POLICY BRIEF

Automated and Autonomous Vehicles

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Project Description

This project reviews and summarizes empirical evidence for a selection of transportation and land use policies, infrastructure investments, demand management programs, and pricing policies for reducing vehicle miles traveled (VMT) and greenhouse gas (GHG) emissions. The project explicitly considers social equity (fairness that accounts for differences in opportunity) and justice (equity of social systems) for the strategies and their outcomes. Each brief identifies the best available evidence in the peer-reviewed academic literature and has detailed discussions of study selection and methodological issues.

VMT and GHG emissions reduction is shown by effect size, defined as the amount of change in VMT (or other measures of travel behavior) per unit of the strategy, e.g., a unit increase in density. Effect sizes can be used to predict the outcome of a proposed policy or strategy. They can be in absolute terms (e.g., VMT reduced), but are more commonly in relative terms (e.g., percent VMT reduced). Relative effect sizes are often reported as the percent change in the outcome divided by the percent change in the strategy, also called an elasticity.

Summary

Strategy Description

Automated vehicles (AVs) are a rapidly developing technology that performs a variety of vehicle driving functions. AVs have varying degrees of vehicle control, from driver assistance such as adaptive cruise control to full automated (driverless) control. AVs are not by themselves a VMT reduction strategy, but the technology has potential impacts on VMT and the policies and regulations of AV deployment can function as levers for VMT reduction. While AV technology will almost universally be applied to electric vehicles (making their miles eVMT), the lack of tailpipe emissions does not make them entirely GHG free, and the eVMT they produce has other important social costs such as safety and upstream emissions from vehicle brake and tire wear.

Behavioral Effect Size

Evidence from three types of studies (model-based simulations, mock AV experiments, and empirical analyses) suggest that deployment of AVs will increase VMT 13-83% depending on the level of automation and ownership model. The wide range of expected effects are also due to the uncertain nature of the deployment and use of AVs and differences in study methods.

Strategy Extent

AV technology is rapidly deploying, but projections are mixed about the speed of market penetration. There is potential for wide private adoption of AVs, although costs (that are expected to be many times greater than current cars) may constrain penetration. Shared fleets are likely to be more widely available before private AVs.

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Strategy Synergy

Existing pricing strategies for reducing congestion and VMT reported in other briefs from this series (e.g., facility-based, cordon, zonal, and distance-based), may be the most effective way to contain VMT from AVs. Other more stringent regulations could include mandating AVs be shared in the form of buses and shuttles to ensure ride pooling.

Equity Effects

Without strong regulations and incentives, AVs are likely to further exacerbate transportation inequities. Concerns include the inequitable design of AVs in terms of safety, particularly bias of software in uniformly detecting pedestrians who are Black or dark colored skin, children, women, etc. Also concerning is the potential job loss for ridehail/taxi drivers, the delivery industry, and other transportation industries including bus, train, or truck operators if AVs replace those jobs. However, AVs may also provide equity benefits. For example, AVs may provide access to destinations for people that are mobility challenged (e.g., disabled, no vehicle access, rural). However, research on the projected costs to purchase or use AVs versus non-AVs is needed to better assess these effects.

Strategy Description

Automated vehicles (AVs)—commonly called autonomous vehicles, self-driving cars, or, when available for hire, robotaxis—are a rapidly developing technology that performs a variety of vehicle driving functions. AVs are not a VMT reduction strategy, but the technology has potential impacts on VMT and policies and regulations of AV deployment can function as levers for VMT reduction. This brief focuses on AVs and their current and projected impact on VMT and equity to provide an estimate of a VMT baseline if AVs are left unregulated in terms of their VMT (not in terms of their safety, of which there are already many regulations). With this purpose, the brief considers two types of AV operations: privately owned and operated (PAVs) and shared (SAVs) in the form of a taxi/ridehail service.

In addition to the operational classification, AVs are often classified by their level of automation. The most common classification system is the six Society of Automotive Engineers (SAE) Automation levels[1] that classify automation from No Driving Automation at Level 0 to Full Driving Automation at Level 5. Level 1 includes steering or brake/acceleration assistance, but not both. Level 2 automation, the highest level on the private vehicle market as of this writing (e.g., Cadillac Super Cruise, Mercedes-Benz Drive Pilot, Tesla Autopilot), possesses both steering and brake/acceleration control (SAE 2021). Under SAE Levels 0-2, drivers are responsible for driving even when features are engaged. In Level 3 automation the vehicle controls all driving tasks but the driver remains alert and ready to take control if necessary. Vehicles at Levels 4-5 do not require a driver and some do not have a steering wheel. Robotaxis (e.g., Waymo) are currently in pilot phases and operate at SAE level 4. As many studies assume full automation without a clear classification, this brief's use of AVs refers to Levels 4 and 5 (L4-5) unless otherwise specified.

Strategy Effects

Behavioral Effect Size

AV adoption and implementation may influence a variety of travel behaviors in the short term. For example, allowing riders to multitask

[1] https://www.sae.org/standards/content/j3016_202104/

reduces the generalized cost of travel which may increase frequency of car trips and increase trip distances (because the burden is less). People may also use AVs to pick up goods, which results in zero-occupancy miles. In addition, at least some stated preference evidence suggests that people would be more likely to replace sustainable modes such as biking or walking with AVs (Heubeck et al., 2023). Parking behavior is also likely to shift, as owners of PAVs could send the vehicle away if a lot is full or if there is a charge for parking. AVs may even be responsible for longer-term changes such as vehicle ownership and residential location choice (Sun et al., 2023). These longer-term changes may also result in positive feedback for VMT generation. For example, if people choose to live farther from destinations because of AVs, it could encourage land use development patterns that are more sprawling, resulting in even more VMT. Without policies and regulations, both long-term and short-term travel behavior changes are likely to further increase existing transportation injustice through the lack of initial AV investments in low-income communities of color, and the initial high costs of AVs which can only be bought by the wealthy. Other issues of justice, such as employment in the ridehail industry being replaced by robo-taxis, are also a concern.

A growing number of studies agree that an important effect of deploying AVs is likely to be greater vehicle miles travel (VMT) in both SAVs and PAVs (Table 1, end of document). The eventual magnitude of VMT increase from shared and private AVs is uncertain due to study variability. Factors contributing to increased VMT generated by AVs include zero-occupancy travel such as sending the AV back due to parking cost or availability, new users (those not able to currently drive themselves), and the lower value of travel time. One experimental study of PAVs suggests AVs will increase trip generation for zero-occupancy trips (picking up goods) and passenger trips (longer and more numerous trips) (Harb et al., 2018 & 2022). The increase in passenger trips in this study was due to the ease of multitasking and traveling while tired or intoxicated. Trips were more frequent especially at night and longer trips were taken out of convenience and not having to drive (Harb et al., 2022). Even when not generating unoccupied VMT, automation is likely to increase VMT. For example, in one study of L2 AVs, automation reduced driver fatigue and stress resulting in longer driving time and distances as well as mode shift such as choosing driving over flying (Hardman et al., 2022).

Without VMT-focused regulation, implementation of shared or private AVs is likely to increase VMT and reduce use of sustainable modes of transport. For studies of VMT impacts from L2 AVs, studies suggest a 13.8% increase in VMT in Austin, Texas, (Asmussen et al., 2022) and a 24.7-28.7% increase in California (Hardman et al., 2022) (Table 2). Model-based studies of L4-5 AVs suggest an increase of VMT from 14-60% from the implementation of PAVs and SAVs (Table 1). The evidence from experimental studies suggests even greater VMT increases from L4-5 AVs of 60-83% (Table 3) (Harb et al., 2018 & 2022). While the current evidence has some validity concerns (e.g., model-based studies must make assumptions of adoption and rely on current travel patterns, and mock-AV studies could be subject to a strong novelty effect), the evidence is consistent in increasing VMT across the study types.

Although VMT increases are expected, the per mile energy efficiency could be improved in AVs through factors such as automated eco-driving, and vehicle right-sizing (Wadud et al., 2016).

Strategy Extent

Scale of Application:

If AV technology is used primarily in SAV form, the technology may follow the spread of the ridehail industry which could lead to general urban use and potential inequity in deployment within and between urban environments. One likely difference between SAVs and existing ridehail fleets is that SAVs will not have to consider driver employment which may lead to a different growth trajectory. If AV technology is deployed as PAV, the scale of impact is likely to follow the impacts of the general vehicle market with the exception that earlier AV adopters are likely to be wealthier than existing car owners due to higher costs (another equity concern).

Efficiency or Cost:

Vehicle purchase costs of AVs are likely to be many times that of non-AVs. However, if AVs are implemented as SAVs, vehicle ownership could be reduced and so may costs for users (Zhang et al, 2018). One study estimating the effects of widespread PAVs suggests that until the price of AV technology drops to $10,000 over non-AV vehicles, most people will not benefit from personal AV ownership (Fagnant and Kockelman, 2015). In addition, estimated per mile cost comparisons suggest that AVs are likely to cost more than non-AVs, but less than human driven ridehail/taxi (Litman, 2024).

Time / Speed of Change:

The deployment of AVs has been slower than anticipated by industry experts (Chiao et al. 2024). While the technology still advances rapidly given strong private investment and support for AVs' potential to improve traffic safety, barriers exist in technology, regulation, and consumer safety (Chiao et al. 2024). The deployment of L4-5 SAVs is likely to lead, followed by L4-5 PAVs. Predictions of AV adoption continue to change. One report summarizing industry expert surveys suggests large scale deployment of L4-5 AVs will be between 2028 and 2032 (Chiao et al. 2024). But industry experts may be optimistic. At least one academic report that based predictions on prior transportation technology adoption suggests it may take until 2060 or 2070 before half of the vehicles on the road are AVs (Litman, 2024).

Location within the Region:

Most model-based studies feature urban areas broadly applicable to most city populations.

With AVs in rural areas, one simulation study suggests that VMT may be relatively unaffected because VMT is already at capacity as users must commute for work or school and will regardless of a mode shift (Sun et al., 2023). But commuting is only one reason for travel. A broader conceptual analysis of potential VMT effects of AVs in rural areas by Dowds et al., (2021) suggests several potential pathways for increased VMT from AVs in rural areas such as generating new and longer trips, as well as zero-occupancy trips.

In urban areas with low car ownership rates, PAV adoption may have less of an effect on VMT (Gkartzonikas et al., 2022). If policies and regulations in cities can effectively enforce or encourage SAVs, the potential VMT increases may be lower if people shift from private vehicles to SAVs (Sun et al., 2023). One study estimates that most of the zero-occupancy VMT will be loaded on interstate highways and expressways and the largest percentage inflation in occupied VMT is predicted to occur on minor local roads (Zhang et al., 2018).

Differences between Regions:

It is not clear how differences in regional VMT will be affected by AV adoption. More research is needed to understand this variation.

Equity Effects

Studies that examine proposed AV implementation segmented by demographics suggest VMT will increase for the travel-restricted, youth, and elderly (Harper 2016, Harb et al., 2018 & 2022). This is explained by the lack of car access for these populations, where AVs provide a needed equity benefit while increasing VMT. The purported safety of AVs may reduce traffic deaths and injuries in a way that helps to remedy the current inequity in these deaths and injuries. However, policies and regulations are needed to ensure safety benefits are equitable.

VMT increases for those with existing car access are not expected to be uniform. Harper (2016) suggests women may make up the greatest increase in VMT, and Assmussen et al. (2022) reports that older women are expected to have the highest percentage increase in VMT from AVs. Because current AV use is from L2 AV owners (a particularly affluent and male population), the mobility benefits are currently inequitable, and even within the L2 AV owner population VMT varies by socio-demographics (e.g., younger demographic groups and residents in urban areas have estimated greater VMT) (Hardman et al. 2022). Additionally, not only are the benefits of L2 VMT inequitable, given the social costs of added VMT have historically disproportionally impacted low-income communities of color, the costs of L2 AVs may go beyond the inequitable access to the technology.

It is important to note that affordability likely impacts whom AVs will serve. It is very likely that the wealthier will benefit more from AVs due to the initial costs to own or use without countervailing pricing policies, exacerbating existing injustice in transportation. SAV business models may be more equitable, although price and regulation play a key role in promoting mobility to those who do not own a vehicle (Sun et al., 2023). The extent of operations of SAVs may also exacerbate inequitable access to AVs if SAVs follow the path of the ridehail industry and put profits (capturing demand) ahead of providing access.

Uptake for PAVs would almost entirely begin with higher income households, while low-income households are less likely to benefit from PAVs (Zhang 2018). To encourage SAV use for lower-income households, policy and price incentives can be used to promote more equitable use of AVs. Additionally, AV technology could be utilized on buses or public transit to reduce VMT and serve those in need by focusing on access and affordability.

AVs also have several other concerns that have been raised by interested groups. One concern is the inequitable design of AVs, particularly their software in detecting pedestrians uniformly. At least one study reported detection bias of those who are Black or dark colored skin, children, women, and suggests biased algorithm training data as the primary cause (Li et al. 2024). This concern is like that documented in using facial recognition for policing.[2]

Another concern is the economic hardship of the ridehail/taxi driver industry if AVs replace those jobs. More public forms of AVs (AV busses and shuttles) or partnerships with transit agencies and private AV companies may be one way forward to increase the equity of the technology and possibly constrain the expected increases in VMT.

Although there is potential for AVs to further injustice, there is also potential for equity benefits. For example, AVs may help provide access to important destinations for people that are mobility challenged if appropriately designed (Harb et al., 2018 & 2022). Finally, several connected indirect equity effects from AV deployment need further study such as where investments in infrastructure supporting

[2] https://www.perpetuallineup.org/

AVs might be made and how those investments might replace others such as in public transit.

Strategy Synergy

While the implementation of AVs will likely increase VMT, methods to prevent or mitigate VMT increases exist.

Existing pricing strategies for reducing congestion and VMT reported in other briefs from this series (e.g., facility-based, cordon, zonal, and distance-based), may be ways to contain VMT from AVs, as one simulation study suggests (Sun et al., 2023).

Confidence

Evidence Quality

The impact of AVs on VMT is still highly uncertain, especially the impact of L4-5 AVs, because of the limited number of available studies. Most evidence comes from model-based simulation studies (Table 1), with a few experimental designs with mock-AVs in real-world settings (Table 3). Some evidence suggests that policies and regulations may allow AVs to have less of an effect on increasing VMT through incentivized pooling (concurrent sharing) of vehicles. However, if pooling is not substantial (and no evidence suggests substantial pooling will happen without strong regulation and incentives), large increases in VMT are expected. Additionally, use of other modes of transportation including biking, walking, and public transit may decrease without appropriate investments.

Caveats

The model-based studies assumed that vehicles were fully autonomous (L4-5) and focused on effects in entire metropolitan regions. Because model-based studies used existing travel survey data with assumptions about future AVs, they may miss important changes in travel behavior that will occur with AVs. For example, the Zhang et al. (2018) model assumes no change in induced travel demand or transportation patterns and 100% market penetration, with the resulting VMT change only from AV zero-occupancy travel to serve multiple members in a household.

Studies of VMT changes from L2 automation are able to examine more empirical data. However, these studies rely on cross-sectional comparisons, not longitudinal change, to understand VMT effects. For example, Hardman et al. (2021) estimates the effect of L2 of automation by comparing mileage of matched drivers with and without L2 to estimate the effect of L2 on VMT.

Finally, experimental studies of mock-AVs (chauffeur simulations), have different types of caveats. While these studies were longitudinal and had experimental control which increases their internal validity in some ways, they were limited by sample size and types of people willing to participate in the study (Harb et al., 2022). These experiments selected individuals who already owned a vehicle. Also, the authors noted the experiment may have had a “novelty effect” where users felt as if they had to use the chauffeur since they had access to it. Actual behavior may vary with a PAV compared to a chauffeur.

Technical & Background Information

Study Selection

The effect of widespread adoption of AVs on VMT is difficult to assess given the lack of available studies on real-world use of AVs. By choosing model and experimental studies, a wider range of results were able to be considered, as the two methods have drastically varying sample sizes and results. Most studies we selected considered the future of L4-5 AVs. Additionally, empirical studies of L2 AVs looked at travel behavior of owners of L2 vehicles with owners of similar vehicles without L2 automation. This L2-related evidence provides an estimate of the immediate effect AV technology is having on VMT today, which may give some indication of the future effects of widespread L4-5 automation.

Methodological Considerations

Model-based Simulation Studies

Model-based simulation studies use data on existing travel behavior (usually data from travel demand models), assumptions about AVs, and simulate the potential outcomes for entire populations or subpopulations in city or regional geographies. These studies have included many assumptions about AV technology and the use of such technology that are needed to project the effects into the future. While these studies are based on existing demand, they have the benefit of predicting the wider scale of effects because of their population-based scope.

Most model-based simulation studies assume a high market penetration rate of light-duty PAVs. Bhardwaj (2023) suggests consumer adoption of AVs will be 15-36% by 2035, and Litman (2024) suggests 2060-2070 before 50% market penetration. Studies that examine VMT changes use existing travel demand models and set assumptions for behavior change to simulate effects. For example, Sun et al. (2023) uses California Statewide Travel Demand Model Version 3.0 (CSTDM V3.0) to forecast travel for years 2015-2050 based on the 2010–2012 California Household Travel Survey (2012 CHTS). Using the 2015-2050 forecast as the baseline and studying various scenarios, Sun et al. (2023) ran several assumed future scenarios with PAVs, SAVs, electrification, and pricing changes. In general, their results suggest without concurrent pricing policies, high growth in PAV and SAV scenarios both greatly increase VMT. Differences between PAV and SAV scenarios were quite similar in their VMT increases, and only by including pricing did their predictions show a chance of reduced VMT (see Table 1). Because the scenario analyses are based on assumptions of adoption and travel behavior, Sun et al. (2023) conducted both lower and upper bounded predictions which indicated roughly a 25% variance in results depending on assumptions.

Additionally, other types of assumptions of more nuanced travel behavior change are made in model-based studies. For example, Harper (2016) separated groups into travel demand scenarios assuming total VMT will increase for underserved populations such as nondrivers (<19 years), elderly without travel-restricted conditions, and working adults (19-64 years) with travel-restricted medical conditions. The study then used 2009 NHTS data to estimate each demand scenario.

In some cases, policy and cost impacts were explored in combination with assumptions of travel behavior change due to AVs. Sun et al. (2023) reported that VMT for both PAVs and SAVs are lower than baseline when coupled with road user pricing strategies (specifically they assumed operating costs increased 50% over the baseline $0.30/mile). Similarly, AV induced GHG emissions were relatively lower under assumptions of ZEV mandates requiring 100% ZEV sales by 2035, going from 1.5% to 0.6% over baseline (Bhardwaj et al., 2023).

Empirical studies of L2 AV use

Assmusen et al. (2022) groups various partially-automated feature (PAFs) such as back-up camera, adaptive cruise control, adaptive breaking, lane keeping, and blind spot monitoring into packages and analyzes VMT and travel behaviors for various demographics. Using a joint model the study examines the uptake of five PAFs based on binary revealed choice data at once. The same study examines how the presence of PAFs affect annual VMT in a joint model. By analyzing PAF uptake and the effects of PAFs on VMT, self-selection is accounted for. Additionally, this model uses stochastic latent attitudes/lifestyle constructs with demographics with adaptation of PAF and their interaction with VMT changes which helps to reduce confounding. The results suggest an increase in VMT due to PAF strongly varies by socio-demographics, with middle-aged men with the highest absolute change (increase of 2,462 miles per year), and older women the largest relative change (40% increase). The types of features also showed signs of variation in effects on VMT increases with packages of more PAFs resulting in greater VMT. For example, on average, only including an automated breaking system (ABS) was expected to increase VMT by 607 miles per year (5%), while a package of ABS with adaptive cruise control and a backup camera was expected to increase VMT by 2,297 miles per year (18.9%).

Hardman et al. (2021) uses data from a cohort survey of plug-in electric vehicle owners in California administered by the authors in 2019. Because the survey has self-selection bias in causal analysis, the study used a pseudo-randomized control trial where the treatment is randomly allocated in the sample, satisfying the assumption of conditional independence or un-confoundedness (Hardman et al., 2021). The study uses a propensity score matching and propensity score stratification, comparing VMT of Tesla vehicle owners with Autopilot and Tesla vehicle owners without Autopilot (control group), and matched L2 AVs to comparable non-AVs to evaluate the impact of L2 automation. Since the sample is choice-based, it cannot rule out the possibility that the differences between the groups in terms of travel need precede the choice to buy the vehicle, but the large differences do suggest a potential ability of L2 automation to induce more miles of travel. The results from this matched analysis indicated Tesla autopilot owners traveled 4,059–4,971 more miles compared to non-autopilot Tesla owners, holding all other covariates at their mean.

Experimental Mock-AV Studies

In the experimental studies, Harb et al. (2018 & 2022) administered a survey before and after the 3 weeks of tracked travel with the middle week being chauffeured (simulating a L4-5 AV). The study recruited various cohorts: millennials, families, and retirees in the San Francisco Bay area and Sacramento regions. While subjects had various socioeconomic characteristics and ages, they all had college education and the recruitment pulled from largely affluent communities. The benefit of this design is the ability to collect revealed preference data on the use of PAVs. No other study design provides this ability. The primary internal validity concern of these studies is the potential for a "novelty" effect of having a chauffeur, and how having a chauffeur might differ from owning an AV. It could be that people used their chauffeur during the experiment because it was free to them, and they were experimenting with the service. In addition, these two studies, because of the small and self-selected samples, may not generalize to the population of AV owners. The first study (Harb et al., 2018) only had a sample of 13 people, 5 of whom were retired. The follow up study (Harb et al. 2022), included a larger and more diverse sample of 43 households reported a large effect size (increases in VMT of 60%) and reductions in more sustainable modes at very high levels (e.g., a 70% reduction in transit trips).

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Table 1: Model-Based Simulations

Model Study	Study Location	Study Size	Study Years	Study	Type	Travel Variable	Association (Percentage)
Harper, et al., 2016	US	2009 NHTS data 150,147 households	2016	AV on 3 sectors (under 19, working adults, elderly)	PAV[3]	VMT	+14% (295 billion miles)
Zhang et al., 2018	Atlanta, (Metropolitan Area) GA, US	2011 Atlanta Travel survey data	2015 trip profile	Vehicle ownership reduction potentials and unoccupied VMT	PAV	VMT	+59.5%
						Vehicle Ownership	-18.7% of households
Bhardwaj et al. 2023	Canada	CPEVS Survey 2017	2020-2035 (simulated)	Long term emissions from AV under climate policies	PAV	GHG from VKT (new users)	+20%
Sun et al., 2023	California, US	California Household Travel Survey (2012 CHTS) 42,500 households	2010-2012 (data) 2050 (simulated)	AV scenarios for pricing strategies on VMT and GHG emissions	PAV & SAV	VMT	+3% – +35% (1,174–1,616 million miles)
						VMT (with pricing)	-23%−+6% (904–1,217 million miles)

[3] Assumed to be PAV because source data is primarily private vehicles.

Table 2: Empirical L2 AV Studies

Model Study	Study Location	Study Size	Study Years	Study	Type	Travel Variable	Association (Percentage)
Asmussen et al., 2022	Austin, (Metropolitan Area) TX, US	978 respondents (with motorized vehicles)	2019	Impact and uptake of partially autonomous features (PAFs)	PAV	VMT	+13.8% (2,462 miles)
Hardman et al., 2022	California, US	4,925 Plug-in Electric Vehicles (PEV) Owners	2019	Comparing travel behavior for L2 vehicles with those of L0 similar vehicles	PAV	VMT	4,059–4,971 more miles per year (+24.7-28.7 %)[4]

Table 3: Mock-AV Experiments

Experimental Study	Study Location	Study Size	Study Years	Variable (PAV)	Travel Variable	Association (Percentage)
Harb et al., 2018	San Francisco Bay Area CA, US	13 individuals[5]	2017	60-hour Chauffeur (mimic PAV)	VMT	+83%
Harb et al., 2022	Sacramento, CA, US	43 households		60h Chauffeur (mimic PAV)	VMT	+60%
					Zero occupancy Trips (of additional trips)	+85%
					Transit	-70%
					Biking	-38%
					Walking	-10%

[4] Calculated from entire study average VMT (from communication with authors), because of the unavailability of the propensity score matched mean VMT.

[5] 5 of the 13 participants are retirees so it is not (meant to be) a representative sample.