uses microsimulation traffic models. More measured data needed. The body of literature on the effect of expanded road capacity and VMT is relatively strong.
Time Cost	Vary widely, but 75% to 82% of current driver values of time may be reasonable. Working may not be a common use of time for AV passengers.	Studies largely extrapolate from car passenger and rail passenger experiences, which may or may not be consistent with the experience of automated vehicle travelers.
Monetary Cost	Reduced monetary cost from lower insurance and fuel costs. Avoided labor cost could enable fleets of AV taxis and shared taxi with use costs lower than personal vehicles. Elasticity of VMT with respect to gas price is -0.03 to -0.10 (short run) and -0.13 to -0.30 (long run). Elasticity of taxi trips with respect to fares is -0.22.	The magnitude of cost reductions is largely speculative, and few peer reviewed studies evaluate these effects. The body of literature on the effect of gas prices on VMT is relatively strong. Gas price is the largest component of the variable cost of driving a conventional owned vehicle. Only one study in New York City estimates taxi fare elasticity.
Mode Choice	Available research suggests that AVs would reduce transit and non-motorized and increase car mode shares.	Limited research confirms expected direction change, but magnitude is highly uncertain due to study quality.
Parking	Fully AV taxis may reduce parking demand by about 90%. However, reduced parking may increase relocation travel.	Only one U.S. study that uses observed travel data. Two other studies are in European cities. All studies use simulation models.
Empty Relocation Travel	Empty relocation travel is positively correlated with distance from the urban core, the price of parking, and per mile user costs, and inversely correlated with ride-sharing and transit. Empty relocation travel may contribute significantly to VMT effects of automated vehicles.	Limited research confirms expected direction change, but magnitude is highly uncertain. The share of relocation travel with respect to total VMT may be significant; however, studies do not fully represent induced travel effects and thus may overestimate the relative significance of this effect.
New Travelers	Most studies estimate an increase in VMT on the order of 10% to 14%.	Extrapolations use 2009 National Household Travel Survey data. Magnitude of effects are based largely on study assumptions.

AV=automated vehicles

In sum, this review suggests that personal automated vehicles and automated taxis are likely to significantly increase VMT and GHG and eliminating parking could exacerbate these increases. Electrifying the automated vehicle fleet could counter GHG growth, but will likely reduce vehicle operating costs and further increase VMT and congestion. Shared automated vehicle taxis could significantly reduce VMT and GHGs, but pricing polies are likely needed to get people to share. City center congestion could increase with significantly higher freeway capacity, which could result in urban flight and suburban sprawl in outlying areas that are relatively less congested. Policies to counter these trends could include (1) reinvesting in heavy rail transit to city centers with expanded first and last mile access in suburban areas by providing by automated vehicle shuttles and (2) cordon pricing around city centers to reduce congestion, make neighborhoods livable, and avoid sprawl.

Introduction

In much the same way that the automobile disrupted horse and cart transportation in the 20th century, automated vehicles hold the potential to disrupt our current system of transportation and the fabric of our built environment in the 21st century. Experts predict that vehicles could be fully automated by as early as 2025 or as late as 2035 (Underwood, 2015). The public sector is just beginning to understand automated vehicle technology and to grapple with how to accommodate it in our current transportation system. The manner in which automated vehicles are integrated into our regional transportation systems could have significant negative and positive effects on congestion, vehicle miles traveled (VMT), greenhouse gas emissions (GHGs), energy consumption, and land development patterns. For example, one study estimates that automated vehicles could double GHG emissions and energy consumption or reduce it by 50%, depending on the magnitude of different travel demand effects (Wadud et al., 2016).

Understanding the potential impacts of automated vehicles is critical to guiding their adoption in ways that improve multi-modal accessibility for all citizens and minimize negative environmental effects. The challenge, of course, is that fully automated vehicles have not yet been introduced into the transportation system and thus observed data is not available on how travelers will adopt and respond.

In this white paper, the available evidence on the travel and environmental effects of automated vehicles is critically reviewed to understand the potential magnitude and likelihood of estimated effects. In section II, we outline the mechanisms by which automated vehicles may change travel demand and review the available evidence on their significance and size. These mechanisms include increased roadway capacity, reduced travel time burden, change in monetary costs, parking and relocation travel, induced travel demand, new traveler groups, and energy effects. In section III, we describe the results of scenario modeling studies. Scenarios commonly include fleets of personal automated vehicles and automated taxis with and without sharing that are fully operational without a driver (i.e., level 5 automation). Travel and/or land use models are used to simulate the cumulative effects of scenarios. These models typically use travel activity data and detailed transportation networks to replicate current and predict future land use, traffic behavior, and/or vehicle activity in a real or hypothetical city or region. In section IV, the results of the review are synthesized to identify the magnitude and strength of the evidence for the effects, lessons learned, and research gaps.

Mechanisms for Changing Travel Demand

Increased Roadway Capacity

Safety improvements from automated vehicles are expected to increase effective roadway capacity by enabling smaller vehicles and shorter headways and by reducing time delays due to accidents and improved operations. Automated taxi and shared taxi services could also enable "right sizing" of vehicles to passenger occupancy.

Overall, the results of modeling and field studies, which largely consider reduced headways between automated vehicles, indicate that a fully automated vehicle fleet could approximately double or triple the effective capacity of existing roadways. Shladover et al. (2012) conduct field tests and microsimulation modeling of connected automated vehicles at differing levels of market penetration and find increases in roadway capacity due to connected automated vehicles that range from 5% to 89%. Ambühl et al. (2016) use a mesoscopic model (VISSIM) to simulate an autonomous vehicle fleet with a simplified car following model, in which headways are reduced from two seconds for conventional vehicles to one half a second, on an abstract four by four gridded network (with 24 road links that are 120 meters long and two lanes in each direction) and report that the effective capacity of the network could be tripled by an automated vehicle fleet. Lioris et al. (2017) apply three queuing models to simulate automated vehicles with headways of three fourths of a second on an urban network with 16 intersections and 73 links. They show that both roadways and intersections can accommodate a doubling and tripling of roadway capacity with connected automated vehicles. In other words, intersections would not act as a bottleneck in a roadway network that served automated vehicles.

Reduced Travel Time Burden

Passengers in fully automated vehicles would be free to use in-vehicle travel time to work and "play" in their vehicle. As a result, the burden of travel time may be lessened. Note, however, that this dynamic could lead to increased vehicle size and weight due to equipment needed to engage in desired tasks. To date, the research that addresses this topic is limited in quantity and is inconclusive due to methodological challenges. The results of this research are summarized here.

Ian Wallis Associates (2014) review the literature on the value of time of vehicle drivers compared to vehicle passengers. They find only five studies that directly address this issue and only one of these studies control for individual socio-demographic differences, such as income and age. In one U.K. study, the results of a stated preference and transfer price surveys[1] of vehicle drivers and passengers indicate that the average ratio for passenger value of time compared to driver value of time is 63% for commuter travel, 75% for other travel, and 78% for

[1] Stated preference surveys ask respondents to choose among different hypothetical options and experiment methods are typically employed to generate hypothetical choices. Transfer price surveys present hypothetical choices in relation to an existing or actual situation experienced by respondents.

business travel (Hague Consulting Group, 1999 cited in Ian Wallis Associates, 2014). A study conducted in Australia, which employs a stated preference survey, finds that the value of travel time for passengers is 75% of drivers (Hensher, 1984 cited in Ian Wallis Associates, 2014). The results of stated preference and transfer price surveys administered in Sweden indicate no significant difference between passenger and driver value of travel time (cited in Ian Wallis Associates, 2014). In Denmark, a stated preference survey shows that passenger value of travel time is 67% that of driver value of travel time, but when value of travel time is adjusted for income the value is 82% (Fosgerau et al., 2007 cited in Ian Wallis Associates, 2014). This study did not detect significant differences in value of travel time by trip purpose. The results of revealed[2] and stated preference surveys in Spain indicate that passenger value of time is 82% of the driver for work/education trips and 69% for all other trip purposes (Roman et al., 2007 cited in Ian Wallis Associates, 2014).

Studies that examine rail passengers' value of time spent on activities while traveling provide some insight into potential travel time benefits of automated vehicles. A survey of rail passengers in the U.K. indicates that only 13% of passengers engage in work or study while traveling, 98% of those passengers rate the time spent on those activities as of some use (59%) or very worthwhile (39%), and 62% to 85% of all passengers rate different non-work activities as of some use or very worthwhile (Lyons et al., 2007). Another study in the U.K., which uses revealed preference and stated preference surveys, finds that train travelers engage in a wider range of activities than car travelers and, on average, about 66 minutes were spent on work related activities by train passengers while only 6 minutes were spent on work related activities by car travelers (Batley et al., 2010). More recently, Malokin et al. (2015) conduct a revealed preference survey of commuters in the San Francisco-Sacramento transportation corridor in Northern California and extrapolate travel time benefits from productive time use during commuter rail and shared ride travel to estimate changes in commuter mode share for a hypothetical automated vehicle scenario. The results indicate that the drive alone mode share increases by 0.95 percentage points and shared ride mode share increases by 1.08 percentage points. However, one on-line survey, the results of which are stratified by gender, age, and income to closely represent the general population, finds that window gazing and relaxing is a more highly valued use of time than working in automated vehicles (Cyganski et al., 2015). However, Le Vine et al. (2015) question the equivalence of traveling in an automated vehicle and in a train due to differences in acceleration and deceleration dynamics, which have been found to impact travelers' comfort. They estimate that these dynamics are significantly worse in automated vehicles based on a microsimulation analysis.

A few surveys have been conducted that explore the factors that may motivate consumers to purchase an automated vehicle; however, the samples of these surveys are typically not representative of the general population in a specific geographic area. Bansal and Kockelman (2016) conduct an internet based opinion survey and report that a significant number of respondents find the ability to engage in other tasks would contribute positively to purchasing

[2] Revealed preference surveys ask respondents questions about actual situations they experience

an automated vehicle. These include texting or talking (74%), sleeping (52%), working (54%), and watching movies or playing games (46%). Menon et al. (2016) administer a survey to a university population in South Florida and find that 73% of respondents believe that more productive (than driving a conventional vehicle) use of travel time is a likely benefit of automated vehicles. On the other hand, Schoettle and Sivak's (2014a) internet-based survey of individuals in the U.K., the U.S., and Australia finds that 41% of respondents would continue watching the road even as passenger in an automated vehicle.

Change in Monetary Costs

Attributes of automated vehicle will tend to reduce the variable per mile cost of operating a vehicle. The improved safety of automated vehicles should reduce insurance costs, which are about 3.3 cents per mile by about 60% to 80% (Wadud et al., 2016). It should also reduce the weight of the vehicle due to safety features. MacKenzie et al. (2014) estimate that removing this weight could reduce fuel consumption by 5.5%. Moreover, automated vehicles may be more likely to be electric vehicles because the vehicle can be recharged without time costs to a driver. Electricity is significantly less expensive than gasoline use in conventional vehicles (about 50% less).

No longer will passengers have to pay the labor costs for taxi or ride-hail services (shared and unshared) and transit. As these modes become more affordable, they may be deployed beyond dense urban areas to suburban and rural environments and to provide first and last mile service to rail transit. Chen et al. (2016) estimate that automated electric vehicle taxis could be operated at a cost of 42 cents per mile (including the cost of charging infrastructure, vehicle capital and maintenance, electricity, insurance, and registration), which is equivalent to owning a vehicle with lower than average mileage. The per mile cost of shared automated electric taxis would be even less.

As described above, automated taxi's may facilitate "right-sizing" of vehicles, which could further reduce the energy requirements and cost of operations; however, it is difficult to estimate the magnitude of this potential benefit (Wadud et al., 2016).

Shared automated services could also significantly impact fleet size as the cost of automated taxis with and without sharing could become significantly less than the cost of a personally owned automated vehicles (Burns et al., 2013). Many studies, see discussion in the next section, show that large reductions in the vehicle fleet may be made possible through shared use mobility service.

Parking and Relocation Travel

Automated vehicles may significantly reduce parking demand. Personal automated vehicles could drop off their passengers and return home to park. Automated taxis and shared automated taxis could drop off passengers and then be relocated to pick up other passengers. A shared fleet would be smaller than a personal vehicle fleet and thus would require less total spaces even when they are not in use for extended hours of the day during non-peak times. Parking could be located at strategic locations throughout a region rather than located at or near a baseness or home. Zhang and Guhathakurta (2017) simulate parking demand for a fleet of autonomous taxis in Atlanta (GA) and find that land devoted to parking could be reduced by 4.5% once the fleet began to serve 5% of trips and could reduce 67% of parking lots in the central business district (CBD). Martinez and Christ (2015) simulate a fleet of automated taxis (100% market penetration) with and without sharing and transit, in Lisbon, Portugal, and find an 84% to 94% reduction in parking. At 50% market penetration levels, the share of baseline parked vehicles is only significantly reduced with transit by 21% to 24%(respectively with and without sharing). Another study (de Alameidia Correla and van Arem, 2016) in Delft, Netherlands, simulates fully automated personal vehicles (100% market penetration) and finds that vehicles spend more time parking (16% and 19%) when parking charges decrease and less time parking (7% to 24%) when parking charges increase (see more detailed discussion of this study in section III below).

The potential magnitude of relocation travel is discussed in more detail in section III below; however, we briefly summarize the results here. Two studies simulate personal vehicles that are fully automated with 100% market penetration. A study in downtown Austin (TX) finds that relocation travel is 83% of total VMT (Levin and Boyles, 2015). The study in Delft (described above) found a that relocation travel as a share of total VMT can range from 10% to 87% with a positive correlation between the price of parking and relocation travel (de Alameidia Correla and van Arem, 2016). Total VMT increases in this study and relocation travel is a significant factor when pricing charges are relatively low.

A number of studies estimate the effect of fully automated taxis on relocation travel. Maciejewski and Bishoff (2016) simulate automated taxis in Berlin, Germany, at different levels of market penetration and find that the share of relocation travel ranges from 17% to 19% of total VMT with higher levels associated with lower levels of market penetration. Bischoff and Maciejewski (2016) simulate automated taxis in Berlin and examine the share of empty vehicle trips by location and find that the share is at least 6% lower than the regional average in the city center and 6% to 29% higher in outlying areas of the region. Bischoff and Maciejewski (2017) show that relocation travel is 13% to 20% of VMT for an automated shared taxi scenario, depending on assumptions about roadway capacity expansion from automation; however, overall VMT declines by 15% to 22% due to sharing rides. Chen and Kockelman (2016) simulate an electric automated taxi service that competes with other modes based on per mile use cost in a hypothetical Austin-like city. They find that relocation travel varies from 7% to 9%, depending on assumptions about value of travel time and per mile user costs. Average trip distances increase from 20% to 35% when overall costs (value of time and user costs) are relatively low and decrease from 3% to 4% when overall costs are relatively high.

Induced Travel

Induced travel is the increase in auto travel that results from a reduction in the cost of auto travel. As described above, automated vehicles may reduce the cost of auto travel by increasing effective roadway capacity and thus auto travel speeds, decreasing the value of time costs of auto travel through the ability to engage in other tasks instead of driving, and reducing the monetary cost of auto travel through lower parking, fuel, and insurance costs and more efficient use of vehicles.

Induced travel effects can be broken down into four basic components. If the cost of auto travel declines, all else being equal, then auto travel becomes more cost-effective relative to other modes of travel (e.g., transit, walk, and bike) and thus auto mode share is likely to increase. Individuals may also decide to travel to more preferred destinations that are further way than less preferred destinations. For example, a traveler may decide to go to a regional mall that is 15 miles away with 50 stores compared to a local mall that is 2 miles away with only 10 stores. Travelers may also decide to make more discretionary trips and/or engage in less trip chaining due to reduced auto travel costs. Finally, over the long run significant changes in auto travel time and cost may affect land use development and population location. Reduced travel time costs may make commuting to work from lower cost housing developments in outlying areas of a region feasible. Businesses may follow as populations relocate further away from city centers.

The evidence for induced travel is strong (Handy et al., 2014). Studies typically calculate elasticities which are equal to a one percent increase in vehicle travel demand over a one percent change in travel cost. Handy et al. (2014) conduct a critical review on the effects of expanded roadways on induced VMT and find that short run effects typically range from 0.3 to 0.6 and long run effects from 0.6 to 1.0. Short run effects are changes in mode, destination, and trips while long run effects include land use effects. Studies of the effect of reduced travel time on vehicle travel indicate short run effects have elasticities that range from -0.27 to -0.5 and long run effects range from -0.57 to -1.0 (Preston et al., 1997 and Goodwin, 1996). Recent studies of the elasticity of VMT with respect to gas price show short run elasticities that range from -0.03 to -0.10 and long run elasticities that range from -0.13 to -0.30 (Circella et al., 2014). Only one study estimates the elasticity of demand for taxi trips with respect to fares in New York City (Shaller, 1999) and finds that the elasticity is -0.22.

New Travelers

Fully automated vehicles could increase mobility for older adults, people with disabilities, young people without driver's licenses, and people living in poverty. The ability of these mobility-limited population groups to travel in automated vehicles, all things being equal, would tend to increase vehicle travel. Our review of the literature identified only four studies that attempt to quantify the magnitude of this increase.

Sivak and Schoettle (2014) conduct an on-line survey of young people (age 18 to 39) without a driver's license and ask the primary reason why they did not have a driver's license. The distribution of respondents without a driver's license aged 18 to 39 is consistent with that of the U.S. population (Schoettle and Sivak, 2014b). They find that four of these reasons would be eliminated by the availability of fully automated vehicles: too busy, disability, lack of driving knowledge, and legal issues. If respondents indicate one of those four reasons, then it is assumed that they would travel in a fully automated vehicle. The increase in total vehicle users was estimated by age group. These figures are then applied to the 2009 National Household Travel Survey (NHTS) data to estimate a 10.6% total average increase in annual VMT with fully automated vehicles for the U.S. population aged 18 to 39.

Brown et al. (2015) use data from the 2009 NHTS and the 2003 "Freedom to Travel Study" to estimate the increase in travel for youth, elderly, and disabled populations. They apply the travel rate of the top age decile (40 years old) to population segments from age 16 to 85. They estimate a total increase of 40% VMT per vehicle due to the availability of fully automated vehicles.

Wadud et al. (2016) use the 2009 NHTS to estimate the increase vehicle travel among those aged 62 and older that may result from the introduction of fully automated vehicles. Their analysis applies the driving rates of those aged 62 to everyone older than 62. The results indicate a 2% to 10% increase in VMT.

Harper et al. (2016) use data from the 2009 NHTS to estimate the potential increase in VMT by non-drivers, seniors (65 years and older), and individuals with travel-restrictive medical conditions. The study assumes that, with fully automated vehicles, non-drivers will use vehicles at the same rate as drivers, seniors will drive at the same rate as those under 65, and that working age adult drivers (19-64) with travel-restrictive medical conditions will travel at the same rate as working age adult drivers without medical conditions. They estimate a 14% increase in annual VMT for the U.S. population aged 19 and older.

Scenario Modeling

Route Choice Modeling and Empty Relocation Travel

The immediate effects of automated taxis and shared taxis (level 4 automation) are summarized in Table 1. The immediate effects of these modes are simulated with dynamic route choice models that represent the empty repositioning travel necessary to pick up and drop off passengers. Dynamic traffic assignment (DTA) route choice models are widely considered to do a better job of representing the interaction of vehicles and resulting traffic flows compared to static assignment (SA) models. Increased roadway capacity would tend to reduce congestion and allow drivers to take more direct routes to destinations, which could reduce VMT.

Early studies of automated taxis in the U.S. simulate travel for small downtown areas in hypothetical U.S. cities that are similar to Austin (TX) and Atlanta (GA) (Faganant and Kockelman, 2014 and Zhang et al., 2015, respectively). Travel demand is randomly generated with limited reference to national observed travel demand (e.g., 2009 NHTS data). The physical representation of these cities includes 10-mile by 10-mile gridded areas, but no physical representation of roadway networks. As a result, automated taxis are simulated with constant peak and off-peak travel speeds for a typical weekday.

Faganant and Kockelman (2014) simulate an automated taxi fleet in the Austin-like city and find that one automated taxi could replace 10 personally owned vehicles. However, this smaller fleet would increase VMT by about 11%. Life-cycle energy and emission effects are also calculated using estimates of VMT, fleet size, parking, and vehicle starts for base and automated taxi scenarios and show reductions in energy use by 12%, GHG by 6%, volatile organic compounds (VOC) by 49%, and carbon monoxide (CO) by 34%. Note that VOC and CO emission are strongly influenced by vehicle cold starts, which are significantly reduced in the automated taxi scenario.

Zhang et al. (2015) compare automated taxi scenarios with and without sharing in their Atlanta-like city. The study assumes that only 50% of travelers will be willing to share a ride with strangers and that the cost and time delay of sharing will be compensated for by lower cost of traveling. They find that one shared automated taxi could replace 14 personally owned vehicles. Relative to the automated taxi scenario, a fleet of shared automated taxis would reduce relocation travel and total VMT by about 5% and 6%, respectively, and reduce daily and peak delays by about 13% and 37%, respectively. Longer vehicle downtime in the shared automated taxi scenario contributes to a 10% increase in chargeable breaks for electric automated taxis but it also increases cold starts by 7%. The authors also find that change in vehicle fleet could reduce parking by 92.5%. Lifecycle energy and emissions impacts of the automated taxi with and without sharing are compared to a base case with conventional vehicles. The analysis considers VMT and reductions in parking infrastructure requirements. The results show no difference between the automated taxi scenarios with and without sharing and reductions of less than 1% compared to the base case.

Later studies conducted by Faganant, Kockelman, and others (Fagnant et al., 2015 and Faganant and Kockelman, 2016) improve their representation of daily travel in Austin (TX) by increasing the size of the core city to a 12-mile by 24-mile area, using a roadway network with link-level travel times, and using origin and destination travel demand data from the regional Metropolitan Planning Organization's (MPO's) four step model. They also use the MATSim dynamic assignment model (Horni et al., 2016). The results from the improved modeling of the automated taxi fleet in Fagnant et al. (2015) show lower increases in VMT (8%), somewhat higher automated vehicle to conventional vehicle replacement rates (1 to 11), and improved energy use and GHG reductions, 14% and 7.6%, respectively using the same methodology in Faganant and Kockelman (2014). The increase in VMT in the shared automated taxi ranged from 17% to 52% of the increase for the automated taxi scenario.

Bishoff and Maciejewski (Maciejewski and Bischoff, 2016; Bischoff and Maciejewski, 2016; and Bishoff et al., 2017) examine automated taxis and shared taxis in Berlin, Germany with the MATSim modeling framework, which includes a dynamic assignment model with vehicle relocation capabilities. The model uses local travel behavior data to dynamically schedule automated vehicle fleets for an average weekday (Maciejewski et al., 2017). Maciejewski and Bischoff (2016) simulate different levels of market penetrations for automated taxis (20% to 100%). They find an automated vehicle to conventional vehicle replacement rate of 1 to 11 or 12 vehicles and that the share of empty drive time to total drive time ranges from 17% to 19%. The percentage change in travel time delay ranges widely from -71% to +173% depending on the changes in roadway capacity due to automated vehicle technology (i.e., equal to 1, 1.5, and 2.0 of current capacity), as discussed above. Bischoff and Maciejewski, 2016 examine the share of empty ride per zones from an automated taxi service at 100% market penetration. They find that the city average is 16%, but in the city center it is much lower (10% or less) and in outlying areas it is much higher (22% to 45%). Bishoff et al., 2017 simulate a fleet of automated taxis with and without sharing. The MATSim model uses GPS trace data for 15,000 taxis collected over a period of 4.5 months. Relative to the automated taxi fleet, they find that shared taxis can reduce VMT by 15% to 22% and that the share of empty relocation VMT to total VMT ranges from 13% to 20%.

Table 1. Summary of Route Choice and Empty Relocation Travel Scenario Modeling Studies

Author(s)	Location	Method	Travel Effects	Time Period	AV	Scenario (compared to conventional vehicles unless specified)	Fleet (% of conventional vehicles)	Relocation travel (share of empty)	Total VMT	Travel Time Delay	Energy & Emissions
Zhang et al. 2015	Hypothetical US city similar to Atlanta, GA US	Agent-based model with travel profile from 2009 NHTS; randomly generated demand for 10 by 10 mile gridded area; constant peak and off-peak speeds (no network)	DTA route choice with relocation travel	Weekday	100% Shared Taxi	Relative to AV taxi	14%	-5%	-6%	-13% daily; -37% peak	+7% cold starts; +10% chargeable breaks
Faganant & Kockelman 2014	Hypothetical US city similar to Austin, TX US	Agent-based model; 10 by 10 mi. gridded area; demand randomly generated with some basis in 2009 NHTS; constant peak and offpeak speeds (no network)	DTA route choice with relocation travel	Weekday	100% Taxi	-	10%	-	+10.7%	-	-12% energy; -5.6% GHG; - 49% VOC; -34% CO
Fagnant et al. 2015	Austin, TX US	Agent-based dynamic assignment (MATSim); 12 by 24 mi. core city; demand from MPO 4 step model; network with link-level travel times	DTA route choice with relocation travel	Weekday	100% Taxi	-	11%	-	+8.0%		-14% energy; -7.6% GHG; -47% VOC; -32% CO
Faganant & Kockelman 2016	Austin, TX US	Same as above	Same as above	Weekday	100% Taxi & Shared Taxi	Taxi	11%	-	+8.7%	-	-
						Taxi & Shared Taxi			+4.5%		
						Taxi & Shared Taxi + 30% TT			+2.7%		
						Taxi & Shared Taxi + 40% TT	12%		+1.5%		
Maciejewski & Bischoff 2016	Berlin, Germany	Agent-based (MATSim): dynamically schedules fleet in response to demand;	DTA route choice with repositioning travel	Weekday	20% Taxi	-	10% to 12%	19%	-	-15% to +9%	-
					40% Taxi			18%		-29% to +39%	

Author(s)	Location	Method	Travel Effects	Time Period	AV	Scenario (compared to conventional vehicles unless specified)	Fleet (% of conventional vehicles)	Relocation travel (share of empty)	Total VMT	Travel Time Delay	Energy & Emissions
		Berlin travel behavior data			60% Taxi			17%		-43% to +85%	
					80% Taxi			17%		-57% to +173%	
					100% Taxi			17%		-71% to +362%	
Bischoff & Maciejewski 2016	Berlin, Germany	Same as above	Same as above	Weekday	100% Taxi	regional average	10%	16%	-	-	-
						city center		10% or less			
						outlying areas		22% to 45%			
Bishoff et al. 2017	Berlin, Germany	Same as above, but with local taxi data	Same as above	Weekday	100% Shared Taxi	Relative to conventional taxi	-	13% to 20%	-22% to -15%	-	-

AV=automated vehicles; VMT=vehicle miles traveled; GHG=greenhouse gas emissions; VOC=volatile organic compounds; CO=carbon monoxide emissions; TT=Travel Time

Short to Longer Run Modeling

In this section, we describe the modeling studies that capture the short run to long run effects of automated vehicles by expanding the simulation of effects beyond route choice to land use, trip, destination, time of day, and/or mode choice. These studies and their results are described in Table 2. The studies simulate the effects of personally owned automated vehicles and automated taxi fleets with and without sharing by representing empty vehicle repositioning travel and changing roadway capacities, value of time (VOT), and the per mile cost of use. All studies assume level 4 vehicle automation.

Only one study represents the effects of personal automated vehicles on home location choice in Melbourne, Australia (Thakur et al., 2016). It uses a travel and land use model calibrated to regional MPO forecasts. The travel model represents destination and mode choice and uses a static assignment route choice model. A fleet of level 4 personal automated vehicles with full market penetration is represented by reducing traveler's value of time by 50%. The land use results show shifts in population locations from the inner suburbs (-4%) to the outer (+2%) and middle suburbs (+1%). Total VMT and average vehicle trip time grows by 30% and 24%, respectively, while transit mode share increases by 3 percentage points and transit mode shares declines by 3 percentage points.

Regional MPO travel demand models are used to simulate personal automated vehicles with 100% market penetration in the cities of San Francisco (CA) and Seattle (WA) by increasing roadway capacity and reducing value of time. Gucwa (2014) uses the San Francisco Bay Area MPO regional activity-based travel demand model to simulate a 100% increase in roadway capacity with and without a 50% reduction in value of travel time and finds a 7.9% and 2%, respectively, increase in VMT. Childress et al. (2014) use an activity based model for the Seattle region MPO and simulate a 30% increase in roadway capacity with and without a 65% reduction in value of time and a 50% reduction in parking costs. When roadway capacity is increased with and without a 65% reduction of value of travel time for high income individuals only VMT increases by 3.6% and 5%, respectively, and average travel delay declines by 17.6% to 14.3%, respectively. However, when the 65% reduction of value of time is applied to all individuals, parking costs are reduced, and roadway capacity is increased, total VMT increases by 19.6% and average delay increases by 17.3%. Childress et al. (2014) also examine changes in accessibility and VMT by zone from the simulated scenarios and find extreme increases in accessibility and VMT in outlying areas of the region and in some core urban areas, which suggest the potential for relocation of households and businesses to those areas. Note that the implied elasticity of demand for travel with respect to capacity increase is low for both these studies (0.002 and 0.012, respectively) relative to the empirical literature, as described in section 1 f above. As a result, the increases in VMT and reductions in travel delay are likely underestimated.

The activity and agent based travel demand model (POLARIS) is applied to the Ann Arbor (MI) region to evaluate different levels of personal automated vehicle market penetration rates, roadway capacity expansion, and value of time (Auld et al., 2017). The model represents trip, destination, mode, and dynamic assignment route choice. Auld et al. (2017) find that, when automated vehicle market penetration rates are at 100% and roadway capacity expands by 12% to 77%, VMT increases by 0.4% and 2% and average vehicle travel time is reduced by about 2% to 5%. When value of travel times of 25% and 75% are applied to market penetration rates of 20% and 70%, VMT increases from about 1% to 19% and average vehicle trip time increases from 2% to 30%. Changes in market penetration, roadway capacity, and value of times are combined and the results indicate an increase in VMT that ranges from 2% to 28% and average vehicle trip times that range from 2% to 30%. The authors note that the implied elasticity of demand for travel with respect to capacity for this study is 0.027 which is low compared with estimates in the empirical literature, as described above.

Levin and Boyles (2015) modify the Austin (TX) regional MPO four step model to simulate personal automated vehicles with 100% market penetration in the downtown areas. This model represents destination, mode, and static assignment route choice. The model simulates personal automated vehicle travel by reducing vehicle following distances and jam densities to increase roadway capacity. The model also represents relocation travel and parking (e.g., to avoid parking cost vehicles will travel home after driving travelers to work). Levin and Boyles (2015) find that, in the peak period, the introduction of automated vehicles increase the disutility for parking and as a result 83% of total trips are round trips for repositioning. Vehicle trips increase by 275.5% while transit trips decline by 63%. However, average link speeds, weighted by length, are reduced by 9%.

Another study (de Alameidia Correia & van Arem 2016) examines the effects of a fully automated personal vehicle fleet with an agent-based model that represents mode choice and dynamic assignment route choice with parking and repositioning in Delft, Netherlands, which is a small city in South Holland. The model uses roadway and transit networks and mode choice coefficients and generalized cost functions from Arentz and Molin (2013). This study examines a fully automated vehicle fleet and varies the paid and free parking and value of travel time (reduced by 50%) and finds that paid parking significantly increases empty vehicle location travel, VMT, and vehicle hours of delay and reduces car mode share and total vehicle parking time. The largest increase in VMT and empty vehicle miles traveled (325% and 87.4%, respectively) and the greatest decline in total vehicle parking time (8.7%) was in the scenario where parking charges were implemented everywhere. Congestion or vehicle hours of delay grew the most (824%) where there was a charge for parking everywhere except for two peripheral lots. Reduced value of time in the paid parking scenarios increases VMT and total vehicle parking time in scenarios with free parking limited to the periphery, but dampens the increase in empty vehicle relocation travel and vehicle hours of delay. Overall, the share of repositioning travel ranges from 11% to 65%, the increase in car mode share ranges from -26 percentage points to 31 percentage points, VMT grows from 17% to 325%, vehicle hours of delay increases from 20% to 699%, and total vehicle parking time ranges from -7% to 25%.

Several studies examine the effects of automated taxi and shared taxi fleets. Azevedo et al. (2016) examine the effect of a policy that prohibits personal vehicle travel in the CBD of

Singapore (i.e., transit access to CBD only) and introduces a fleet of shared automated vehicles with a fare that is 40% of the taxi fare. The policy is simulated with an activity and agent based model (SimMobility) that makes use of local travel survey data, roadway and transit networks, and local taxi data. The model represents trip, destination, time-of-day, mode, and route choice. They find that the shared automated taxi to vehicle replacement rate of 1 to 4 and a 29 percentage point increase in the daily shared automated taxi mode, a 3 percentage point increase in transit mode share, and a 1 percentage point increase in both taxi and walk mode share.

Chen and Kockelman (2016) simulate an automated electric taxi fleet that competes with other modes by per mile cost of use and with travel time benefits in a hypothetical mid-sized region (100-mile by 100-mile gridded area) similar to Austin (TX). The agent-based MATSim framework is implemented with MPO trip generation rates by population densities, trip length distributions from the 2009 NHTS, and fixed peak and off-peak travel speeds that vary by area type (downtown, urban, suburban, and exurban). The model represents both mode and DTA route choice with vehicle repositioning. In these scenarios, value of time is reduced to 25%, 35%, and 50% of current value of travel time and per mile charges are 75 cents, 85 cents, and one dollar. As value of time and average per mile cost increases average trip length decreases. When the automated electric taxi service costs 85 cents per mile, average trip distance increases by 20 to 29 percent at 25% and 35% values of travel time, but declines somewhat (4%) at 50% value of travel time. At 35% value of travel time, average trip distance increases by 20% and 35% when per mile costs are 75 and 85 cents, respectively, but declines (3%) when per mile costs are one dollar. This study shows that at the right per mile cost an automated vehicle fleet may not increase VMT and congestion.

Martinez and Christ (2015) use a SA route choice model with a rule-based mode choice model (using proximity and trip length) to simulate an automated taxi and shared taxi fleets with and without transit. The models use population attributes and travel demand data from a local travel survey and travel times are based on hourly updated link speeds from a roadway network. In general, high market penetration (100% versus 50%) of shared automated taxis (versus automated taxi) with transit (versus no transit) produces greater replacement rates of automated taxis to private cars and decreases the growth in VMT and parked vehicles. However, all scenarios see increases in VMT (from a low of 6% to a high of 88%) and reductions in parked vehicles (6% to 104%) due to empty vehicle travel and the elimination of bus routes. The vehicle fleet replacement rate varies from a low of 1 to 10 in the 100% shared taxi with transit scenario to a high of 1.1 to one in the 50% taxi without transit.

Table 2. Summary of Short to Long Run Scenario Modeling Studies

Author	Location	Method	Travel Effects	Time Period	AV	Scenario Parameters	Fleet (% baseline)	Relocation VMT	Mode Choice	Total VMT	Travel Time	Land Use/Parking
Thakur et al. 2016	Melbourne, Australia	Travel & land use model calibrated to regional forecasts	Home location, destination, mode & SA route choice	Weekday	100% Personal	50% VOT	-	-	+3 PP Car; -3 PP Transit	+30%	+24% Avg. VTT	Suburb pop.: +2% outer; -1% middle; -4% inner
Childress et al. 2014	Seattle, WA (US)	MPO regional activity-based travel model	Destination, mode & SA route choice	Weekday	100% Personal	+30% road capacity	-	-	0 PP	+3.6%	-17.6 Avg. Delay	Outlying & some core high access & VMT increase
						+30% road capacity; 65% high income VOT			-1 PP Car	+5%	-14.3 Avg. Delay	
						+30% road capacity; 65% VOT; -50% parking cost			+1 PP Car; -2 PP Walk	+19.6%	+17.3 Avg. Delay	
Gucwa 2014	San Francisco, CA (US)	MPO regional activity-based travel model	Destination, mode & SA route choice	Weekday	100% Personal	+100% road capacity	-	-	-	+2%	-	-
						+100% road capacity; 50% VOT				+7.9%		
Auld et al. 2017	Ann Arbor, MI (US)	Activity & agent-based travel model (POLARIS) with data from MPO (survey & network)	Trip, destination, mode & DTA route choice	Weekday	100% Personal	+12% to +77% road capacity	-	-	-	+0.4% to +2%	-1.8% to -4.5% Avg. VTT	-
					20% Personal	25% to 75% VOT				+1.3% to +5%	+1.8% to +7.1% Avg. VTT	
					75% Personal	25% to 75% VOT				+5.7% to +18.6%	+8% to +30% Avg. VTT	
					20% Personal	25% to 75% VOT; +3% road capacity				+1.6% to +5.3%	+1.6% to +7.1% Avg. VTT	
					75% Personal	25% to 75% VOT; +12% road capacity				+4.3% to +12.7%	+3.2% to +15.9% Avg. VTT	
					100% Personal	25% to 75% VOT; +77% road capacity; AV Int.				+10% to +28.2%	+4.5% to +30.1% Avg. VTT	

Author	Location	Method	Travel Effects	Time Period	AV	Scenario Parameters	Fleet (% baseline)	Relocation VMT	Mode Choice	Total VMT	Travel Time	Land Use/Parking
Levin & Boyles 2015	Downtown Austin, TX (US)	Modified 4 Step Model & MPO travel data	Destination, mode & SA route choice (parking & repositioning)	Peak Period	100% Personal	Reduced following distance & jam densities	-	83%	-63% transit trips; +274.5 vehicle trips	-	-9% Avg. Link Speed (weighted by length)	Increased parking disutility
Azevedo et al. 2016	CBD Singapore	Activity & agent travel model (SimMobility) with travel survey, network & taxi data	Trip, destination, time of day, mode & DTA route choice	-	Shared Taxi	No private vehicles; areas only accessed by transit; service cost 40% current taxi	40%	-	+3% PP transit; +29% PP shared taxi; +1% PP taxi; +1% PP walk	-	-	-
de Alameidia Correia & van Arem 2016	Small city Delft, Netherlands (South Holland)	Agent-based model with travel survey data, networks; mode choice coefficients & generalized cost functions from Arentz and Molin, 2013	Mode & DTA route choice with parking and vehicle repositioning	Weekday	100% Personal	Free home parking & 2 free peripheral lots	-	11.5%	+3.4 PP car	+17.3%	+20.0% VHD	-7.0% VPT
						Paid parking everywhere (same price)		87.4%	-26.2 PP car	+325.6%	+228.9% VHD	-8.7% VPT
						Free parking everywhere		10.8%	+30.6 PP car	+20.9%	+49.3% VHD	+15.8% VPT
						2 free peripheral parking lots		64.8%	-20.3 PP car	+142.6%	+824.1% VHD	-23.5% VPT
						1 free peripheral parking lots		53.2%	+16.1 PP car	+119.1%	+699.2% VHD	+18.8% VPT
						50% VOT		10.3%	+6.2 PP car	+49.4%	0% VHD	+8.2% VPT
						50% VOT & 2 free peripheral parking lots		62.8%	-9.7 PP car	+190.3%	+276.1% VHD	-19.4% VPT
						50% VOT & no free parking except 1 lot		50.4%	+10.6 PP car	+165.7%	+796.7% VHD	+24.8 VPT
Chen & Kockelman 2016	Hypothetical mid-sized city	Agent-based (MATSim);	Mode & DTA route choice with vehicle	Weekday	Electric Taxi compete	Electric Taxi: 25% VOT & $0.85/mile	-	7.2%	-	+29% Avg. TD mi.	-	-

Author	Location	Method	Travel Effects	Time Period	AV	Scenario Parameters	Fleet (% baseline)	Relocation VMT	Mode Choice	Total VMT	Travel Time	Land Use/Parking
	like Austin, TX (US)	MPO trip generation rates; 2009 NHTS trip distance; fixed vehicle speeds	repositionin g		s with other modes	Electric Taxi: 35% VOT & $0.85/mile		7.7%		+20% Avg. TD mi.		
						Electric Taxi: 50% VOT & $0.85/mile		9.1%		-4% Avg. TD mi.		
						Electric Taxi: 35% VOT & $0.75/mile		6.8%		+35% Avg. TD mi.		
						Electric Taxi: 35% VOT & $1.00/mile		9.4%		-3% Avg. TD mi.		
Martinez & Christ 2015	Lisbon, Portugal	Model with population & travel demand from travel survey data; travel times based on hourly updated link occupancy	SA route choice & rule based mode choice (proximity & trip length)	Weekday	100% Shared Taxi	No Transit	12.8%	-	-	+21.6%	-	7.2% BPV
						Transit	10.4%			+5.5%		5.6% BPV
					100% Taxi	No Transit	22.8%			+88.2%		16% BPV
						Transit	16.8%			+43.2%		10.7% BPV
					50% Shared Taxi + 50% private car	No Transit	102.4%			+58.9%		99.4% BPV
						Transit	78.2%			+7.6%		75.8% BPV
					50% Taxi + 50% Private Car	No Transit	107%			+89.5%		103.8% BPV
						Transit	82%			+49.7		78.8% BPV

AV=automated vehicles; VMT=vehicle miles traveled; SA=static assignment; DTA=dynamic traffic assignment; VOT=value of in vehicle travel time; PP=percentage point; Avg. VTT=average vehicle travel time; NHTS=National Household Travel Survey; VHD=vehicle hours of delay; VPT=total vehicle parking time; BPV=% share baseline parked vehicles

Extrapolation Studies

Two studies take an extrapolation approach to representing the effect of automated vehicles. These studies use existing case studies and analysis of new data to quantify the magnitude of change by specific effect. The advantage of this type of analysis is that more effects can often be incorporated into the analysis; however, the disadvantage is that effects are fixed and countervailing and compounding effects of scenario effects are difficult to represent. See Table 3.

Brown et al. (2004) use a modified Kaya Identity, where use intensity is VMT/vehicle, energy intensity is Energy/VMT, and fuel intensity is Liquids/Energy, and quantify the following potential effects of automated vehicles: platooning, efficient driving, efficient routing, travel by underserved populations, faster travel, induced travel, lighter vehicles, reduced parking search time, more carpooling and electrification. They create three scenarios, one of which includes all the potential effects that would tend to increase fuel use, another which includes all the potential effects that would tend to decrease fuel use, and finally, one that includes all effects. The results show increases in VMT that range from 74% to 90% and a 16% reduction in VMT. Vehicle fuel demand increases by 173% in the scenario that includes all potential fuel increasing factors, but it decreases by 91% to 95% in the other two scenarios.

Wadud et al. (2016) use the ASIF framework, which is equal to activity level multiplied by mode share multiplied by energy intensity multiplied by fuel carbon content, to estimate the effect of scenarios in which the effects of changes in congestion, eco-driving, platooning, highway speeds, performance, crash avoidance, right-sizing vehicles, feature content, generalized cost (reduced value of time and induced travel), new users, new mobility models, and fuel mix are represented. Their analysis represents modest to aggressive implementation of automated vehicles, in which VMT increases from 15% to 75% and energy demand is reduced by 70% or increases by 120%.

Table 3. Summary of Extrapolation Scenario Modeling Studies

Author(s)	Location	Method	Travel and Energy Effects	Time Period	AV	Level	Scenario Parameters	Total VMT	Energy Demand
Wadud et al. 2016	US	Energy decomposition framework (ASIF=Activity Level x Mode Share x Energy Intensity x Fuel Carbon Content) including factors that may changes travel and energy demand with AVs; magnitude of change by factor extrapolated from literature or new analysis of existing data	Congestion, eco-driving, platooning, highway speeds, performance, crash avoidance, right-sizing vehicles, feature content, generalized cost (reduced VOT and induced travel), new users, new mobility models & fuel mix	Annual	100% Personal	3	-25% platooning, -4% congestion, -20% eco-driving, -23% performance, -5% crash avoidance, +56% generalized cost & +7% new user groups	~ +70%*	~ -70%
					98% Personal; 2% Carsharing	2	-14% platooning, -5% eco-driving, +9% generalized cost & +2% car-sharing	~ +15%*	~ -10%
					80% Personal; 20% Car-sharing	4	-25% platooning, -4% congestion, -20% eco-driving, -23% performance, -5% crash avoidance, -45% eco-driving; +20% highway speeds, +10% increased features; +89% generalized cost, +11% new user groups & -20% carsharing	~ +75%*	~ -50%
					100% Personal	4	+20% highway speeds, +10% features, +49% generalized cost; +11 new user groups	~ +75%*	~ +120%
Brown et al. 2014	US	Modified Kaya Identity (where use intensity is VMT/vehicle, energy intensity is Energy/VMT & fuel intensity is Liquids/Energy) including factors that may changes travel and energy demand with AVs; magnitude of change by factor extrapolated from literature or new analysis of existing data	Platooning, efficient driving, efficient routing, travel by underserved populations, faster travel, induced travel, lighter vehicles, reduced parking search time, more carpooling and electrification	Annual	100% Personal	4	All identified potential fuel use increases: +40% travel by underserved populations, +30% faster travel & +50% induced travel	90%	+173% vehicle fuel demand
					88% Personal; 12% Carpool	4	All identified potential fuel use decreases: -10% platooning, -45% efficient driving, -5% efficient routing, -50% lighter vehicles, -4% parking search travel, -12% carpooling & -75% electrification	-16%	-95% vehicle fuel demand
					88% Personal; 12% Carpool	4	All effects	74%	-91% vehicle fuel demand

AV=automated vehicles; VMT=vehicle miles traveled; VOT=Value of Time

Conclusion

Research on automated vehicles is extremely important because they may significantly disrupt our transportation system with potentially profound effects, both positive and negative, on our society and our environment. However, this research is very hard to do because fully automated vehicles have yet to travel on our roads. As a result, automated vehicle research is largely conducted by extrapolating effects from current observed behavior and drawing on theory and models. Both the magnitude of the mechanism of change and secondary effects are often uncertain.

Moreover, the potential for improved safety in automated vehicles drive the mechanisms by which VMT, energy, and GHG emissions may change. We really don't know whether automated vehicles will achieve the level of safety that will allow for completely driverless cars, very short headways, smaller vehicles, lower fuel use, and/or reduce insurance cost. We don't know whether automated vehicle fleets will be harmonized to reduce energy and GHG emissions.

Given these caveats, we summarize findings from the existing literature on this subject and evidence quality.

- **Road Capacity**: Safety improvements from automated vehicles could significantly reduce headways on roadways and the results could be an almost doubling or tripling of capacity. These findings are based on a limited number of microsimulation studies that draw on traffic flow theory. Only one study uses field data. However, there is a relatively strong body of literature on the induced travel effects of roadway capacity on VMT. This literature suggests that the elasticity of VMT with respect to road capacity is 0.3 to 0.6 (short run) and 0.6 to 1.0 (long run).
- **Time Costs**: The ability to engage in other activities while traveling in an automated vehicle may reduce the time burden of travel. Potential reductions in the value of travel time from automated vehicles are largely extrapolated from the results of stated preference surveys of car passengers and rail passengers, which may or may not be transferable to the experience automated vehicle passengers. The results of these studies vary widely, but 75% to 82% of current driver values of time may be reasonable. Studies also indicate that working may not be a common use of time for those traveling in automated vehicles.
- **Monetary Costs**: Safety improvements in automated vehicles may lower vehicle insurance costs. Reductions in fuel costs could be enabled from lighter vehicles, lower time costs of refueling electric vehicles, and harmonization of vehicle flows. Avoided labor cost could enable fleets of automated taxis and shared taxi with user costs lower than personal vehicles. The magnitude of cost reductions is largely speculative, and few peer reviewed studies evaluate these effects. Reduced monetary costs of vehicle travel would tend to increase VMT. The body of literature on the effect of gas prices, which is the largest component of variable cost for conventional vehicles, on VMT is relatively strong. Elasticity of VMT with respect to gas price is -0.03 to -0.10 (short run) and -0.13

to -0.30 (long run). Only one study in New York City estimates the elasticity of taxi trips with respect to fares at -0.22, which may be applicable to automated taxi fleets.

- **Mode Choice**: Available research suggests that automated vehicles would reduce transit and non-motorized mode shares and increase car mode shares. The limited available research on this subject confirms expected direction change, but magnitude is highly uncertain due to study quality.
- **Empty Vehicle Relocation Travel**: Automated vehicles may travel while empty to pick up passengers and to avoid parking where it is scarce, or costs are high. The limited research on this topic shows that empty relocation travel is positively correlated with distance from the urban core, the price of parking, and per mile user costs, and is inversely correlated with ride-sharing and transit. Empty relocation travel may contribute significantly to VMT effects of automated vehicles; however, studies do not fully represent induced travel effects and thus may overestimate the relative importance of this effect. U.S. studies are simulated only in Austin (TX).
- **Parking**: There are very few studies that evaluate the effect of automated vehicles on parking. Three simulation studies (one in the U.S. and two in the E.U.) suggested that automated taxis may reduce parking demand by about 90%.
- **New Travelers**: Automated vehicles may allow many people to engage in car travel who cannot now drive a vehicle because of young-age and/or medical disabilities. Also, if shared automated taxis provide travel at a cost lower than current costs, then many lower income people who do not have access to a reliable car may also begin traveling more by car. Only a few studies evaluate the potential magnitude of this effect by extrapolating from 2009 NHTS Household Travel Survey data. Most studies estimate an increase in VMT on the order of 10% to 14%. However, the magnitude of effects is based largely on study assumptions.

In sum, this review suggests that personal automated vehicles and automated taxis are likely to significantly increase VMT and GHG and eliminating parking could exacerbate these increases. Electrifying the automated vehicle fleet could counter GHG growth, but will likely reduce vehicle operating costs and further increase VMT and congestion. Shared automated taxis could significantly reduce VMT and GHGs, but pricing polies are likely needed to get people to share. City center congestion could increase with significantly higher freeway capacity, which could result in urban flight and suburban sprawl in outlying areas that are relatively less congested. Policies to counter these trends could include (1) reinvesting in heavy rail transit to city centers with expanded first and last mile access in suburban areas by providing by automated vehicle shuttles and (2) cordon pricing around city centers to reduce congestion, make neighborhoods livable, and avoid sprawl.

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