Title

A Beauty or a Beast? Estimating Travel Behavior Impacts of Privately Owned Autonomous Vehicles via The Chauffeur Experiment

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By

Mustapha R. Harb

A dissertation submitted in partial satisfaction of the requirements for the degree of

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Committee in charge:

Professor Joan Walker, Chair

Professor Mark Hansen

Professor Maximilian Auffhammer

Professor Michael Cassidy

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Abstract

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Today's automotive industry is witnessing unprecedented technological change. Automation is particularly expected to revolutionize how we travel and to have profound impacts on the transportation system. Whether autonomous vehicles (AVs) will improve our lives, exacerbate existing mobility challenges, or lead to currently unimagined ramifications, however, is still an open question. On one hand, the improvements in safety, efficiency, and accessibility are thought by many to be the answer to our transportation problems. However, others project a dystopian future where the efficiency improvements, while real, are not enough to counteract the trends of increasing population, urbanization, and vehicle miles traveled (VMT) per capita, as well as induced demand. While it is not certain which future beckons, there is certainty that human travel behavior, the focus of this dissertation, will be central to determining the outcome.

The objectives of this dissertation were to:

1) Collect new data on the travel behavior implications of privately owned autonomous vehicles through an innovative method that overcomes the limitations of the current literature.

2) Analyze the data to quantify the implications of privately owned autonomous vehicles on human travel behavior and the heterogeneity in the response to the technology by different demographic and lifestyle groups.

3) Integrate privately owned AVs into an activity-based model framework by estimating short-term travel demand models and proposing additional components unique to privately owned AVs.

The first step to achieving our objectives was to conduct a literature review. We identified 78 published studies that address issues of travel behavior implications of AVs. We summarized the methods currently being used to address research questions on travel behavior changes caused by AVs, highlighted their strengths and limitations, and proposed ways to improve upon these methods. We then identified critical research questions to be addressed and summarized results from the studies that addressed them. We organized the research questions into four categories: the first are research questions that have been explored by many studies, where the direction of the impact is consistent across the literature, albeit the magnitude varies considerably. For example,

the impact of (shared) AVs on VMT has been well explored and most studies predict an increase which is projected to range from 1% to 90%. Similarly, many studies explored future mode choice preferences with results indicating that, overall, people prefer owning AVs over sharing them. The second category of research questions are ones with limited and consistent results, albeit the range varies widely. For example, a few stated preference survey studies indicate that reduced stress and multitasking during travel will reduce the value of time of AV riders by 5% to 55%. The third category of research questions are ones with few but conflicting results. For instance, a few survey studies indicate that people (up to 80%) do not believe their residential location will be affected by the adoption of AVs. Some simulation studies, however, indicate that lower travel costs will encourage people to move away from cities and into suburbs while other studies report the opposite. The final category of research questions are ones that received little to no attention in the literature. For instance, very few studies focus on exploring how AV owners plan to use zero-occupancy vehicles (e.g., to run errands) in order to quantify their impact on travel behavior and the transportation system.

From the literature review, we found that the two most common methods currently used to study the travel behavior implications of AVs are surveys and simulation studies. In this dissertation, however, rather than relying on surveys or simulations, we proposed a different method to explore the impacts of AVs on travel behavior: an experiment in which we simulate the experience of owning personal AVs by providing subjects with personal chauffeurs. Thus, we essentially installed the driverless feature onto their own vehicles. Just like an AV, the chauffeur took over driving duties so that subjects could relax or use their travel time productively. Subjects were also able to send out their chauffeurs to run errands that AVs will run in the future (e.g., filling up gas, picking up groceries, picking up friends and family). Subjects were tracked and their travel diaries were recorded for three to four weeks, with the outer, non-chauffeur weeks serving as control weeks (i.e., status quo conditions), and the middle chauffeur week(s) serving as treatment week(s) (i.e., "AV" weeks). By comparing travel behavior during the chauffeur weeks to the non-chauffeur weeks, we gained novel insights into what the potential shifts in travel behavior might be in an AV future.

We ran two iterations of our experiment. The first was a pilot that involved 13 subjects from the San Francisco Bay Area during the summer of 2017. The sample was a convenience sample stratified mainly by demographic (families, retirees, and millennials), where all subjects received one chauffeur week. We then ran a second, larger experiment in 2019/20 on 43 households in the Sacramento area, incorporating several improvements over the pilot study. To obtain a more diverse sample in terms of demographics, modal preferences, and mobility barriers, we partnered with the local metropolitan planning agency, the Sacramento Area Council of Governments (SACOG), who gave us access to travel survey data for a representative sample of households. We also provided a portion of our households with an extended chauffeur period (two weeks) to explore the impact of the treatment period on the results. Finally, we tracked all members and vehicles in the household and used a different phone tracking app to record a richer dataset that includes more detail on trip purpose, modes (private vs shared), parking, and vehicle occupancy.

We present two types of results in this dissertation. The first set of results are descriptive statistics that analyze basic shifts in travel behavior and the heterogeneity in the response to the chauffeur service by different demographic groups. These results are largely consistent across both iterations of the experiment. The second type of results are based on the estimation of typical travel demand models where we explore the factors behind the behavioral shifts observed in the first set of results, as well as investigate how AVs should be incorporated into an activity based-model framework. These modeling results are exclusive to the second iteration of the experiment since they require a larger sample and detailed trip data only available from the newer tracking app. Since descriptive statistics are consistent across experiments, and the second iteration included a more comprehensive set of results, we only present key findings from the larger experiment here. The sample for the second iteration was fairly representative of the population of Sacramento (the study region), albeit included a higher share of females and was more affluent and educated than the general Sacramento population. Due to the relatively small sample size and potential self-selection issues, results reported here are not projected to the general population and are only representative of our sample.

Overall, households used their household vehicles substantially more during the chauffeur weeks compared to the non-chauffeur weeks. The total vehicle miles traveled (VMT) of our sample increased by 60%, which falls in the higher end of the range reported in the literature (1% - 79%). The elderly and individuals with mobility barriers exhibited the highest percent increase in their VMT (150%) while families with kids observed the lowest increase (17%). Moreover, almost all households (95%), at some point during their chauffeur week, sent their chauffeur out alone to run errands (equivalent to zero occupancy vehicle (ZOV) or "ghost" trips in an AV future), and this made up half of the increase in VMT. During the chauffeur weeks, the overall systemwide trips increased by 25%, which drops to only a 3% increase if ZOV trips are excluded from the analysis. Moreover, subjects' average trip length increased by 16% during the chauffeur weeks, which falls in the lower end of the range predicted in the literature (2.5% - 45%). During the chauffeur weeks, we observed a 20% increase in night trips (after 7 pm), 76% increase in trips between 20 and 50 miles, and 81% increase in trips longer than 50 miles. However, if only person trips are considered (i.e., ZOV trips are excluded), these numbers drop to 5%, 50% and 61% respectively. During the chauffeur weeks, subjects also became more auto-oriented, relying more on their "AV" and shifting away from transit trips which dropped by 70% (compared to the 9% - 70% decrease predicted in the literature). Similarly, subjects shifted away from active modes of transportation with biking and walking trips dropping by 37% and 13% respectively. The increase in vehicle miles traveled, therefore, came from three sources: 1) 50% of the increase came from subjects sending out their chauffeurs to run errands and serve friends and family; 2) 40% came from the increase in the average trip length as subjects traveled to farther locations; and 3) 10% came from subjects switching from non-auto modes to using their "AV."

For the second set of results, we explored how to integrate AVs into activity-based models, including model specifications and parameter estimates. We investigated four components of activity-based models: activity patterns, destination choice, mode choice, and time of day, which also provided insights on the potential factors that led to the behavioral changes described above. Our formulations were inspired by the Sacramento regional model, albeit kept parsimonious with limited heterogeneity due to the small sample size. We compared the models estimated with data from the chauffeur weeks to those during the non-chauffeur weeks. We found that there were no statistically significant differences in the parameters of the individual activity patterns, destination choice, or time of day models. For the mode choice model, however, while the constant for auto did not change, the value of time dropped by 60% during the chauffeur weeks. Moreover, as the destination choice model included a logsum from the mode choice model, this resulted in longer average tour lengths, even though the parameters (beyond those in the logsum) of the destination choice model did not change. Moreover, while the trip-making propensity of individuals did not change significantly, there was a 25% increase in systemwide trip rates due to the "AV" (chauffeur) being sent on errands. This pointed to the importance of incorporating zero-occupancy vehicle trips into the activity-based modeling framework. By observing how subjects used their ZOV trips (i.e., sending their chauffeurs to run errands) we were able to propose a way to integrate these trips within a standard activity-based model framework. Our findings suggested that if ZOV trips are compartmentalized and separated from individual person trips/tours, the existing structure and parameters of an activity-based model do not need to be modified, apart from the reduction in the VOT for the auto mode. Zero-occupancy vehicle trips can then be added either as additional ZOV home-based tours or as ZOV sub-tours within the standard activity-based model process. Lastly, as inter-regional travel (e.g., tours outside the Sacramento area in our study) is modeled outside the activity-based model framework, our results indicated that modifications should be made to account for the increase in inter-regional tours, which were 54% more frequent in our sample during the chauffeur weeks.

To summarize, in this dissertation we designed and executed a unique revealed preference AV experiment that allowed us to quantify many of the potential travel behavior changes that might result from AVs. A key benefit of having access to an "AV" was the enhanced mobility and accessibility our subjects experienced during the chauffeur weeks, which was manifested by the increase in average trip and tour lengths and was highlighted by many subjects, e.g., "I love the chauffeur service. I've already gone to two places I would never have driven to on my own and it's been wonderful." At the other end of the spectrum, however, an undesirable consequence of private AV adoption was the increase in car usage which led to an increase in overall VMT and a shift away from transit and active modes of travel. Mode choice and destination choice model estimations indicated that the primary factor behind these behavioral shifts was the reduction in subjects' VOT for the car mode, leading to an increase in accessibility (as measured, for example, via the logsum). The experiment also highlighted another undesirable consequence of private AV adoption, which was the reliance on zero-occupancy vehicles ("ghost" trips). We identified these trips as a primary source of travel behavior change, highlighting the importance of incorporating them into simulation studies. We then suggested a way to incorporate ZOV trips into an ABM framework as additional model components that consist of ZOV home-based tours and ZOV subtours using a standard ABM process. Finally, even though our sample size was relatively small, we were able to quantify the heterogeneity in the response to AVs. Results indicated that changes in travel behavior were largest for individuals with mobility barriers, the elderly, and single occupancy households and lowest for families with kids. Similarly, non-auto dependent households also observed a substantial shift in travel behavior as they became more auto-oriented.

While our dataset is for a relatively small number of individuals, we were able to obtain detailed revealed preference insight for each of these individuals into their travel behavior choices with privately owned AVs. To our knowledge, this is the first such exercise using this chauffeur approach, and we were able to quantify important travel behavior metrics for privately owned AVs as well as estimate traditional (albeit parsimonious) travel demand models. Our results provide quantitative and qualitative information on both the many benefits of privately owned AVs ("the beauty"), but also the potential drawbacks of their adoption ("the beast"). As policy makers contemplate regulations for AV deployment, it will be critical to identify and evaluate the tradeoffs between enhancing the quality of life versus the environmental and social costs of the additional travel induced by AVs.

To Ramadan and Rola Harb
for their unconditional love and support.

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Chapter 1
Introduction

1.1 Motivation

Today's automotive industry is witnessing unprecedented technological. Automation is particularly expected to revolutionize how we travel and to have profound impacts on the transportation system: "Just like freeways shaped past cities and lifestyles, self-driving vehicles will remake the metropolis once again" (Walters and Calthorpe, 2017). A study by Intel (2017) projected that the autonomous vehicles industry (also referred to as automated vehicles or self-driving cars) will be worth $7 trillion by 2050. The battle to develop autonomous vehicle (AV) technologies is led by traditional car manufacturers and major tech industry players, spending billions to ensure leadership. In September 2016, Uber launched a self-driving taxi fleet in Pittsburgh (while retaining a 'driver' for legal and safety purposes). Similarly, since April 2017, participants of Waymo's early riders' program have had access to a fully autonomous fleet, sans a human backup driver, a service that is now open to the public in Phoenix, Arizona as of October 2020. Waymo's autonomous vehicles drove one million miles on public roads in total between 2009 and 2015 and have driven an additional 19 million miles since then (Waymo, 2020). In January 2020, Honda and General Motors unveiled their autonomous vehicle "the Origin" with no steering wheel or break and acceleration pedals (McFarland, 2020). In addition to these companies, the intense competition to develop driverless vehicles is spearheaded by a host of companies such as Tesla, Ford, Cruise, BMW, and Apple. In California alone, the DMV reports 68 testing permit holders as of September 1, 2020 (DMV, 2020).

AVs and shared AVs (SAVs) blend features of multiple traditional modes—they combine the convenience and comfort of private vehicle ownership with key public transit advantages, like the ability to multitask or relax during one's commute or share rides with other passengers for discounted fares. AVs, together with advances in information technology, have the potential to change our lives, from how we commute to where we live and work, and will impact a host of industries (for a summary of these impacts, the reader is referred to Manyika et al., 2013 and Clements and Kockelman, 2017). Whether self-driving technology will improve our lives, exacerbate existing mobility challenges, or lead to currently unimagined ramifications, however, is still an open question. On one hand, automation is expected to improve the transportation system through increased road capacity, fewer accidents, reduced parking demand, and increased mobility and accessibility. However, the concern is whether the efficiency gains are enough to counteract the opposing forecasts of increased travel demand, urbanization, and growth in vehicle miles traveled (VMT) per capita as a result of improved mobility and accessibility and lower travel costs. While it is not certain how the AV future will look like, there is certainty that the impact on human travel behavior, the main focus of this dissertation, will be central to determining the outcome.

The literature distinguishes between five levels of automations. In this dissertation, we focused on full automation, also referred to as levels four and five, where vehicles can operate without human intervention or presence. These levels have the potential to result in the most radical behavior change as they take over driving duties, allowing users to relax or productively use their in-vehicle travel time, and to send out vehicles to autonomously run errands. Consequently, understanding the impact of fully autonomous vehicles on travel behavior is imperative to properly regulating them and realizing a "utopian AV future".

1.2 Methods Used to Explore the Impact of AVs on Travel-Related Behaviors and Their Limitations

Four method have been used to explore the implications of AV technology on travel-related behaviors—controlled test beds, driving simulators and virtual reality, surveys, and microsimulations/travel demand models.

Controlled testbeds (i.e., testing the technology is a controlled and isolated environment to minimize safety risks) play an important role in integrating the technology into the transportation system by ensuring its safety. However, this method is unlikely to provide insights on the travel-related behavior changes the technology will induce. Driving simulators and virtual reality can provide insight on pedestrian interaction with the technology, people's driving behavior, and their use of in-vehicle travel time. Similar to controlled testbeds, however, driving simulators and virtual reality do not provide direct insights on changes in users' travel-related behaviors. For studies based on microsimulations, researchers modify existing travel demand models to incorporate AV options and simulate an AV future. This requires making assumptions on travel behavior changes caused by the technology. Consequently, microsimulations help in assessing the impact of changes in travel behavior on the transportation system, but not in identifying what these changes will be. Finally, in survey studies, respondents are asked to imagine how they would feel toward, pay for, and use automated vehicles in hypothetical scenarios. Although a valuable technique to provide initial insights, it is problematic to employ in contexts that are too far removed the subjects' realities. This is precisely the situation with autonomous vehicles. Each method, its strengths, limitations, and contributions to the AV travel behavior literature will be discussed in more detail in chapter 2.

1.3 Objectives

It is difficult to predict the future of mobility after the adoption of autonomous vehicles for the simple reason that they do not currently exist. Consequently, the root of the limitations of current methods reviewed above is the lack of the right data. Therefore, this research effort was motivated by three main objectives:

1) Collect new data on the travel behavior implications of privately owned autonomous vehicles through an innovative method that overcomes the limitations of the current literature.

2) Analyze the data to quantify the implications of privately owned autonomous vehicles on human travel behavior and the heterogeneity in the response to the technology by different demographic and lifestyle groups.

3) Integrate privately owned AVs into an activity-based model framework by estimating short-term travel demand models and proposing additional components unique to privately owned AVs.

1.4 Methodology

Instead of using microsimulations or surveys, in this dissertation, we proposed a different method—an experiment where we simulated people's lives with personal AVs by providing them with personal chauffeurs.

The feature that will cause the most change in travel behavior is the driverless feature, as it allows riders to productively use their travel time and owners to send their AVs to autonomously run errands. By providing study participants with personal chauffeurs, we essentially installed the driverless feature onto their vehicles. Just like an AV, the chauffeur fully took over driving duties so subjects could relax or productively use their travel time. Subjects were also able to send out their chauffeurs to autonomously run errands that AVs will run in the future (e.g. filling up gas, picking up groceries, picking up friends and family). The experiment allowed subjects to experience the driverless feature and adjust their daily travel and activities the way they will in an AV future[1]. This allowed us to study these behavioral shifts through observational data rather than the more common survey data. The advantage of experiencing the self-driving feature rather than responding to hypothetical scenarios was highlighted by two study participants:

- "Before this experiment, I could not see me ever having a self-driving car, but now I can see how useful it would be."

- "[After the experiment] my daughter and I commented on how the self-driving cars would affect our behavior in ways we had not thought about."

Figure 1 below illustrates the key components and flow of the experiment. First, subjects and drivers were recruited and onboarded. Then comes that heart of the experiment: tracking subjects' travel for three to four weeks, with the chauffeur intervention occurring in the middle week(s). Finally, an online survey was administered before and after the three/four weeks of travel. The details of each components of the experiment (e.g. recruitment, tracking, the chauffeur service) are discussed in more detail in chapters 3 and 4.

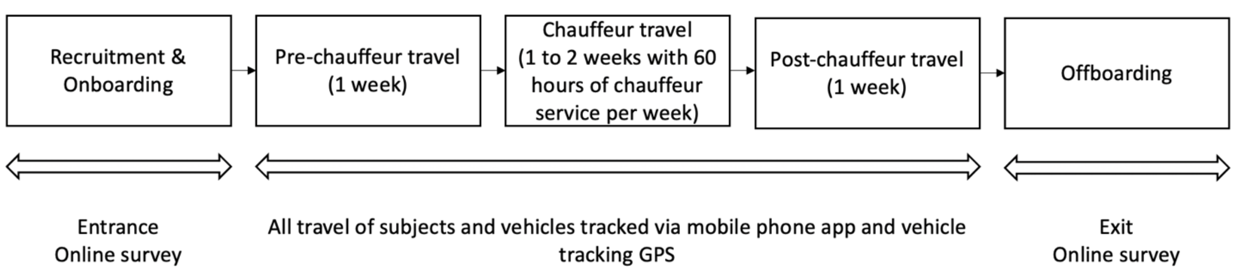

Figure 1: Flow of experiment and primary data collected

The set-up of our experiment falls under the category of before and after studies (also called pre-post studies), where a researcher can compare the outcomes (or treatment effect) of the same group of individuals before and after participating in a program. In their book "Impact Evaluation in Practice", Gertler et. al (2011) discuss these experiments and indicate that problems with these

1 Individuals are also expected have access to a shared fleet of autonomous vehicles in an AV future. Therefore, a complement to our experiment would be to investigate the travel behavior impacts if people were to make use of a shared fleet of autonomous vehicles (rather than private ownership), and this is left for future research.

studies arise when programs are implemented over a long period (months or years), since the conditions during one time period might be significantly different than those in the other time periods, creating biases in the results. However, if the time period is short and conditions are stable, one can assume that the effect of time is negligible, and the average treatment effect (e.g. change in VMT) can be identified by taking the difference between the treatment (chauffeur) weeks and control (non-chauffeur) weeks. A limitation of the short treatment period, however, is that changes in long-term decisions (e.g., residential location, car ownership) cannot be studied through the experiment, however, they could still be investigated via the entrance and exit surveys.

1.5 Contributions

The focus of the dissertation was to quantify and model the travel behavior implications of privately owned autonomous vehicles. The contributions of this dissertation are summarized below:

First, we collected revealed preference data on the potential travel behavior implications of privately owned AVs through an innovative method that overcomes the limitations of current methods used in the literature. While most studies rely on stated preference data or simulations, we proposed running an experiment in which we used a personal chauffeur to simulate life with a privately owned AV. The experiment allowed our study participants to experience, first-hand the benefits of some of the more salient features of owning an autonomous vehicle, namely the driverless feature. This allowed us to observe how subjects adjusted their “real life” everyday travel decisions as a result of having access to an “AV”. An anonymized version of this dataset will be made available to other researchers.

Second, we quantified the impact of AVs on travel behavior using the revealed preference data collected. We quantified the impact of the chauffeur service on areas that have been explored in the literature such as vehicle miles traveled, trip rates, average trip length, and mode choice, albeit with our revealed preference setting. Beyond these important metrics, our dataset also allowed us to provide unique insights on central topics that have received little to no attention in the literature. For instance, we quantified the heterogeneity in the response to “AVs” by individuals from different demographics and with unique lifestyles, modal preferences, and mobility barriers (e.g. retirees and individuals with disabilities). This information will be key in ensuring that policy decisions made will lead to an equitable transportation system in an AV future. Another key aspect of AVs that has received little attention in the literature is zero-occupancy vehicle trips. As subjects were able to send out their drivers to run errands and serve friends and family, we gained access to unique insights on how zero-occupancy vehicle trips will impact travel behavior, as well as how often and for what purposes will these trips be used. This allowed us to identify zero-occupancy vehicle trips as a primary source of travel behavior change, highlighting the importance of incorporating them in simulations, which has been a shortcoming of most AV-based simulation studies thus far.

Third, we proposed a way to model privately owned AVs by incorporating them within a standard activity-based model framework. Our focus was on short-term travel decisions, and longer-term impacts such as vehicle ownership and residential choice were outside our scope. We showed that zero-occupancy vehicles trips can be compartmentalized and separated from individual person trips and tours, and then the existing structure and parameters of an activity based-model do not need to be significantly modified. The only parameter we found to be significantly different was a reduction in the value of time for the auto mode, which we were able to estimate using real world mode choice decisions by our study participants. This resulted in both a shift towards auto from other modes as well as longer trip distances. We then proposed a way to incorporate zero-occupancy vehicle trips into the activity-based model framework as additional zero-occupancy vehicle home-based tours and as zero-occupancy vehicle sub-tours within the standard activity-based model framework. While inter-regional travel is exogenous to the activity-based model framework, a significant increase in inter-regional tours in our dataset suggests that modification should be made to account for this increase.

While our dataset is for a relatively small number of individuals, we were able to obtain detailed revealed preference insight for each of these individuals into their travel behavior choices with privately owned AVs. To our knowledge, this is the first such exercise using this chauffeur approach, and we were able to quantify important travel behavior metrics for privately owned AVs as well as estimate traditional (albeit parsimonious) travel demand models.

1.6 Dissertation Outline

The remainder of the dissertation is organized as follows. In Chapter 2, we review the literature that addresses relevant research questions on changes in travel-related behaviors induced by autonomous vehicles. First, we identify the methods currently used to address research questions on travel behavior changes caused by AVs, highlight their strengths and limitations in contributing to the literature, and propose ways to improve upon these methods. We then identify the critical research questions, summarize results from studies addressing these questions, and categorize questions based on the amount of attention they received in the literature. Chapters 3 and 4 then present detailed descriptions of the experimental design and the key findings from the 13-household pilot experiment in the San Francisco Bay Area and the expanded 43 household experiment in the Sacramento area, respectively. In Chapter 5, we present results from short-term travel demand models where we estimate key parameters, such as value of time, that are often modified/assumed in AV-based simulation studies. We also propose a way to integrate zero-occupancy vehicles within an activity-based model framework. Finally, in Chapter 6 we summarize the work done in this dissertation, our contributions to the field, as well as provide a roadmap for future work.

Chapter 2

What Do We (Not) Know About Our Future with Autonomous Vehicles? A Literature Review of Travel-Related Behavior Implications

Mustapha R. Harb
Amanda Stathopoulos, Ph.D.
Yoram Shiftan, Ph.D.
Joan Walker, Ph.D.

Abstract

While research on developing and testing automated vehicles (AVs) is well underway, research on their travel behavior implications is in its infancy. The aim of this chapter is to summarize and analyze the literature that focuses on travel-related behavior impacts of AVs, namely levels 4 and 5, as well as highlight important directions of research. We review five methods used to quantitatively investigate these implications and how each method contributes to this literature: 1) controlled testbeds, 2) driving simulators and virtual reality, 3) agent-based and travel-demand models, 4) surveys, and 5) field experiments. We also present five critical research questions regarding the implications of AVs on the demand side of transportation and summarize findings from the current literature on: 1) what is the willingness to adopt the technology? and what are the impacts of the technology on 2) in-vehicle behavior? 3) value of time? 4) travel-related behaviors (activity pattern, mode, destination, residential location)? and 5) vehicle miles traveled (VMT)? Results can be divided into four categories. The first category corresponds to results on research questions with numerous data points where the *direction of the impact* is consistent across the literature, albeit the magnitude varies considerably. For instance, surveys indicate 19% to 68% of people are unwilling to adopt AV technology, a sentiment that is fading over time. Moreover, people prefer owning AVs over sharing them. Regarding VMT, most studies predict an increase that varies from a low of 1% to a high of 90% depending on the scenario and assumptions under study. The second category of findings corresponds to research questions with limited and consistent results, albeit the range varies widely. For example, a few stated preference survey studies indicate that reduced stress and multitasking during travel will reduce the value of time between 5% and 55%. The third category of results is on research questions with a few but conflicting data points. For instance, surveys indicate that people (up to 80%) do not believe their residential location will be impacted by the adoption of AVs. Some simulation studies, however, indicate that lower travel costs will drive people away from cities and into suburbs while other studies report the opposite. The final category of results corresponds to research question with a single or no data points. For instance, one study explores how users will use vehicles to run errands while no studies investigate user preferences for vehicle types (e.g. mobile-homes vs. right-sized) or how they plan to use their vehicles when they are not needed (e.g. rent out vs. leave them idle). Moving forward, the goal is to shift all results into the first category while simultaneously tightening the prediction interval of the magnitude of the impacts. This can be achieved by: 1) focusing more efforts on research questions that fall under the three remaining categories to fill the holes in the literature, and 2) establishing clarity of assumptions used by researchers to enable comparisons and transferability of results.

2.1 Introduction

The development of self-driving technology is well underway, with several companies already testing level 4 AVs on public roads without a human safety driver (DMV, 2020). Consequently, governments are working diligently to keep up with the advancements in these technologies, studying their implications to propose effective policies. In 2018, the USDOT released "Preparing for the Future of Transportation: Automated Vehicle 3.0," which focuses on safety, policy, and process of AV deployment. The National Conference of State Legislatures reports that 29 states have enacted legislation related to autonomous vehicles. For example, in 2018 the Colorado Department of Transportation announced its plans for the first autonomous vehicle lane on highway C-470 as a first step to embracing AV technology (Aguilar, 2018). However, regulating this technology is challenging, considering that the availability of the technology for commercial use is still limited and the implications are difficult to predict.

Two main business models are speculated to shape the future of transportation. The first is a private ownership model where people own their personal AVs. The second is a sharing model (i.e. SAVs) where carsharing and ridesharing companies (e.g. ZipCar and Uber/Lyft) offer on-demand mobility services. In both scenarios, automation is expected to improve the transportation system, however, researchers (Fagnant and Kockelman, 2018; WEF, 2018; Wen et al., 2018; Zhang and Guhathakurta, 2018; Creger at al., 2019; Kim et al., 2020) believe that the key to capitalizing on the advantages of the new era in transportation is to: 1) integrate its use with high capacity transit systems; 2) increase vehicle occupancy levels through pooling and ride-sharing; and 3) encourage multimodality and the use of active modes—walking and biking. The combination of these features is closely associated with the concept of Mobility as a Service (MAAS) (Matyas and Kamargianni, 2018) where users access bundled services and modes using a single platform[2].

Automation levels four and five have the potential for the most radical change in activity and travel-related behaviors, and these implications are the least understood today. Therefore, in this chapter, our main focus, albeit not the sole one, is on research regarding automation levels four and five. While research on developing and testing these technologies is well underway, research on its implications on travel-related behaviors is still in its infancy. The topic, however, is receiving growing attention. For example, workshops have been held at the annual Autonomous Vehicles Symposium (San Francisco, 2014-2019) and the tri-annual conference of the International Association of Travel Behavior Researchers (Windsor, 2015; Santa Barbara, 2018), and it was a topic of emphasis at events such as UC Davis' “The Three Revolutions of Future Mobility" (UC Davis, 2018). A recurring theme at all these events, however, is how little we know about the travel behavior implications of automation and the high degree of uncertainty surrounding its future.

The first goal of this literature review is to summarize and analyze the behavioral implications that could emerge from increasing automation, and deliver a more detailed treatment of these impacts, informed by joint analysis of a broader range of studies and methodologies than is considered elsewhere in the literature. A detailed comparative analysis against previous review

[2] E.g. Moovit (Moovit, 2019) and TriMet Tickets (TriMet, 2019) are phone applications that allow users to plan multi-modal trips (bike/scooter sharing, walking/biking, public transit, ride/car sharing) on a single platform, while providing real time trip information.

papers focusing on automation is delivered in Section II. The second goal is to outline a roadmap for future research regarding travel behavior implications of AVs. This is done in three steps: 1) summarizing and analyzing the current literature on travel behavior implications of AVs, 2) identifying the topics that require further investigation, and 3) concluding with guidance that can help advance this field moving forward.

The remainder of this chapter is structured as follows: section two describes the methodology and the contribution of this paper in more detail. Section three reviews the methods used to study the impact of AVs on travel-related behavior. Section four then summarizes the key research questions regarding the impacts of these technologies on activity and travel-related behavior and the key findings from the literature. Section five discusses suggestions to improve future research. Section six then discusses critical future research directions, and finally, section seven presents a conclusion.

2.2 Methodology

The literature search process was limited to papers published between 2011 and July 2020 and included scientific papers, academic reports, and private sector reports. The search process was conducted using various queries in scientific literature databases, such as ScienceDirect, Web of Science, Scopus, and Google Scholar. The literature has grown considerably, as illustrated by initial search keywords including various synonymous terms "autonomous vehicle/car", "autonomous vehicle/car", "self-driving vehicle/car" yielding 22,890 records in Scopus. Further refinement coupled these AV terms with behavior keywords; "travel behavior", "value of time", "adoption", "residential location", "activity patterns" and derivations. Backward and forwards snowballing was used to retrieve relevant studies from identified literature reviews and other papers found via the database searches. The procedure to narrow down and classify the search results was carried out in 2 steps: Step 1) papers were screened to verify that the main focus of the study is in scope—i.e. behavioral response to AVs and their impact on travel demand. Studies with a supply focus and research on logistics and goods delivery are beyond the scope of this review. An important observation needs to be made concerning supply effects that indirectly affect travel behavior. Importantly, we exclude from the review studies that focus on changes in road capacity and in the operating costs of AVs and SAVs from the supply perspective. While the operating and usage costs will likely cause behavior changes (e.g. in mileage and residential location over time), this review maintains the focus firmly on the acceptability and demand in response to pricing. We direct the reader to Milakis et al. (2017) for notable examples of these supply-focused analyses. Following the content scrutiny was the exclusion of duplicates and non-English language papers. Step 2) was to define the research questions that will be addressed. The final list was a combination of research questions that were predetermined by the research team from their existing knowledge and experience and ones identified during the literature review. The five behavioral research questions selected and discussed in this review are: 1) what is the willingness to adopt AV technology? and what are the impacts of the technology on 2) in-vehicle behavior? 3) value of time? 4) travel-related behaviors (activity pattern, mode, destination, residential location)? and 5) vehicle miles traveled? We note that with the high volume of studies on AV acceptance, reviewing and including studies from around the world would be a challenging task. Therefore, for studies that address this specific research question, the inclusion criterion was limited to studies conducted in the US. A high-level comparison with studies from other regions was included, however. For the remaining research questions, there were no geographic restriction and all relevant studies were included. This review encompasses a broad range of methodologies used to examine the five focus questions. Studies in five domains are covered in the review, namely controlled testbeds, driving simulators and virtual reality, agent-based and travel demand models, surveys, and field experiments. Following these considerations, 78 papers were included in this review.

The literature search also led to identifying four related AV literature review papers: Becker and Axhausen (2017); Milakis et al. (2017); Soteropoulos et al. (2018); and Gkartzonikas and Gkritza (2019). Our literature review contributes to the understanding of automation impacts by adding an original focus on multiple travel behavior impacts studied using a broader range of research methods. Firstly, we expand and update insights from more narrowly focused reviews. For instance, Becker and Axhausen (2017) provide a detailed review of surveys on AV acceptance focusing on the methods and variables studied. Relatedly, Gkartzonikas and Gkritza (2019) review survey studies on AV adoption intentions while focusing on patterns of perceptions and attitudes comparing general users, vehicle owners, and transportation experts. Expanding on these, the current review examines surveys alongside numerous other data-collection methods. Moreover, our review has a different focus than the two remaining review efforts. Soteropoulos et al. (2018) review studies that investigate the impact of the technology on travel behavior and land use, while considering only modelling based studies such as Agent-Based Models. Milakis et al. (2017), on the other hand, review the literature on implications of autonomous vehicles while covering a wider array of topics (e.g. road capacity, travel cost, economy, travel choices, etc.) and study types. While Milakis et al. (2017) cover some behavior-related issues, they jointly analyze infrastructure and policy variables. Interestingly, Milakis et al. (2017) conclude that “More creative techniques such as virtual reality or serious gaming would be useful in behavioral experiments about the impacts of autonomous vehicles” (p 343). Our review is the first effort to combine the focus of behavioral understanding gained via a larger set of data collection and research methods. This approach enriches our understanding of the automation phenomenon by allowing more dialogue between research disciplines while maintaining the focus on the cascading behavioral effects related to self-driving.

2.3 Review of Methods

In this section, we review the five methods used to explore the implications of AV technology on travel-related behaviors. The goal of this section is to summarize the strengths and limitations of each method in the context of travel behavior and make this information accessible. Specifically, we focus on examining the coupling between specific methods and behavioral research questions. This will guide researchers to select the appropriate research method and address the behavioral research questions of interest more robustly.

For human factors and safety research, the three methods of choice are controlled testbeds, and driving simulators or virtual reality combined with a survey. For attitudes towards the technology and changes in travel-related behaviors, agent-based and travel demand models, surveys, and field experiments are the most commonly used methods. Each of the five subsections outlines the strengths and limitations and discusses specific contributions of each method to our understanding of the impacts of AVs on travel-related behavior, or the lack thereof. The methods are organized in an ascending order according to their level of contribution to the travel behavior literature on automated vehicles:

2.3.1 Controlled testbeds

The first method we discuss in this section is controlled testbeds, a common tool used to test new products and technologies in controlled environments shielded from most of the real-world hazards. For AV technology, this means testing the technology in areas with a limited number of intersections, pedestrians, traffic, etc.

Controlled test beds are central in ensuring the technology works as expected, and that it can be integrated into the transportation system smoothly and safely. They could also provide insight on how different traveler segments, such as pedestrians, bikers, and other drivers, will interact with the AVs. Therefore, controlled testbeds play an additional important role in integrating the technology, by familiarizing people with the technology and getting them comfortable with having it on public roads. Yet, controlled testbeds are unlikely to provide insights on the changes the technology will induce in people's travel-related behaviors. Consequently, this method is promising for studying human factors and safety, but not as useful for gaining insight on the questions raised in the literature review section.

2.3.2 Driving simulators and virtual reality

2.3.2.1 Driving simulators

Similar to controlled testbeds, researchers use driving simulators (DS) and virtual reality (VR) to study the impacts of the technology while minimizing real-world risk on their subjects. In driving simulators, individuals experience a vehicle-like setting, including a car seat, driving wheel and pedals, and a screen that simulates a road network. After the driving simulator, a survey is often administered to gain insight on the subject's experience and opinions. This method has been used to study safety and human factors in transportation for a long time (e.g. Stein et al., 1983, Akerstedt et al., 2005). Recently, driving simulators have been used to study the impact of semi and highly automated vehicles on driver behavior and in-vehicle activity engagement (e.g. Vollrath et al., 2011, Jamson et al., 2013, Buckley et al., 2018). The limitation of driving simulators, however, is that people may fail to perceive the true risks associated with driving (e.g. it is regarded as 'just a game'). Driving simulators also can't reflect the new travel services and opportunities provided by automation. Results from these studies, therefore, may not reflect behavior under real-world conditions.

2.3.2.2 Virtual reality

To overcome this limitation, researchers attempt to make their simulations more realistic by using virtual reality to immerse their subjects into the simulated world. Similar to DS, a survey is often administered after the VR experiment to gain insight on the subject's experience and opinions. Even though VR makes simulations more realistic and immersive, the degree to which VR can lead to realistic behavioral results has not yet been established. Similar to driving simulators, people in a VR system know it is not real life, and thus might still not perceive the true risks and consequences of real-world decisions. In their study, however, Farooq et al. (2018) argue in favor of VR and the increased sense of reality it offers over other techniques. They explore the efficacy of using text-only, visual-aids (e.g. pictures and videos), and VR on the quality and consistency of results from survey studies (the fourth method discussed in this section). They find that using VR improves respondents' understanding of the choice situation and produces more consistent results. Similarly, Pillai (2017) uses subjects' body language and reactions during a VR pedestrian crossing experiment to argue in favor of VR, giving examples of subjects making statements such as: “It's crazy that I feel a bit of cold just because it's raining” and showing hesitancy to cross when vehicles arrive.

Driving simulators and virtual reality can be powerful tools to study safety and human factors. They can provide insight on pedestrian interaction with the technology (VR), people’s driving behavior (DS), and their use of in-vehicle travel time (DS). This information allows for a better design of vehicles and a safer integration of the technology into the system. Similar to controlled testbeds, however, driving simulators and virtual reality do not provide direct insights on changes in users’ travel-related behaviors. However, researchers have used DS and VR to complement surveys to produce more credible and consistent results regarding the impacts of AVs on travel-related behavior, namely trust in the technology and intentions to adopt (e.g. Buckley et al., 2018, Jamson et al., 2013, Chang et al., 2017, and Jayaraman et al., 2018).

2.3.3 Agent-based and travel-demand models

To assess the impacts of policy decisions on the transportation system, researchers and practitioners have traditionally relied on aggregate models. However, the rise of more powerful computers allowed researches to run large scale disaggregate agent-based microsimulations[3]. Agent-based models are a modeling approach where a system is broken down to its individual components—the agents, then the actions and interactions of the individual agents are simulated to evaluate their effects on the system as a whole (Zheng et al., 2013).

There are two types of agent-based models: 1) network analysis (e.g. Fagnant and Kockelman, 2014); and 2) activity-travel-based models (e.g. Childress et al., 2015). Travel-demand models consist of the demand side, usually the traditional first three steps of the traditional four step models of generation, distribution, and mode choice or the daily activity patterns in activity-based models. The network analysis deals with the supply side, finding the equilibrium between demand and supply. Accordingly, the main difference between the two approaches is that in network analysis, researchers assume a pre-defined demand and assign it on the network making various assumptions of changes in the supply side, such as the road capacity, to study the impact of introducing the technology on the system’s performance, *without accounting for changes in travel-related behaviors or induced demand*. The limitation of network analysis, therefore, is that it focuses on the supply side of the transport system and does not provide insights on changes on the demand side, namely travel-related behaviors—our focus in this literature review. On the other hand, the purpose of travel demand models is to assess and quantify the impact of changes in travel-related behaviors on the transportation system. These models rely heavily on the assumptions made by researchers on the changes the technology will bring to the system. On the demand side, the most common assumptions made by researchers are the willingness to pay for automation, the demand for AV modes (also referred to as market penetration), and the change in value of time (VOT). On the supply side, assumptions include an increase in capacity, lower parking costs, lower/higher operating costs, etc.

The advantage of travel demand models is that travel-related behaviors are built into the model, which makes assessing the impact of changes in these behaviors relatively straightforward.

[3] Several software tools are now available to run these simulations such as VISSUM, CUBE, POLARIS, and MATsim. Extensions are being added to these software tools to allow for the integration of AVs into the network (e.g. robotaxi package in MATsim)

However, a key limitation of these models in a travel behavior context, is that they do not inform what the travel-related behavior changes will be, rather they require assumptions on these changes as input. The reliability and accuracy of the results, therefore, hinge on researchers making thoughtful, realistic, and representative assumptions. However, with a technology that doesn't yet exist for large scale commercial use, the validity of these assumptions cannot be tested.

2.3.4 Surveys

In the lack of real market AV application, researchers have relied mostly on surveys where respondents are asked questions and/or presented with hypothetical scenarios about the technology under study, and state their preferences, attitudes, and intended choices under those scenarios (Ben-Akiva et al., 2019). An advantage of (stated preference) surveys is the ability to solicit preferences and provide insights on potential changes in travel-related behaviors for technologies and market products that do not currently exist (Hensher, 1982, Louviere and Hensher 1983).

There are two types of survey questions: 1) direct questions about attitudes, intentions, and perceptions; and 2) stated preference (SP) and choice-based conjoint analysis (namely discrete choice experiments (DCEs)). In discrete choice experiments, respondents are presented with a hypothetical scenario and a set of alternatives—the choice set, to choose the one they find most attractive. The advantage of these questions is that, when making a choice, people make tradeoffs between attributes of the different alternatives, allowing researchers to estimate the respondent's sensitivity to attributes, as well as key tradeoffs they make to reach their decisions (e.g. willingness to pay for the technology and their value of time). A key factor in the success of these experiments in eliciting true preferences is having the scenario, alternatives, and their attributes and corresponding levels mimic, to the extent possible, the true market and decision-making situation a respondent faces in that market (Ben-Akiva et al., 2019). This is challenging in the context of AVs since they are not available in the market for consumers.

Although a very useful tool, analysts should draw inference from (SP) data with care for two reasons. The first is that (SP) survey studies are often criticized due to the perception that preferences elicited in hypothetical settings do not reflect respondents' real preferences (Louviere et al., 2000, Ben-Akiva et al., 2019). This is particularly a concern when the context is remote from respondents' experiences. It is the responsibility of the researcher, therefore, to bring the context closer to the respondent. To do so, some researchers use VR and driving simulators, as discussed previously, while others rely on videos and text descriptions. The drawback of the latter methods is that different people interpret descriptions and videos differently, introducing undesirable and unobserved heterogeneity in the results. The second reason for drawing inference from (SP) survey studies with care has to do with the technology under study. On one hand, current policies governing the use and adoption of AVs, or the lack thereof, will develop in the future, which means the context in which we frame questions about the technology today might not be representative of the future. On the other hand, people's preferences change as their lifestyles change, which means results will change and evolve over time, as we will see in section four. Finally, results from (SP) survey studies today represent preferences of current generations. However, future generations, born in a time when using the technology is second nature, will have different attitudes and preferences towards it.

2.3.5 Field experiments

The last method we discuss in this section is field experiments. Unlike controlled testbeds, field experiments are conducted in the real world with real (human) subjects. Researchers conducting field experiments have less control over the variables of the experiment than in controlled testbeds. However, since AVs are not yet available for commercial use on a large scale, and regulations on the technology do not permit it yet, running field experiments in non-controlled environments using fully automated vehicle is not feasible. Two types of field experiments are currently used to study the impacts of AVs on travel behavior. In the first type of field experiments, subjects get access to fully automated vehicles (sans human backup in some cases), in a *bounded geographical region,* however. In the second type of field experiments, researchers simulate automated vehicles using a "ghost driver"[4] to give the illusion of an AV or using personal chauffeurs as a proxy to owning a personal AV[5]. Similar to an automated vehicle, the personal chauffeur takes over the duties of driving, relieving subjects from the stress associated with driving, and allowing them to make productive use of their in-vehicle travel time. The chauffeurs can also "autonomously" look for parking, run errands, and chauffeur friends and family.

The main advantage of field experiments is allowing subjects to experience firsthand some of the features of AVs and adjust their lives accordingly, rather than answering questions on hypothetical scenarios. This gives researchers access to revealed preference data on changes in travel-related behaviors rather than the more common survey data. Using this data, researchers can validate results from survey studies and estimate models to calculate changes in VOT, sensitivity to distance, mode choice, etc. Consequently, instead of making assumptions on the changes in travel-related behaviors, researchers using travel-demand models can then use results from these studies as input to run more accurate and realistic simulations. Moreover, these experiments provide insights on how different demographics with different lifestyles react uniquely to the technology. Finally, simulating privately owned AVs using chauffeurs provides insight on the purpose and frequency of zero passenger errands AVs will perform for owners in the future.

Nevertheless, these studies have their limitations. A general limitation of field experiments is that they are conducted in a specific area under unique conditions and regulations. Results from these studies, therefore, might not be externally valid, which means one might not be able to extrapolate and generalize results to other areas and settings. In the first type of field experiments, the main limitation is the restrictions on the locations where vehicles are allowed to operate. This can influence subjects' travel patterns by restricting their destination and mode choice decisions, introducing biases to the results. For the second type of field experiments, the main limitation is the presence of a chauffeur, since people might behave and travel differently when dealing with a machine than with humans, introducing biases to the results. In addition, in each of these field experiments, only one adoption model is considered (i.e. shared or privately owned AVs), whereas in the future, users will likely have access to various subscription, sharing and ownership models. Finally, as these experiments are typically conducted over a relatively short time period, long-term decisions such as vehicle ownership or residential location choice cannot be studied.

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[4] A driver camouflages by dressing up as a car seat, giving pedestrians, drivers, and bicyclists the illusion of a driverless car. See for example Rothenbucher et al. (2016).

[5] This is the methodology we proposed in this dissertation

2.4 Literature Review of the Critical Travel Behavior Research Questions

In this section, we identify critical research questions regarding the implications of autonomous vehicles on travel-related behaviors. For every question, we summarize findings from the literature. The organization of this section follows the flow illustrated in figure 2. The figure summarizes the five research questions emerging in this section and their relationship with one another. As illustrated in the figure, the relationship between demand (the solid rectangles on the left portion of the figure), and the environment (the dashed rectangles on the right portion of the figure) is dynamic, and any change in one component induces change in the other. Our focus in this literature review is on the demand side of the equation. Tables 1 through 11 summarize the reviewed studies, broken down by the research questions addressed and methodological focus. Information on the level of automation considered, the adoption model (e.g. privately owned vs. shared), main assumptions, and main results of each paper are also provided. Since some studies address multiple research questions, they were included multiple times under each corresponding research question.

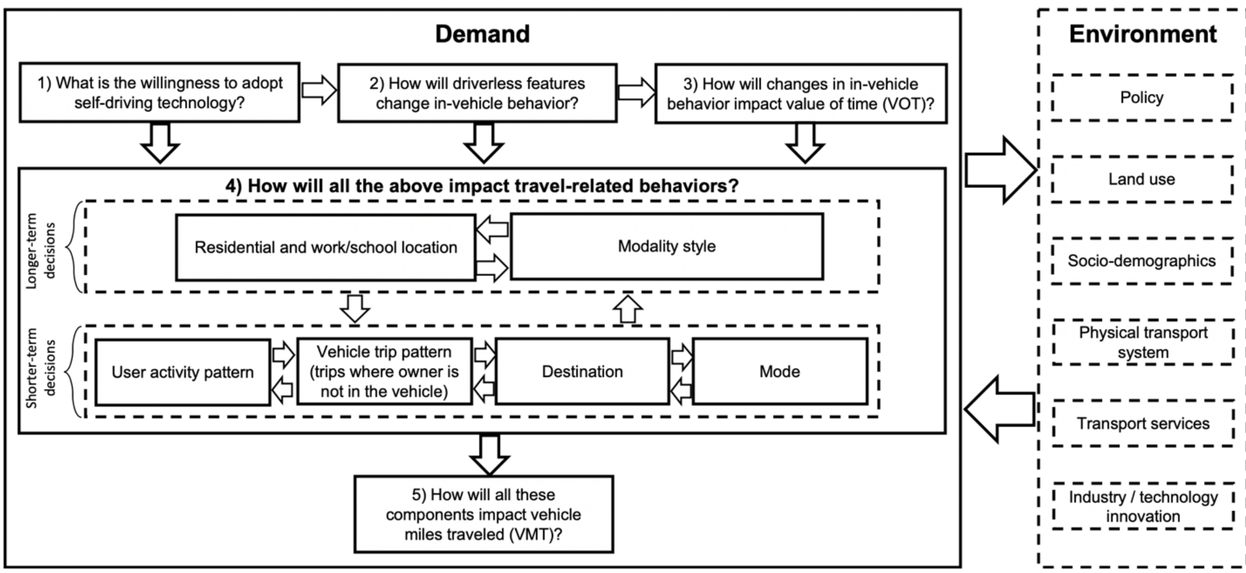

Figure 2: Flow diagram of the critical travel-related behavior research questions

2.4.1 What is the willingness to adopt self-driving technology?

Prior to studying the impacts of self-driving technology, it is essential to investigate people's willingness-to-adopt patterns. The review identified 27 papers centered on exploring acceptance and intention to adopt automation technology, and the factors that influence these decisions (e.g. perceived benefits and risks of the technology, trust in self-driving vehicles safety, etc.). In the examination of adoption studies, the questions of interest are: what is the range of AV acceptance levels across studies, and what are the main factors that influence the decision to adopt? What segments of the population are more willing to adopt the technology, and when are they planning to adopt it? How much are they willing to pay for automation? And finally, how do acceptance and adoption intentions evolve over time and in different contexts?

These questions are addressed to date using three of the research methods—driving simulators, virtual reality, and survey studies. Tables 1-3 summarize the key results from studies that explore people's intentions to adopt and willingness to pay for AV technology:

Table 1: Summary of results on trust & intention to adopt technology

Topic	*Method*	*Paper*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Trust & Intention to adopt technology	Driving simulator	Buckley et al. (2018)	Level 3	N/A	Subjects experience periods of autonomous driving and manual control	Trust is a main factor in intent to use the technology
		Molnar et al. (2018)	Level 3	N/A	Subjects experience periods of autonomous driving and manual control	Frequent passengers tend to trust the technology more than frequent primary drivers
		Zontone et al. (2020)	Level 5	N/A	Put 13 subjects through a driving simulator and measured the heart rate and Electrodermal Activity Skin Potential Response (SPR) signal	Autonomous driving is less stressful as a whole but when the stress is present, it is stronger
	Virtual Reality (VR)	Chang et al. (2017)	Level 5	N/A	Cars have eyes that make eye contact with pedestrians to signal intent to stop	If vehicles communicate their intent to stop, pedestrians feel safer and make faster decisions
		Chang et al. (2018)	Level 5	N/A	Measure the effectiveness of different vehicle to pedestrian communication methods	Text communication is most preferred by pedestrians among possible communication methods
		Jayaraman et al. (2018)	Level 5	N/A	Test the impact of trust and AV driving style on pedestrian crossing	People who have more trust in the technology are more aggressive in crossing
	Survey	JD Power (2012)	Level 5	N/A	General question on the attitudes towards the technology and intention to adopt	67% of U.S. residents are not willing to adopt the technology
		Vallet (2013)	Level 5	N/A	General question on the attitudes towards the technology and intention to adopt	20% of U.S. vehicle owners are willing to "hand over the keys to an AV if it is safe"
		Seapine Software (2014)	Level 5	N/A	General question on the attitudes towards the technology and intention to adopt	88% of U.S. residents are worried about riding in a fully autonomous vehicle
		Pigge and Charles (2014)	Levels 2 to 5	N/A	General question on the attitudes towards the technology and intention to adopt	66% of U.S. residents are not willing to adopt the technology
		Brown et al. (2014)	Levels 1 to 5	N/A	General question on the attitudes towards the technology and intention to adopt	60% of U.S. residents are not willing to adopt the technology
		Schoettle and Sivak (2014)	Levels 4 and 5	AVs	General question on the attitudes towards the technology and intention to adopt	33.7% of U.S. residents are not willing to adopt the technology
		Abraham et al. (2018)	Levels 1 to 5	AVs	General question on the attitudes towards the technology and intention to adopt	48% of U.S. residents are not willing to adopt the technology
		Ipsos (Carmichael (2018))	Level 5	AVs, SAVs	General question on the attitudes towards the technology and intention to adopt	26% of U.S. residents are not willing to adopt the technology
		Haboucha et al. (2017)	Level 5	AVs, SAVs	Discrete choice mode choice experiment between currently owned conventional vehicle, AVs, and SAVs	54% of Americans prefer their conventional vehicle over self-driving options
		Bansal and Kockelman (2017)	Levels 4 and 5	AVs	Questions on attitudes towards the technology, intention to adopt AVs, and willingness to pay for automation	55% of U.S. residents perceive the technology as a useful advancement but 58% are still worried about riding in it
		Hardman et al. (2019)	Levels 4 and 5	AVs	General question on the attitudes towards the technology and intention to adopt	Electric vehicle owners are not more likely to adopt AVs than conventional vehicle owners. 37% of U.S. individuals are pro level 4 and 5 AVs and 12% are against both levels of automation
		Schoettle and Sivak (2015)	Levels 1 to 5	N/A	General question on the attitudes towards different levels of automation and intention to adopt	The most desirable level for U.S. residents is no automation (43.8%) and the least preferred is full automation (15.6%)
		Lavieri et al. (2017)	Level 5	AVs, SAVs	General question on the attitudes towards the technology and intention to adopt	68.5% of Washington State residents are not interested in using shared or privately owned AVs

Topic	Method	Paper	Level of automation	Adoption model	Research approach	Main Finding(s)
Trust & Intention to adopt technology	Survey	Bansal et al. (2016)	Levels 4 and 5	AVs, SAVs	General question on the attitudes towards the technology and intention to adopt	19% of Austin, Texas residents are not willing to adopt the technology
		Zmud and Sener (2017)	Level 5	AVs, SAVs	General question on the attitudes towards different levels of automation and intention to adopt	50% of Austin, Texas residents are not willing to adopt the technology
		Bansal and Kockelman (2018)	Levels 3 to 5	AVs, SAVs	Questions on attitudes towards the technology, intention to adopt private and shared vehicles, and willingness to pay for automation	39% of Texans are not willing to adopt the technology
		Rahman et al. (2019)	Level 5	AVs	General question on the attitudes towards the technology and intention to adopt among the population aged 60+	Males trust AVs more and perceive them as more useful than females. Familiarity with AVs leads to more favorable perception.

2.4.1.1 Intention to adopt

2.4.1.1.1 Driving simulators

Driving simulators, combined with surveys, have been used to study the factors associated with the intention to use AVs. For example, Buckley et al. (2018) find that the most significant factors in the intention to adopt include trust in the technology and other people's perceptions of it. Complementing this study, Molnar et al. (2018) use driving simulators to study the psychological factors that influence people's trust in technology (i.e. being comfortable with transferring control to the vehicle). They find that individuals who frequently travel as passengers (as opposed to drivers) tend to be more comfortable with transferring driving control to an AV. The studies also find that age (Buckley et al., 2018) and gender (Molnar et al., 2018) have no significant effect on the intention to use or trust automation technology.

2.4.1.1.2 Virtual Reality

In the context of autonomous vehicles research, VR has been used predominantly to explore pedestrian interaction with the technology. Jayaraman et al. (2018) place their subjects on an omni-directional treadmill and use a VR headset to simulate a pedestrian crossing scenario. They find that people who trust the technology more are more aggressive when crossing. They also report that trust is affected by the driving style of the vehicle (i.e. perceived aggressiveness of driving) and increases when intersections are signalized. Chang et al. (2017) and Chang et al. (2018) look at the effect of vehicle to pedestrian communication on crossing behavior. In the former, the researchers provide vehicles with eyes that make eye-contact with pedestrians to signal the intent to stop. They find that this addition helps pedestrians feel safer and make faster decisions. In the latter study, the researchers explore the efficacy of various communication methods on crossing behavior—adding eyes to the vehicle, adding a panel that displays a text command (e.g. "do not cross"), a smile, or a green light on the dashboard that signals it is safe to cross. They find that text communication is the most effective way to express the vehicle's intentions [to stop] to crossing pedestrians, who also indicated that they prefer this method over the rest.

2.4.1.1.3 Survey studies

Finally, the majority of adoption studies rely on (SP) surveys, administered since 2012 allowing the U.S. to track adoption intentions over time. Findings suggest that the overarching sentiment towards the technology is one of concern[6], a sentiment however, that seems to be fading with time. The main sources of concern are safety—mechanical and software failure (e.g. malfunctions or failing to recognize objects), and security—hackers interfering with vehicles or data theft, with the former being the primary concern (Schoettle and Sivak, 2014, Kyriakidis et al., 2015, Zmud and Sener, 2017, Abraham et al., 2018, Shabanpour et al., 2018, Barbour et al., 2019). On the other hand, the main benefits of AVs are perceived to be decreased congestion and reduced travel times, fewer crashes and reduced crash-severity, lower travel costs—parking and fuel, and a less stressful driving experience (Schoettle and Sivak, 2014, Abraham et al., 2018, Bansal and Kockelman, 2018, Shabanpour et al., 2018).

Table 2: Summary of results from surveys on AV acceptance by year and region

Study	***Survey year***	***Population***	***Result***
JD Power (2012)	2012	U.S.	67% unwilling to adopt AVs
Vallet (2013)	2013		20% are willing to "hand over the keys to an AV if it is safe"
Seapine Software (2014)	2014		88% are worried about riding in AVs
Pigge and Charles (2014)	2014		66% are not willing to adopt AVs
Brown et al. (2014)	2014		60% are not willing to adopt AVs
Schoettle and Sivak (2014)	2014		33.7% are not willing to adopt AVs
Bansal and Kockelman (2017)	2015		58% are worried about riding in AVs
Abraham et al. (2018)	2017		48% are not willing to adopt AVs
Carmichael (2018)	2017		26% are not willing to adopt AVs
Haboucha et al. (2017)	2014		54% prefer their conventional vehicle over AV options
Schoettle and Sivak (2015)	2015		Most desirable level is no automation (43.8%), and the least preferred is full automation (15.6%)
Bansal et al. (2016)	2014	Austin, Texas	19% are not willing to adopt AVs
Zmud and Sener (2017)	2016		50% are not willing to adopt AVs
Bansal and Kockelman (2018)	2016	Texas	39% are not willing to adopt AVs
Lavieri et al. (2017)	2014	Puget Sound, Washington	68.5% are not willing to adopt AVs

Table 2 highlights the trend of the decrease in unwillingness to adopt AV technology in the U.S. The highest percentage of unwillingness to adopt AVs is recorded in 2014 by Seapine Software (2014) (88%), while the lowest percentage is recorded in 2017 by Carmichael (2018) (26%). Schoettle and Sivak (2015) and Haboucha et al. (2017), however, highlight the fact that Americans still prefer their conventional vehicles over AV options. On another note, Hardman et al. (2019) surveyed 2,715 conventional and electric vehicle owners in the U.S. to explore if the latter are unique in their attitudes towards the technology. The results refute the researcher's hypothesis that electric vehicle owners are more likely to adopt AVs compared to their

[6] This is most evident amongst the residents of the areas in Phoenix where Waymo is pilot testing their technology. To date, at least 21 attacks by residents have been registered, including slashing tires and waving a gun at a Waymo vehicle and its emergency backup driver (Romero, 2018)

conventional vehicle owners counterpart. They then group respondents into 5 clusters based on their attitudes towards the technology and found that level 4 and 5 AV enthusiasts constitute the largest cluster (37%), while 12% had no intention to opt into any of the two levels of automation. For the remaining clusters (51% of the respondents), 16% of them were pro level 4 AVs, and the rest are skeptical of either level of automation.

Other studies focused on specific regions within the U.S., and as illustrated in table 2, Texans seem to have higher trust in the technology compared to the U.S. population with a lower percent of the populations expressing unwillingness to adopt AVs. On the other hand, Puget Sound residents are closer in their preferences to the general U.S. population. This heterogeneity by region is important to capture, and more studies need to target different regions to understand how and why people in different states/cities differ in their opinions and preferences towards the technology. Capturing this heterogeneity will allow for more effective policies; however, this angle of AV acceptance has not received enough attention in the literature. Relatedly, limited comparative research across countries indicates that individuals in the U.S. are more concerned about the technology and are less likely to adopt compared to their counterparts in China, India, Japan, and the UK (Schoettle and Sivak, 2014, Pigge and Charles, 2014, Hulse et al., 2018).

Numerous studies also examine the role played by age and gender for the intention to opt into automation. JD Power (2012), Schoettle and Sivak (2015), Haboucha et al. (2017), Lavieri et al. (2017), Abraham et al. (2018), Anania et al. (2018), Bansal and Kockelman (2018), Hulse et al. (2018), Hardman et al. (2019), and Rahman et al. (2019) all find that males and/or younger individuals are more likely to opt into automation. Contrary to these studies, Becker and Axhausen (2018) find that males and younger individuals are less likely to use autonomous vehicles. Finally, Seapine Software (2014) and Kolarova et al. (2018) find that age and gender have no significant impact, while Zmud and Sener (2017) find that age has no significant impact.

Reviewing studies since 2012, the evidence for a positive trend in adoption intentions over time cannot be ascribed solely to differences in question wording and presentation of the AV acceptance context. Despite this, explaining how adoption intentions are formed behaviorally remains an understudied area. A couple of studies by Anania et al. (2018) and Sanbonmatsu et al. (2018) examine possible channels for the emergence of intentions. In the former, the researchers analyze the effects of positive and negative information on consumers' willingness to ride in a self-driving vehicle. They first present people with different media headlines (positive or negative), then ask them to indicate their willingness to ride in an autonomous vehicle. They show that participants who were presented with positive information have a higher willingness to ride score. Sanbonmatsu et al. (2018), on the other hand, investigate the relationship between people's knowledge about AVs and their attitudes towards them. They show that the most negative views are held by people with the least knowledge about AVs. The general positive trend in stated intention to adopt in the above studies may indeed be supported by the increase in familiarity with AVs due to the growing number of autonomous vehicle urban testbeds including actual customer rides (e.g. Waymo in Phoenix). It is likely that the predominantly positive media coverage has engendered greater public trust in the technology. More recently, however, negative reporting has increased, related to fatal crashes involving AV technology (e.g. Uber's accident in Tempe, Arizona). It remains to be seen how the evolving public and media debate will impact people's perceptions of AVs.

2.4.1.2 Willingness to pay (WTP)

Another important aspect in understanding the intentions to adopt a technology centers on people's willingness to pay for it. Six studies, all using (SP) survey methods, were identified.

Table 3: Summary of results on willingness to pay for automation

Topic	Method	Paper	Level of automation	Adoption model	Research approach	Main Finding(s)
Willingness to pay for automation	Survey	Bansal et al. (2016)	*	*	*	The average WTP for Austin residents is $7,253
		Schoettle and Sivak (2014)	*	*	*	54% are not willing to spend anything on the technology. The 75th percentile willingness to pay is $2,000
		Bansal and Kockelman (2017)	*	*	*	59% of U.S. residents are not willing to spend anything on the technology with average willingness to pay of $5,857 for all respondents and $14,196 excluding individuals not willing to pay anything
		Bansal and Kockelman (2018)	*	*	*	Texans are willing to pay (WTP) $2910, $4607, $7589, and $127 for Level 3, Level 4, and Level 5 automation respectively
		Daziano et al. (2017)	Levels 4 and 5	AVs	Discrete choice vehicle choice experiment with level of automation (full, partial, and no automation) as an attribute of the vehicle	U.S. residents' average willingness to pay for partial and full automation is $3,500 and $4900 respectively
		Asgari et al. (2018)	Level 5	AVs, SAVs, PSAVs	Discrete choice mode choice experiment to estimate demand for AVs, SAVs, and PSAVs	U.S. residents' Average willingness to pay for partial and full automation is $1,483 and $1,639 respectively

2.4.1.2.1 Non-DCE survey questions

In general, surveys indicate that a large share of people are still not convinced about the benefits of automation, which is manifested in their reluctance to spend anything on the technology. Bansal and Kockelman (2017) and Schoettle and Sivak (2014) report that 58.7% and 54% of U.S. respondents are unwilling to spend anything on self-driving technology. Among those who are willing to spend, Schoettle and Sivak (2014) find that the 75th percentile of their respondents would pay $2,000, compared to $14,196 in Bansal and Kockelman (2017) (this number drops to $5,875 if people who have zero willingness-to-pay are included). Asgari et al. (2018), on the other hand, look at U.S. individuals' WTP for different levels of automation and report that the average WTP for advanced features, partially autonomous vehicles, and fully autonomous vehicles is $1,052, $1,483, and $1,639, respectively. Finally, Bansal et al. (2016) and Bansal and Kockelman (2018) report that, on average, Austin residents and Texans are willing to pay $7,253 and $7,589 for full automation, respectively.

2.4.1.2.2 DCE scenarios

Daziano et al. (2017) use results from a discrete choice experiment to estimate a multinomial logit model, where the level of automation is an attribute of the alternatives presented to the respondents. They find that the average willingness to pay for partial and full automation is $3,500 and $4,900, respectively. They also estimate a latent class mixture model to capture heterogeneity in the population and find three segments in the population: 1) a group (29%) with zero willingness to pay for automation; 2) a second group (33%) with a modest willingness to pay of $1,187 and

$1,422 for partial and full automation respectively; and 3) a third group (38%) with a high willingness to pay of $2,784 and $6,580 for partial and full automation respectively. The last group is described as the most eager to purchase the technology, they drive longer distances and have a higher education than the other two segments. Interestingly, the choice experiment results appear to mirror the survey-based willingness-to-pay responses summarized above, following the higher estimates for the enthusiastic population segment.

2.4.2 How will driverless features impact in-vehicle behavior?

The second research question of interest is the impact of emerging driverless features on in-vehicle behavior. Once people adopt AVs, they get access to the benefits of the driverless feature, namely relieving riders from the duty of driving and allowing them to engage in a wider range of activities during their commute. Consequently, the three research questions of interest within this topic are: will people take advantage of the opportunity to engage in other activities during their commute? If they will, what type of activities will they engage in? And finally, how will this impact the demand for new vehicle types with configurations that allow for more in-vehicle activities such as sleeping, working, eating, etc.?

The eight identified papers rely on two main methods; driving simulators and surveys, summarized in table 4 below:

Table 4: Summary of results on driving & in-vehicle behavior

Topic	*Method*	*Paper*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Driving & in-vehicle behavior	Driving simulator	Vollrath et al. (2011)	Level 2	N/A	Study driving behavior under no automation and partial automation	Automation results in lower maximum speeds at the expense of delayed driver reaction when human intervention is required
		Strand et al. (2014)	Levels 2 to 4	N/A	Study reaction time to automation failure in semi and highly autonomous vehicles	The higher the automation the worse the reaction is to automation failure
		Jamson et al. (2013)	Level 3	N/A	Subjects experience periods of autonomous driving and manual control	Subjects perform secondary tasks more in automation mode but experience more fatigue
	Survey	Sivak and Schoettle (2015)	N/A	N/A	Questions on in-vehicle behavior	The most popular in-vehicle activity (46%) is watching the road. People will engage in in-vehicle activities that will increase the likelihood of motion sickness
		Asgari et al. (2018)	*	*	*	28% prefer not to multitask in a fully autonomous vehicle
		Bansal and Kockelman (2018)	*	*	*	Texans will spend their commutes primarily looking out the window, talking to others, eating, and on the phone
		Wadud and Huda (2019)	Level 5	N/A	Asked subjects about current in-vehicle activity patterns and intended activity patterns in AVs	Riders engage in productive activities (e.g. work/study) more during outbound trips than during return trips where they "switch off" and relax
		Pudāne et al. (2019)	Level 5	N/A	Conducted a focus group with 27 subjects regarding their in-vehicle behavior and its impact on their daily activity schedule	Some subjects believe they will productively use in-vehicle travel time while other prefer to just relax

2.4.2.1 Driving simulators

Driving simulators are commonly used to study driving behavior as well as in-vehicle behavior. Looking at early automation technologies, Vollrath et al. (2011) and Strand et al. (2014) examine the influence of technologies like cruise control and adaptive cruise control on driving behavior. The findings point to a seeming paradox; while the assistive technologies result in lower maximum velocities and fewer speed violations, they appear to come at the expense of delayed driver reaction when human intervention is required. Interestingly, it appears that higher levels of automation lead to worse reaction times. Concerning in-vehicle activities, Jamson et al. (2013) examine multitasking behaviors and fatigue in highly autonomous vehicles and report that subjects perform secondary tasks (e.g. listening to the radio, watching a DVD, etc.) much more in self-driving mode than in manual mode. They also find that subjects show more fatigue during self-driving mode. Taken together, the driving simulator studies point to some of the risks that emerge with increasing automation. Zontone et al. (2020), on the other hand, put 13 subjects through a driving simulator and measured the heart rate and Electrodermal Activity Skin Potential Response (SPR) signal. Their analysis shows that autonomous driving is less stressful as a whole compared to conventional driving, but when the stress is present, it is stronger. This could be attributed to the lack of trust in the technology in critical or stressful situations.

2.4.2.2 Surveys

Survey studies thus far indicate that the population is split on the question of productive use of in-vehicle travel time. Asking U.S. respondents what activities they would perform if they did not have to drive, 46% indicate that they would "watch the road even though I would not be driving" (Sivak and Schoettle, 2015). This value was three times the share of the second most popular activity, reading (14%), followed by texting (12.7%) and sleeping (9%). Similarly, Asgari et al. (2018) report that 28% of their respondents prefer not to multitask in a fully autonomous vehicle. Bansal and Kockelman (2018) report that Texans will spend their commutes primarily looking out the window (59%), talking to others (59%), eating (56%), and texting or talking on the phone (46%)[7]. Wadud and Huda (2019) conducted a survey to investigate the (possible) link in in-vehicle behavior between current vehicles and fully autonomous vehicles. They surveyed 620 responses from Bangladesh (35%), UK (37%), U.S. (14%), and "other countries" (10%), with some respondents from Bangladesh being individuals who have personal chauffeurs. They differentiate between inbound and outbound trips and trip purpose. Analyzing the responses for current in-vehicle behavior, they find that the most popular activity during outbound trips is "thinking and planning" (54%) followed by working and studying (25% and 44% respectively). On the other hand, social media is the most popular activity of car passengers during return trips (47.8%). They conclude that people "switch off" during return trips and prefer to relax rather than engage in "productive activities". Analyzing intended in-vehicle time use in AVs, however, they find that the largest share of respondents will continue to keep watching the roadway (46% and 43% for outward and inward trips, respectively). Finally, Wadud and Huda compare the intention to use in-vehicle time of all respondents to current in-vehicle behavior of individuals with private chauffeurs. Ignoring the option to 'keep watching the roadway', which was not available for existing car users, they find similar patterns for primary activities in both groups and a high correlation in "revealed" time use in chauffeur-driven cars in Bangladesh and "intended" time use in AVs. Pudāne et al. 2019 on the other hand, conducted a focus group with 27 subjects regarding their in-vehicle behavior and its impact on their daily activity schedule. They found heterogeneity in in-vehicle behavior depending on how busy people's schedule is. Individuals with busy schedules indicated that they would like to productively use their in-vehicle time (e.g. to work)

[7] Percentages sum to more than 100% since respondents were able to select multiple options.

while others indicated they will not change their in-vehicle behavior and will simply relax during travel.

Finally, the reason for people's hesitancy to engage in in-vehicle activities could be the lack of trust in the technology or the concern over motion sickness (which will become more likely in vehicles designed to encourage in-vehicle activities (Diels and Bos, 2016)). Sivak and Schoettle (2015) predict the percentage of individuals that would suffer from motion sickness as a result of in-vehicle activities. They report that 37% are expected to be involved in activities that increase the frequency and severity of motion sickness, 6-10% would often, usually, or always experience some level of motion sickness, and 6-12% would experience moderate or severe motion sickness at some time. However, studies have been conducted to overcome this issue. Solutions involved using medication and changing the design of the vehicle—e.g. increase windows area, raise seats, and switch seats' direction (Sivak and Schoettle, 2015, Diels and Bos, 2016).

2.4.3 How will changes in in-vehicle behavior impact the value of time?

There is consensus in the literature that the ability to engage in in-vehicle activity and productively use commute time will likely decrease people's sensitivity to in-vehicle travel time. Pinpointing the magnitude of this change is of particular importance since the decrease in value of time (VOT) is one of the key drivers of change in mobility behaviors. Each of the eight studies addressing the VOT to date rely on SP surveys and are summarized in table 5.

Krueger et al. (2016) conducted a stated preference survey on 435 Australians to explore their willingness to switch from the mode used on their most recent trip to an SAV or a pooled SAV. Their results indicate that the VOT estimates for SAVs and pooled SAVs decreased to about 65% and 90% of that of the current mode, respectively. Becker and Axhausen (2018) also conducted a DCE (in Zurich, Switzerland) with alternatives including conventional modes, and added an AV feeder to public transit, SAV, and pooled SAV options. They report a decrease in value of time of 38% and 30% for shared and pooled AVs compared to conventional options respectively. Similarly, Zhong et al. (2020) conduct an SP survey with a discrete choice experiment to explore the reduction in VOT for AVs and SAVs. They survey 1,881 individuals in the US and their DCE mode options are a conventional vehicle, an AV, and an SAV. Attributes of the alternatives are based on a reference trip provided by the respondent. They find that AVs reduction in VOT ranges from 18% for rural residents to 32% for suburban residents while for SAVs, the reduction ranges from 8% for rural residents to 14% for suburban residents.

Table 5: Summary of results on changes in value of time

Topic	*Method*	*Papers*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Value of time	Survey	Krueger et al. (2016)	Level 5	SAVs, PSAVs	Discrete choice mode choice experiment for AVs and pooled SAVs	VOT estimates for SAVs and pooled SAVs is 65% and 90% of that of the current mode the respondent uses
		Kolarova et al. (2018)	Levels 4 and 5	AVs, SAVs	Discrete choice mode choice experiment for AVs and SAVs	The VOT for AVs is lower than that of a conventional vehicle
		Becker and Axhausen (2018)	Level 5	SAVs, PSAVs	Discrete choice mode choice experiment to estimate demand for SAVs, PSAVs, and transit with a SAV feeder	The value of time of shared self-driving vehicles is 38% lower than that of conventional vehicles

Topic	*Method*	*Papers*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Value of time	Survey	Bergman (2018)	Level 5	AVs	Discrete choice mode choice experiment for AVs	VOT of AV passengers is similar to those of car passengers, higher than rail and lower than car drivers
		Correia et al. (2019)	Level 5	AVs	Discrete choice mode choice experiment for AVs with interiors built for leisure vs. work	AVs with an office interior have 26% lower VOT than a conventional vehicle while an AVs with a leisure interior have a 9% higher VOT
		Krueger et al. (2019)	Level 5	AVs	Joint DCE for residential location and mode choice (AVs, conventional cars, and transit)	mean VOT is greatest for conventional cars (25.3 AUD/h), followed by self-driving car (24.0 AUD/h) and is smallest for transit (19.0 AUD/h)
		Kolarova et al. (2019)	Level 5	AVs	Discrete choice mode choice experiment for AVs	VOT for AVs is 40% lower than conventional vehicles for commute trips only. The difference disappears for leisure trips
		Singleton (2019)	Level 5	AVs	Qualitative analysis of reduction in VOT based on other studies and comparison with other modes of transport	The overall reduction in VOT will be smaller than what is currently being assumed in some simulation studies, especially for pooled SAVs and shorter trips
		Zhong et al. (2020)	Level 5	AVs and SAVs	Discrete choice mode choice experiment for AVs and SAVs	Reduction of VOT ranges from 18% to 32% for AVs and from 8% to 14% for SAVs
		Rashidi et al. (2020)	Level 5	AVs and SAVs	Qualitative and quantitative analysis of VOT change	VOT might increase for AV riders compared to conventional vehicle riders

The reduction of willingness to pay for time-savings in (S)AV travel is evident, but more research is needed to understand the motivation for the shift, particularly seeing the large variation for stated in-vehicle activities in Sec. 4.2.1.2 above. Singleton (2019), qualitatively explores the reduction in VOT for AVs as attributed to either: 1) the ability to multitask; or 2) an increase in subjective well-being (e.g. reduced stress during commute). He argues that the reduction in VOT will be lower than what is currently assumed in the literature and will be closer to that of a car passenger rather than a transit rider. That is because the hypothesized rate and benefits from multitasking are likely much lower than currently expected, especially for pooled SAVs and shorter trips (Singleton 2019). This observation is supported by Bergman (2018), Kolarova et al. (2018), Correia et al. (2019), and Krueger et al. (2019). Bergman (2018) estimates a joint revealed preference (RP)-stated preference (SP) mode choice model. The RP modes includes a conventional vehicle as a driver, a conventional vehicle (as a passenger), and rail, and the SP experiment adds an AV alternative. Indeed, the results confirm that the VOT of AV passengers is similar to those of car passengers, higher than rail and lower than car drivers. Moreover, people who multi-task are found to have a lower VOT than people who don't. Similarly, based on the respondents' most recent trip, Kolarova et al. (2018) create a DCE (in Germany) with all conventional modes available and add AV and SAV options. Their results confirm that the AV and SAV time-values lie somewhere in-between that of public transit and private driving. Notably, the value of time for autonomous options was significantly lower than conventional vehicles (55% reduction for AV). SAV's that are theoretically more similar to transit, had a smaller reduction (31% for low income, 13% for high-income). Kreuger et al. (2019) conducted a SP survey to analyze respondents' joint commuting mode choice and residential choice decision. Their mode choice DCE includes a conventional car, AV, and public transit. While the modeling suggested some conflicting conclusions on the VOT for AVs compared to conventional vehicles and transit, their "best" model confirms the observed ordering. The mean VOT is greatest for conventional car (25.3 AUD/h), followed by AV (24.0 AUD/h) and public transit (19.0 AUD/h). On the other hand, Correia et al. (2019) conducted an SP survey to study the change in VOT in AVs for vehicles designed with a leisure vs. work interior. The results confirm the ranking of time-evaluations according to implied ease of working. Indeed, the AV with an office interior has 26% lower VOT (5.50€/h) than a conventional vehicle (7.47€/h), while an AV with a leisure interior has a 9% higher VOT (8.17€/h) compared to a conventional vehicle. Relatedly, Kolarova et al. (2019) estimated a mode choice model from the SP survey and found that AVs have a 40% lower VOT for commute trips; however, this difference disappears when considering leisure trips. Jointly, this research demonstrates that a) the VOT reduction is largely determined by the ability to multitask and the overall experience, summarized as subjective well-being, and b) (S)AVs are viewed as a hybrid between private car and transit rides, which is reflected in the VOT positioned in-between these alternative modes, c) there is variation in implied VOT tied to the perceived work-friendliness of the AV and tied to income. The researchers also run the same experiment but switching the AV options with chauffeur driven options. They report that the chauffeur options always yielded VOTs lower than those for AVs, differences that were statistically significant. They attribute these differences to the respondents' lack of trust in the technology and the fact that it is easier to imagine and relate to the chauffeur scenario.

2.4.4 What is the impact on travel-related behaviors?

Travel decisions are complex processes that involve a myriad of factors and constraints, making the study of changes in travel-related behaviors challenging. We break the problem down into two longer-term travel-related behavior changes: 1) residential and work/school location choice; and 2) modality style, and four shorter-term changes: 1) user activity patterns; 2) vehicle patterns (e.g. zero occupancy vehicles); 3) location decisions; and 4) mode choice.

2.4.4.1 Long-term impacts

2.4.4.1.1 Changes in residential and work/school location

Travel behavior researchers have long been interested in understanding the relationship between land use and travel behavior, with a wide literature devoted to this topic. Residential and work location choices are long-term decisions that impact a host of travel-related behaviors such as car ownership, activity patterns, mode choice, and VMT (Eluru et al., 2010). The study of long-term impacts of AV technology is centered on how it changes accessibility and mobility factors that drive residential and work/school location choices. For example, automation will enter a context of historical U.S. trends of expansive highway systems and urban sprawl centered on private vehicle ownership to maintain mobility and accessibility. AVs are likely to reproduce these effects. On one hand, the convenience of AVs will increase mobility and make longer commutes less onerous, facilitating residential location in lower density areas. Similarly, the ability to send children alone to school and send zero-occupancy vehicles to run errands will also make living in suburban and rural areas more attractive. On the other hand, the ability of vehicles to autonomously look for parking, and the availability of shared services to eliminate the hassle of commuting and parking, is likely to increase residential location in dense urban areas. In the longer run, the lowered demand for parking infrastructure can result in urban re-design to allow wider-sidewalks and more green spaces, making cities more attractive. The research questions of interest, therefore, are: how will AVs impact land use related behavior? Will it exacerbate urban sprawl and encourage the relocation away from cities? Will it attract more demand towards cities? Or will it have no discernable impact on residential and work/school location choices compared to other factors?

Six identified papers have addressed these questions using three methods; agent-based models, 4-step models, and surveys. Table 6 summarize results from studies that explore changes in residential location choice:

Table 6: Summary of results on changes in residential location choice

Topic	*Method*	*Papers*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Changes in residential location choice	Agent-based model	Zhang and Guhathakurta (2018)	Level 5	SAVs	Serving all travel demand by SAVs with low per mile cost	People will move away from their work location due to lower travel costs, and some people will move closer to the central business district
	4-step model	Thakur et al. (2016)	Level 5	AVs and SAVs	Three scenarios compared to a no-change scenario: 1) only AVs with 50% reduction in VOT; 2) only SAVs with no reduction in VOT; 3) only SAVs with 50% reduction in VOT	Scenario 1 leads to a 4% drop in the inner-city population and a 2.4% increase in the outer-suburbs population. Scenario 3 leads to a 2% increase in the inner-city population and 2.7% decrease in the outer-suburb population
	Survey	Bansal et al. (2016)	*	*	*	74% of Austin residents believe their home location will not change
		Zmud and Sener (2017)	*	*	*	80% of Austin residents believe their home location will not change
		Bansal and Kockelman (2018)	*	*	*	81.5% of Texans believe their home location will not change
		Kim et al. (2020)	Level 5	AVs	Survey Georgia residents to understand long term behavior changes induced by AV.	Majority of respondents expect no change in their future residential location and car ownership.

*** Information that is provided in an earlier table for studies that address multiple research questions**

2.4.4.1.1.1 Agent-Based Models

Zhang and Guhathakurta (2018) explore the changes in residential location decisions under the assumption that cost-effective SAVs are the only mode available in the system. Using a combination of a residential location choice model with network analysis they first estimate a residential location choice model from a 2011 Atlanta Travel Survey and Zillow home sales data. Then, they use network analysis to calculate the level of service variables when a SAV fleet is serving all travel demand. The model compares four population segments — households over and under 40 years with and without kids — and find that each group will move further away from their work location due to lower travel costs (lower value of time and cheaper per mile cost). The paper hinges on the strong assumption that SAV travel is the only option available. Yet the paper discovers an important new insight, namely: the lower travel costs will make properties with preferred structural characteristics, school districts, and neighborhood features more appealing to home buyers. This suggests that SAV diffusion can increase the distance range of competition between neighborhoods more than current sprawl by expanding accessibility to current non-drivers.

2.4.4.1.1.2 Integrated land use and 4-step model

Thakur et al. (2016) use a Land Use and Transport Integrated model, which incorporates a 4-step model, to explore the impact of AVs on mode choice and residential location decisions. They compare three scenarios to a base scenario (e.g. no change in the system): 1) a system with no SAVs and where AVs have a 50% reduction in VOT; 2) a system that includes only SAVs, with no private AVs, with no reduction in VOT; and 3) a system with only SAVs, with no private AVs, with a 50% reduction in VOT. Compared to the base scenario, they find that the first scenario leads to a 4% drop in the inner-city population and a 2.4% increase in the outer-suburbs population. The third scenario, on the other hand, leads to a 2% increase in the inner-city population and a 2.7% decrease in outer-suburbs population.

2.4.4.1.1.3 Surveys

Four surveys have been used to explore people's intention to relocate their residence once autonomous vehicles are available. In general, people believe that the introduction of AVs will not affect this decision. In their survey, Bansal et al. (2016) and Zmud and Sener (2017) respectively report that 74% and 80% of Austin residents believe their home location will not change when AVs become available. Similarly, Bansal and Kockelman (2018) report that 81.5% of Texans believe AVs will not change their residential location. Confirming earlier findings, Kim et al. (2020) find that the majority of people expect no change in their residential location and car ownership. On the whole, it appears that respondents under-report their intentions for major life-changes that are hard to envision. Yet the study by Kim et al. (2020) does reveal that the opportunities unlocked by automation can have dual effects. Current non-car dependents are more willing to move closer to frequently visited locations and shed cars. On the other hand, the more people expect AVs to benefit them by increasing their time flexibility and making it easier to travel longer distances, the more likely they are to move farther away from work and other currently frequently visited places.

2.4.4.1.2 Changes in modality styles

The second long-term decision AVs can impact is modality styles—the set of travel modes an individual habitually uses when they travel (Vij et al., 2013). A modality style reflects a higher-level orientation, or a lifestyle, that influences both short-term (e.g. mode choice) and long-term (e.g. car ownership) dimensions of an individual's travel and activity behavior (Vij et al., 2013). Analysis from the U.S. indicates a recent shift away from auto-dependency towards multimodality (Vij et al. 2017). This shift may be attributed to the introduction of shared services such as carsharing and ridesharing, and more recently, bike and scooter sharing. These novel modes give commuters more options and have relieved constraints of conventional modes such as limited parking and poor accessibility to/from transit. By combining the features of several modes, AVs will similarly offer commuters more options, potentially causing another shift in modality style trends.

The natural questions that arise from these observations are: what will happen to modality styles in the AVs era? Will auto-ownership rise as individuals shift back to auto-dependency? Or will the technology encourage multimodality and sharing through high quality, smartphone based, and flexible shared services (i.e. moving toward Mobility as a Service)? Moreover, what will happen to active transportation (i.e. biking and walking)? And finally, will the technology cannibalize or rejuvenate transit by complementing it and solving the first mile, last mile challenge.

Addressing these questions is important since the degree to which people decide to adopt privately owned AVs vs. shared services and transit will dictate the net impact on the transportation system and the wider society.

The only technique used thus far to address these questions has been survey studies. Results from these studies are summarized in table 7. Respondents in these studies are asked about potential changes in car ownership and their likelihood of adopting different modes (i.e. if the mode is part of their consideration set). This can provide insights on potential modality styles that will be prevalent in a self-driving future. To gain further insight, we also look at some studies that investigate the current state of shared mobility. Although these studies are not on autonomous vehicles, they provide valuable insight on potential future adoption of SAVs.

Table 7: Summary of results on changes in modality style

Topic	*Method*	*Papers*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Changes in modality style	Survey	Zmud and Sener (2017)	*	*	*	60% of people in the U.S. prefer owning vehicles as opposed to sharing them and 61% believe their car ownership will not change
		Bansal et al. (2016)	*	*	*	35% and 70% of Texans will not use shared vehicles at 1$/mile and 3$/mile respectively
		Bansal and Kockelman (2018)	*	*	*	41% and 60% of Texans will not use shared vehicles at 1$/mile and 3$/mile respectively
		Haboucha et al. (2017)	*	*	*	25% of individuals are not willing to use SAVs even if they are completely free
		Barbour et al. (2019)	Level 5	SAVs	General questions on the willingness to adopt SAVs and factors that influence these decisions	60% of Americans from 12 states indicate no interest in using SAVs
		Kim et al. (2019)	Level 5	AVs	Survey Georgia residents to understand perceptions regarding AVs and mode choice between AVs and non-AV options	There are 4 groups individuals: 1) AV over walk/bike, 2) AV over transit, 3) AV over flight, and 4) ZOV over non-ZOV

*** Information that is provided in an earlier table for studies that address multiple research questions**

Many claims have been made that the sharing model will dominate the future of transportation, and that car ownership will become obsolete. In 2016, the president of Lyft, John Zimmer, made a bold statement, saying that car ownership will “all but end” in major U.S. cities by 2025 (Zimmer, 2016). In that same year, the Rocky Mountain Institute (Walker and Johnson, 2016) released a report called “Peak Car Ownership” where they claim that car ownership will peak in 2020 and sharply drop after that. Yet, the diffusion of sharing service use is far from universal. In 2016 a Pew Research Center study (n=4,787) found only 15% of American adults had used ride-hailing apps, typically sporadically, while just over half (51%) were familiar but non-users (Smith, 2016). These rates are echoed in a survey of California residents by Alemi et al. (2018). Just three years later, in 2018, another national Pew panel (n=10,683) found that 36% of Americans are users, and the share of familiar non-users grew to 61% (Jiang 2019). Still, the national survey suggests that use is higher in specific segments, namely for young, higher income, urban and male population segments (Jiang 2019). These findings on general sharing uptake help inform estimates of future shared AV options. Results from SP studies suggest that, in general, people favor owning AVs over sharing them. Zmud and Sener (2017) report that 60% prefer owning vehicles as opposed to sharing them. Similarly, Barbour et al. (2019) survey Americans from 12 states to investigate their propensity to use SAVs and find that 60% of respondents are not interested in using them. Concerning car ownership, only 23% believe it will decrease when AVs become available (Zmud and Sener 2017). Bansal et al. (2016) and Bansal and Kockelman (2018), on the other hand, do not compare mode shares but ask respondent about their willingness to use SAVs. They find that 35% of Austin residents and 41% of Texans are not willing to rely exclusively on SAVs at 1$/mile, respectively. These numbers increase to 70% and 60%, respectively, for a 3$/mile fare. Finally, Haboucha et al. (2017) use a discrete choice experiment to explore people's willingness to use SAVs. They report that 25% of their respondents are not willing to use SAVs *even if they are completely free*—i.e. zero trip and subscription cost.

2.4.4.2 Short-term impacts

We now move to the short-term impacts of AVs on travel related behaviors, namely changes in user activity patterns, vehicle trip patterns, destination choices, and mode choices.

2.4.4.2.1 Changes in user activity patterns

In their everyday lives, people make decisions on what activities to perform, where and when to perform these activities, and who to perform them with. These decisions are influenced by long-term decisions—residential location and modality style, and short-term temporal and spatial constraints—people's schedules and activity locations. The emergence of AVs will relax temporal constraints, thereby giving people the opportunity to modify their current activity patterns. The flexibility can occur at the individual trip level, for instance, by sending out zero-occupancy vehicles to run errands (e.g. picking up groceries) and thereby freeing up time for other [new] activities. Similarly, flexibility is also associated with the time-saving that occurs when automation enables productive use of commute time. Moreover, AVs can add flexibility at a household level by removing parental driving duties and autonomously shuttling between trips to serve multiple household members and free up schedule-dependencies (e.g., among parents and their children). Therefore, changes in activity patterns that will arise from the flexibility, extra time, and freedom that the AV technology can offer should be explored in detail: will people travel more? Will they modify their schedules to [no longer] accommodate other people sharing the same vehicle? Will they engage in new activities? Will the time of day of activities change? And finally, how will the different demographic segments of the population, with their unique lifestyles and constraints, react to the technology? Table 8 summarizes results from studies that address relevant questions:

2.4.4.2.1.1 Activity-based models

Childress et al. (2015) and Kim et al (2015a) respectively modify Seattle and Atlanta's activity-based models to study the impact of privately owned AVs under different scenarios. Respectively, their four scenarios are based on assumptions of: 1) a 50% and 100% reduction in parking costs; 2) an increase (to 1.65 $/miles) and a decrease (of 70%) in operating costs of AVs; 3) a 35% and 50% decrease in the value of time; and 4) a 30% and a 50% increase in network capacity. While results varied across scenarios, implied increase in daily trips remained modest (of up to 5% in the former study, and up to 2.5% in the latter).

Table 8: Summary of results on changes in user activity patterns

Topic	*Method*	*Paper*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Changes in user activity patterns	Activity Based Model	Childress et al. (2015)	Level 5	AVs	50% reduction in parking cost, increase in operating cost (1.65$/mile), 35% decrease in VOT, 30% increase in road capacity	Increase in daily trips of up to 5%
		Kim et al. (2015a)	Level 5	AVs	100% reduction in parking cost, 70% increase in operating cost, 50% decrease in VOT, 50% increase in road capacity	Increase in daily trips of up to 2.5%
		Vyas et al. (2018)	Level 5	AVs	Lower VOT (25 to 50%), increased road capacity (15 to 80%), 100% market penetration, no-escort trips (e.g. kids), AV is available all the time	20% decrease in escort trips, increase is highest in shopping and eating out trips, person trips will decrease from -0.3 to -1.5%, vehicle trips will increase by 7% to 8.5%
		Kröger et al. (2018)	Level 5	AVs	25% VOT reduction, 8% to 40% market penetration, no zero-occupancy trips allowed, minimum age to ride alone in AV is 10 and 14, and AVs can be used by mobility impaired individuals	The number of vehicle trips increases by up to 7% and 8% for USA and Germany respectively
	Survey	Kim et al. (2020)	Level 5	AVs	Surveyed people in Georgia about their use of new technologies including ICTs, ride hailing services, and (prospectively) AVs	46% believe there will be no or minimal change in their activity patterns, and for those who believe there will be, it is mostly changes in the distance of travel (longer) rather than frequency

Vyas et al. (2018) also study the impact of private AVs by modifying Columbus, Ohio's Activity based model, but their study incorporates more features of AVs. They assume that AVs have 25% to 50% lower VOT, 15% to 80% increased road capacity based on the road type (e.g. highway vs. arterial), can avoid parking by returning home, and have a 100% market penetration rate. Moreover, they allow for no-escort trips for people who cannot drive (e.g. elderly, disabled, and youth), and set the minimum age for traveling alone in an AV to 10 years. The allowance for no-escort trips appears to be core in determining the distinctive trip-rate changes. Notably, while person-trips are reported to decrease (by 0.3% to 1.5%), vehicle trips will increase by 7% to 8.5%. Connecting back to the observations about schedule flexibility, the results indicate that, due to the no-escort AV option, the percentage of escorting activity would drop by around 20%. Kröger et al. (2018) compare the impact of private AVs on the transport system in the U.S. vs. Germany. They run two scenarios, a “trend scenario” and an “extreme scenario”. In the “extreme scenario” market launch of AVs takes place five years earlier and market uptake is quicker. Here, the modeling assumptions include that zero-occupancy trips are prohibited, AVs can be used by mobility impaired individuals, and a 25% reduction in VOT. AV market penetration scenarios range from 8% to 40%. The researchers find that the number of vehicle trips per year increases by 2.2% in Germany and 3.1% in the U.S. for the trend scenario, and by 8.3% in Germany and 7.0% in the U.S. for the extreme scenario. Finally, Bernardin et al. (2019) modify Vermont’s travel demand model by incorporating an AV and a pooled SAV option. The scenarios analyzed assume 80% or 100% AV penetration with varying rates of SAV pooling and vehicle occupancy rates. Rather than banning ZOV travel, a tax is imposed. Interestingly, despite the allowance for pooled rides, the study reports a 45% increase (for 100% AV, 50% pooling scenario) and 21% increase (for 80% AV, 65% pooling scenario) in vehicle trips. This is largely driven by ZOV trips (from both AVs and SAVs) which make up 30% and 33% of vehicle trips in each scenario respectively. In summary, all activity-based model studies presented above find an increase in vehicle trips, however, it is challenging to draw definitive conclusions as the range of the increase varies significantly. This is largely due to the inherent differences between cities under study and in the modeling assumptions made across studies.

2.4.4.2.1.2 Surveys

Kim et al. (2020) survey people in Georgia about their use of new technologies including ICTs, ride-hailing services, and (prospectively) AVs. They find that 46% believe there will be no or minimal change in their activity patterns, and for those who believe there will be, it is mostly changes in the distance of travel (longer) rather than frequency.

2.4.4.2.2 Changes in vehicle trip patterns

The independence of the vehicle from the user creates a new area of exploration, namely vehicle trip patterns. When studying the implications of automation on travel behavior, it is important to differentiate between user activity patterns and vehicle trips patterns. Here, we are particularly interested in zero-occupancy vehicles trips, or trips made by the vehicle without its owner. Researchers should explore the frequency at which autonomous vehicles will be used to run errands, and the type of errands they will perform. Moreover, researchers should investigate how people intend to utilize their vehicles when they are not needed: will cars be left idle during that period? Will people offer to give friends and family members rides? Or will vehicles be used to earn extra money by renting them out?

This is the least explored topic among travel-related behavior questions. To our knowledge, only two studies provide some insight on this topic. Bansal and Kockelman (2017) ask respondents if they intend to send their kids alone to school in AVs, and only one third indicated that they plan to do so. Bernardin et al. (2019) report that 30% and 33% of trips in scenarios 1 and 2 respectively were ZOV trips (including deadheading for SAVs).

2.4.4.2.3 Changes in destination choices

When choosing which grocery store to go to, consumers are subject to trade-offs such as: visiting a nearby store or one further away but with better produce. AVs will relax existing trade-offs by relaxing location constraints associated with destination choices—i.e. distance and parking constraints. The decrease in sensitivity to travel time implies that distance becomes less of a factor in destination choices. Therefore, we are interested in exploring the impact of AVs on destination choices and whether individuals will take advantage of more pleasant commutes to travel longer distances and explore new locations.

The methods used to address changes in destination choice are activity-based models and surveys. Results from relevant studies are summarized in table 9:

Table 9: Summary of results on changes in destination choice

Topic	Method	Papers	Level of automation	Adoption model	Research approach	Main Finding(s)
Changes in destination choice	Activity-Based Model	Childress et al. (2015)	*	*	*	Average trip length will increase by up to 14.5%, and can decrease by 16% in the case of increase in operating costs
		Kim et al. (2015a)	*	*	*	Average trip length will increase by up to 20%
		Vyas et al. (2018)	*	*	*	Average trip length will increase by 2.5 to 5.5%
		Auld et al. (2018)	Level 4	AVs	Extra cost of automation ranges from 0$ to $15K, 0% to 50% decrease in VOT, 0% to 100% market penetration	Average trip length will increase by up to 47%
		Bernardin et al. (2019)	Level 5	AVs and SAVs	80% - 100% market penetration of AVs, ZOV tax policy, 5% increase in elderly and children trips, 100 - 200% increase in highway capacity, 5% - 80% increase in intersection capacity	Average trip length dropped by 1.15 and 1.48 in scenarios 1 and 2 respectively
	4-step model	Thakur et al. (2016)	*	*	*	Scenario 1 leads to a 26% increase in average trip length while scenario 3 leads to an 8% decrease in average trip length
		Huang et al. (2019)	Level 5	AVs and SAVs	15% increase in trip generation rate, AVs cannot avoid parking, higher operating costs for AVs options, ASC for AVs and SAVs are set to be negative, VOT decrease from 10% to 50%	Average trip distance increases from 14 to 16 miles (14%)
	Survey	Bansal and Kockelman (2017)	*	*	*	Long-distance trips will increase by an average of 1.3 per month

*** Information that is provided in an earlier table for studies that address multiple research questions**

2.4.4.2.3.1 Activity-based models

Childress et al. (2015) and Kim et al (2015a) also explore the impact of AVs on average trip length. The former report a 16% decrease in average trip length under the assumption of increased travel cost for AVs. In the absence of that assumption, the average trip length increases to a similar degree, by up to 14.5%. On the other hand, since Kim et al (2015a) assume a decrease in operating costs, they find an increase in average trip length of up to 20% (from 10 to 12 miles), based on the scenario. Similarly, Vyas et al. (2018) report an increase in average trip length from 2.5% to 5.5%, based on the scenario. Auld et al. (2018) modify Chicago’s activity-based model while making assumptions on the decrease in VOT (between 0% and 50%), the additional cost of an AV compared to a conventional vehicle (0$, $5K, and $15K), and the market penetration of the technology (between 0% and 100%). They report an increase of average trip length by up to 47%, from 11.8 to 17.4 miles. On the other hand, Bernardin et al. (2019) find a drop in average trip length of 1.15 and 1.48 miles in each scenario respectively.

2.4.4.2.3.2 4-step model

In their first scenario, where AVs have a 50% reduction in VOT and no SAVs are available, Thakur et al. (2016) find that the average trip length increases by 26%. However, when no private AVs are available and SAVs, with a 50% lower VOT, are available, the researcher report a more limited 8% decrease in the average trip length. On the other hand, Huang et al. (2019) modify Texas’ 4-step travel demand model to study the impact of introducing AVs and SAVs the transportation system in Texas' mega-regions (i.e., Houston, San Antonio, Austin, Dallas, and Fort Worth). They assume an overall 15% increase in trip generation rate, that AVs cannot avoid parking, a 10% to

50% decrease in VOT, and that the operating cost of (S)AVs is equal to or higher than that of a conventional vehicle. They also assume, and that conventional vehicles, all else equal, are preferred to AV options (i.e. the alternative specific constant for AVs and SAVs are set to be negative, at -0.05 and -0.2). The addition of AV options results in a 14% increase in average trip length from 14 to 16 miles.

2.4.4.2.3.3 Survey studies

Bansal and Kockelman (2017) inquire about the type of trips their respondents would use autonomous vehicles for. The largest share of respondents (37.2%) indicated that they plan to use AVs in the context of long-distance travel (between 100 and 500 miles). Moreover, they report that people believe the number of long-distance trips they make will increase by an average of 1.3 per month after they acquire an AV.

2.4.4.2.4 Changes in mode choice

Finally, the last travel-related behavior research question is mode choice, which is the short-term product of modality style. Since AVs combine features of private vehicles, public transit, and private transportation services, they represent an attractive travel mode alternative. In this research question, we are interested in exploring how the availability of new AV options in one's modality style impacts their short-term mode choice decisions. To address this topic, activity-based models, 4-step models, and (SP) surveys have been used. Table 10 summarize key results from relevant studies:

Table 10: Summary of results on changes in mode choice

Topic	*Method*	*Papers*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Changes in mode choice	Activity-Based Model	Childress et al. (2015)	*	*	*	Transit and walking shares decrease by about 9% and 21% respectively. In the case of increased operating cost, demand for AVs is reduced by a third while the demand for transit and walking increases by 140% and 50% respectively
		Kim et al. (2015a)	*	*	*	Transit shares will drop by up to 42%
		Hörl et al. (2016)	Level 5	SAVs	65% reduction in VOT, and $0.85/mile fare, and varied the number of SAVs in the system	Mode share for transit and walking will drop by 12% and 10% respectively
		Liu et al. (2017)	Level 5	SAVs	Taxi fares are $0.50, $0.75, $1, and $1.25 per-mile, SAV VOT is half that of a conventional vehicle while value of waiting time is double the VOT of conventional vehicle	Demand for SAVs is 50.9%, 12.9%, 10.5%, and 9.2% based on fare, respectively
		Heilig et al. (2017)	Level 5	SAVs	No private AVs, only SAVs that have 70% lower operating cost compared to conventional vehicles. All passengers going from the same origin to the same destination during the same 15-minute period are pooled together (max. 4 riders per SAV)	Mode shares for transit, walking, and biking will increase by 4%, 8%, and 5% respectively
		WEF (2018)	Level 5	AVs, SAVs	Discrete choice mode choice experiment to estimate demand for AVs and SAVs, 6.3% increase in road capacity, occupancy-based pricing scheme, convert parking to driving lanes, and dedicate lanes to AVs	Combined mode share of 37.5% for shared and pooled self-driving cars, and a 16% drop in transit ridership

Topic	Method	Papers	Level of automation	Adoption model	Research approach	Main Finding(s)
Changes in mode choice	Activity-Based Model	Kröger et al. (2018)	*	*	*	Transit ridership will decrease by up to 17.6% and 10.6% for USA and Germany respectively
		Bernardin et al. (2019)	*	*	*	21% - 45% increase in vehicle trips. ZOVs accounted for 30% and 33% of trips
		Perrine et al. (2020)	Level 5	AVs	AVs have 18% higher operating cost 50% reduction in VOT compared to conventional vehicles	Air travel trip generation will drop by 53% while vehicle trips will increase by over 100% (for 500+ mile trips)
	4-Step Model	Levin and Boyles (2015)	Level 5	AVs	Varying VOT (1.15 to 22 $/hour) with higher VOT individuals adopting the technology earlier, higher road capacity, and return home option of vehicles to avoid parking	Transit ridership will decrease by 64%, demand for AVs that avoid parking is 83% at market saturation
		Huang et al. (2019)	*	*	*	Car mode share increases by 16.1% while bus and rail are reduced by 66.1% and 71.1% respectively, Air travel across Texas decreases by 61.8%, Market share for SAVs nearly doubles as fare drops from $1/mile to $0.6/mile
	Survey	Haboucha et al. (2017)	*	*	*	54% of Americans prefer their conventional vehicle over the AV options
		Asgari et al. (2018)	*	*	*	Private vehicle is preferred to SAV and pooled SAV. Transit riders are more likely to pool
		Becker and Axhausen (2018)	*	*	*	Among AV options, pooled SAVs are most popular for short trips, and transit with SAV feeder is most popular for long trips
		Malokin et al. (2019)	Level 5	NA	Assume AV riders can multitask just like transit riders to explore impacts on mode choice	Mode share for transit will drop from 8.174% to 7.157%, while mode share for drive alone will increase from 77.117% to 78.596%
		Hardman (2020)	Level 2	AVs	Interviewed 36 Tesla autopilot users and asked questions on their travel behavior	Autopilot users prefer driving over flying

*** Information that is provided in an earlier table for studies that address multiple research questions**

2.4.4.2.4.1 Activity-based models

Mode choice is another output of activity-based models. For instance, Kim et al. (2015a) find that the introduction of AVs could result in a drop in transit ridership by up to 42% based on the scenario. Similarly, Childress et al. (2015) report that transit and walking mode shares could drop by about 9% and 21%, respectively. However, in one scenario where they imposed a policy that increases the operating cost of AVs (1.65$/mile) compared to the base case (0.15$/mile), Childress et al. (2015) actually find a decrease in demand for drive alone AVs by a third and an increase in demand for transit and walking by 140% and 50%, respectively. This indicates that pricing could be an effective policy to regulate AVs. Finally, Kröger et al. (2018) find that, for the trend scenario, the transit mode share will drop by 6.3% and 2.8% for the U.S. and Germany respectively, and these rates increase in the extreme AV scenario to 17.6% and 10.6% for the U.S. and Germany respectively. On another note, Perrine et al. (2020) use the rJourney data set and modify the travel demand model used by the U.S. Department of Transportation's Federal Highway Administration for long distance travel (500+ miles) by adding an AV mode. They assumed that AVs have 18% higher operating cost and 50% lower VOT compared to conventional vehicles. They find that the addition of the AV alternative reduces air travel trip generation by 53% and increases vehicle trips by over 100%. Hardman (2020) also finds a similar result when he interviewed 36 Tesla Autopilot users. He reports that autopilot users prefer driving over flying given the increased convenience of driving the technology provides.

Looking at SAVs, Hörl et al. (2016) use an agent-based model to study the impact of adding a single passenger SAV service on the transport system in Sioux Falls, USA. They assume a 65% reduction in VOT for SAVs compared to conventional vehicles, an operating cost of $0.85/mile, and varied the number of SAVs in the system which impacts the level of service. They find that, for all levels of service, the number of public transport trips decreases for all hours of the day. Moreover, as the number of SAVs increase in the system, demand for private cars drop from 73% to roughly 30%, while the demand for walking and transit drops from 15% for both modes to roughly 5% and 3% for each mode respectively. Heilig et al. (2017), on the other hand, explore the impact of the introduction of pooled SAVs into Stuttgart, Germany's transport system if no private AVs are available. The researchers assume a cost reduction per mile of about 70% for SAVs compared to a private car. They also pool together all trips starting within the same 15-minute time slot and sharing the same origin and destination, with a maximum of 4 riders per SAV (e.g. number of cars needed = number riders / 4). Their results indicate an increase in the mode share for transit, walking, and biking by 4%, 8%, and 5% respectively. Moreover, Liu et al. (2017) explore the impact of the user fare on SAV demand. With fare changes ranging from $0.5/mile to $1.25/mile, the demand for SAVs drops from 50.9% to 9.2%, respectively. Finally, in a more recent study, the world economic forum, in collaboration with the Boston Consulting Group, investigated the impact of a mixed fleet of AVs, SAVs, and conventional vehicles for the city of Boston (WEF, 2018). A mode choice model is estimated from stated preference data to calculate the mode share for AVs and SAVs (a combined mode share of 37.5%). Based on these mode shares, they assume a 6.3% increase in road capacity. They report that the introduction of AVs and SAVs into the system will reduce transit ridership by up to 16%.

2.4.4.2.4.2 4-step model

Levin and Boyles (2015) modify a 4-step model to explore the impact of AV use on Austin, Texas' downtown network. The study includes three modes: 1) an AV with regular parking; 2) an AV that repositions to avoid parking; and 3) transit. There results suggest a 64% reduction in transit demand and an 83% mode share for the repositioning AV option. In their study, Huang et al. (2019) find that the mode share for car options overall increases by 16% and drops by 66% and 71% for bus and rail. Similarly, air travel across Texas decreases by 61.8% while decreasing by 82.5% across the mega-region (i.e., Houston, San Antonio, Austin, Dallas, and Fort Worth). They also find that the market share of SAVs nearly doubles as the fare drops from $1/mile to $0.6/mile.

2.4.4.2.4.3 Survey studies

Malokin et al. (2019) explore the impact of the ability to multitask and productively use in vehicle time on mode choice and find that this feature will decrease transit mode share from 8.2% to 7.2% and increase the mode share for the drive alone option from 77.2% to 78.6%. On the other hand, Haboucha et al. (2017) explore people's propensity to switch from their current conventional vehicle to either an AV or SAV. They find that 54% of Americans prefer their conventional vehicle over the AV options. An important observation is that increasing parking costs can encourage users to switch to autonomous options with a higher preference for SAVs. In their study, Asgari et al.

(2018) present respondents with DCE scenarios comparing different modal options. In the two scenarios where a private vehicle is available, both as a driver and as a passenger, the option was preferred by 66% and 50% of the respondents respectively, with pooled SAVs being least desirable. Importantly, for captive transit riders, 42% chose public transit and 32% chose the pooled SAVs, indicating that people who currently rely on public transit have a higher propensity to share rides. Finally, Becker and Axhausen (2018) estimate demand for SAVs and pooled SAVs. For short trips (<50 Km) they report a 20%, 8% and 4% share for pooled SAVs, SAVs, and public transit with an AV feeder system respectively. These numbers become 17%, 7%, and 19% for trips longer than 50 Km.

2.4.5 How will changes in all the above impact vehicles miles traveled (VMT)?

The final research topic of interest is the impact of the technology on VMT. Vehicle miles traveled have been steadily increasing over time, increasing mobility and environmental costs, and AVs are hypothesized to further contribute to this trend. Consequently, the research topic of interest is quantifying the impact of automation on the system wide VMT. Moreover, since changes in VMT induced by automation are the byproduct of the changes in all travel-related behaviors discussed thus far, researchers should quantify the contribution of the individual changes in travel-related behaviors to the change in VMT. The following are results from studies that investigate changes in VMT, summarized in table 11 below:

Table 11: Summary of results on changes in vehicle miles traveled

Topic	*Method*	*Paper*	*Level of automation*	*Adoption model*	*Research approach*	*Main Finding(s)*
Vehicle Miles Traveled	Network Analysis	Fagnant and Kockelman (2014)	Level 5	SAVs	Serve 3.5% of private vehicle demand by SAVs	VMT will increase by 10%
		Zhang et al. (2015)	Level 5	SAVs and PSAVs	Serving all personal vehicle trips by a SAV fleet while allowing for ridesharing	Ridesharing can reduce VMT by 4.74% as opposed to no ridesharing
		Fagnant and Kockelman (2018)	Level 5	SAVs, PSAVs	Serve different levels of private vehicle demand by a shared and pooled fleet	Ridesharing can limit the increase in VMT, and can result in a decrease if demand for ridesharing is high enough
		Schoettle and Sivak (2015)	Level 5	AVs	A vehicle can autonomously shuttle between trips to serve multiple members of the same household	VMT will increase by 75%
		Zhang et al. (2018)	Level 5	AVs	A vehicle can autonomously shuttle between trips to serve multiple members of the same household	VMT will increase by 13.3%
	Activity-Based Model	Gucwa et al. (2014)	Level 5	AVs	Increase in road capacity ranging from 10% to 100%; decrease in VOT of up to 50%	VMT increase will range from 8% to 24%
		Biersted et al. (2014)	Levels 3 and 4	AVs	Market penetration (25% to 95%), vehicle operating costs, and highway capacity increase (25-35%)	VMT increase will range from 5% to 35%
		Childress et al. (2015)	*	*	*	VMT increase will range from 4% to 20%, but in the case of increase in operating costs, it could decrease by up to 35%
		Kim et al. (2015a)	*	*	*	VMT increase will range from 4% to 24%
		Hörl et al. (2016)	*	*	*	VMT will increase by up to 60%, 30% of which comes from empty SAVs making pickups
		Auld et al. (2017)	Levels 2 to 4	AVs	20% to 100% market penetration, 20% to 75% decrease in VOT, and 12% to 77% increase in road capacity	VMT increase will range from 1% to
		Heilig et al. (2017)	*	*	*	VMT will decrease by 20%

Topic	Method	Paper	Level of automation	Adoption model	Research approach	Main Finding(s)
Vehicle Miles Traveled	Activity-Based Model	Auld et al. (2018)	*	*	*	VMT will increase by up to 42%
		Vyas et al. (2018)	*	*	*	VMT will increase by 3 to 9%, with empty AV trips contributing approximately 2-3% to the regional VMT
		ITF (2015)	Level 5	SAVs, PSAVs	Assumptions on market penetration of SAVs (50-100%), with and without public transportation, ridesharing vs. no ridesharing, car configuration (2, 5, and 8 passenger vehicles), reduced parking needs	VMT will increase by 90 % for 50% market penetration of shared self-driving taxis and no public transport system
		Liu et al. (2017)	*	*	*	VMT increase will range from 9.8% to 15.1%
		Zhang and Guhathakurta (2018)	*	*	*	VMT will increase by 11% to 23% due to residential relocation
		WEF (2018)	*	*	*	VMT will increase by 16%
		Kröger et al. (2018)	*	*	*	VMT will increase by up to 8% and 6% for USA and Germany respectively
		Taiebat et al. (2019)	Level 5	AVs	Estimate people's elasticity to travel demand and induced VMT under different scenarios of reduced VOT (25% to 60%), and higher fuel efficiency vehicles (5% to 20%)	VMT will increase between 2% and 47% based on the scenario
		Bernardin et al. (2019)	*	*	*	VMT will increase between 7% and 34% based on the scenario
	4-step Model	Zhao and Kockelman (2017)	Level 5	AVs, SAVs	Lower VOT (25% to 75%), higher operating cost (1$/mile and 1.5$/mile for AVs and SAVs compared to 0.6 $/mile for conventional vehicles), lower parking costs, higher preference for conventional vehicles	VMT will increase by 18% to 41%
		Huang et al. (2019)	*	*	*	VMT will increase by 46.7% in Texas
	Survey	Hardman et al. (2019)	Level 2	AVs	Surveyed users of Tesla's Autopilot and compared their travel behavior	Very frequent users and Frequent users have significantly higher VMT than non-frequent users (almost 50% higher annual VMT).

*** Information that is provided in an earlier table for studies that address multiple research questions**

2.4.5.1.1 Network Analysis:

Network analysis has mainly been used to explore the fleet reduction achievable from autonomous vehicles, and its impact on VMT. Most studies find an increase in VMT, mainly due to the relocation of empty vehicles. Fagnant and Kockelman (2014) find that, in a hypothetical city, a SAV fleet with no pooling serving 3.5% of private vehicle demand can reduce the number of vehicles on the road[8] at the expense of a 10% increase in VMT. Zhang et al. (2015), on the other hand, conclude that, in a hypothetical city, ridesharing can reduce VMT by 4.74% as opposed to no ride sharing, while Fagnant and Kockelman (2018) report that overall system wide VMT in Austin, Texas can decrease under the condition that demand for shared rides is high enough.

Finally, Schoettle and Sivak (2015) and Zhang et al. (2018) find that a reduction in household car ownership can be achieved if vehicles can autonomously return home to pick up other members, but at the expense of a 75% and 13.3% increase in total VMT respectively. In the

[8] Each SAV can replace 11 privately vehicle while serving the same prespecified demand

latter study, this number rises to 60% if households that reduce their vehicle ownership are solely considered.

2.4.5.1.2 Activity-based models:

Activity based models have been used extensively as evidenced by 16 studies. To study the impact of AVs on the San Francisco network, Gucwa et al. (2014) modify the city's activity-based model, assuming an increase in road capacity ranging from 10% to 100% and a decrease in users' VOT of up to 50%. Based on the scenario, they find that the increase in VMT ranges between 8% and 24%. For Childress et al. (2015) and Kim et al (2015a), their results varied across scenarios, with an increase in VMT ranging from 4% to 20% for the former and 4% to 24% for the latter. Under the scenario of an increase in operating costs, however, Childress et al. (2015) find that VMT can decrease by 35%. Fehr & Peers (Biersted et al., 2014) also study the impact of personal self-driving cars on VMT, making assumptions on the increase in highway capacity, the market penetration of the technology, and vehicle costs. They find a 5% to 20% increase in VMT under a 50% market penetration of private self-driving vehicles, and this number rises to 35% with full market saturation. Similarly, Auld et al. (2017) use Chicago's activity-based model to study the impact of personal self-driving vehicles. They make assumptions on the increase in road capacity (between 12% and 77%), the decrease in value of time (between 25% and 75%), and the market share of the technology (between 20% and 100%). The increase in VMT varied by scenario from a best case of 1% to a worst case of 79%. Likewise, after manipulating Chicago's activity-based model, Auld et al. (2018) report that VMT increase varies by scenario, and in the worst case, will reach 42%. Moreover, Vyas et al. (2018) find that, based on the scenario, VMT will increase by 3 to 9%, with empty AV trips contributing approximately 2-3% of the regional VMT increase. Furthermore, Kröger et al. (2018) find that, for the trend scenario, VMT will increase by 3.4% and 2.4% for the U.S. and Germany respectively, and these numbers rise in the extreme scenario to 8% and 6% respectively. Finally, Taiebat et al. (2019) use the U.S. national household travel survey (NHTS) data to run a regression of VMT per trip on fuel cost and travel time cost (using people's VOT). From the model, they estimate people's elasticity to travel demand and induced VMT under different scenarios of reduced VOT (25% to 60%), and higher fuel efficiency vehicles (5% to 20%). Their results indicate that higher income groups have the lowest elasticity to fuel cost and the highest elasticity to time cost, resulting in the highest overall elasticity to VMT demand. They report that lower travel costs will lead to an overall increase in VMT between 2% and 47% based on the scenario. For the lowest income group, the average household is forecasted to increase VMT by 1% to 35%, while the corresponding range is 3% to 58% for the highest income group.

The studies mentioned thus far only look at privately owned vehicles. Regarding SAVs, Hörl et al. (2016) find that introducing the SAV service to the transport system could result in an increase of VMT by up to 60%, where 30% of this increase comes from empty SAVs making pickups. Similarly, Liu et al. (2017) find that changing the fare can increase VMT between 10% and 15.7%. On the other hand, Heilig et al. (2017) find that introducing the pooled SAV system and removing private ownership reduced VMT by 20%. Moreover, Zhang and Guhathakurta (2018) find that when cost effective SAVs are the only mode of transport available, VMT will increase by 11% to 23% as a result of the increase in commute trip length due to residential relocation. On the other hand, WEF (2018) find that the mixed fleet of conventional vehicles, AVs, and SAVs will result in a 15% decrease in the number of vehicles on the road at the expense of a 16% increase in VMT. Similarly, Bernardin et al. (2019) find that a mixed fleet of AVs and SAVs increases VMT by 45% and 21% based on the scenario. These studies, however, assume fairly marginal impacts on travel behavior, in that the basic decision protocols and transport system are fairly consistent with the status quo. The International Transport Forum (2015) took it a step further in terms of behavioral assumptions and the configuration of the transport system in their analysis in Lisbon. They study the impact of a SAVs while making assumptions on the market penetration of the technology, whether a high-quality public transit system exists or not, the trip generation process, parking, and car sizes. Their results vary by scenario, with their most extreme outcome arising from the case of 50% market penetration of single-passenger SAVs and no public transport system, which leads to a 90% increase in VMT. This sizeable body of works shows consistent VMT increases with advanced automation, a finding that is replicated also when SAVs are modelled. The range varies widely however, according to the application context and assumptions.

2.4.5.1.3 4-step model:

4-step models have also been used to predict impacts of automation on VMT. Zhao and Kockelman (2017) manipulated Austin, Texas' 4-step travel demand model to explore the impact of AVs on the system. They replaced the gravity model with a destination choice model and included 4 modes in their analysis—conventional vehicles, privately owned AVs, SAVs, and bus. Compared to the conventional vehicles, AV options were assumed to have a lower VOT (25% to 75%), higher operating cost (1\$/mile and 1.5\$/mile for AVs and SAVs compared to 0.6 \$/mile for conventional vehicles), and lower parking costs for AVs (0% to 100%). The model constants were set to give a boost to the conventional vehicle market-share, reflecting status quo predilection. Based on the scenario, they report an increase in VMT ranging from a low of 18% to a high of 41%. Similarly, Huang et al. (2019) report that the decrease in demand for flying caused by the introduction of AVs leads to an 46.7% overall increase in VMT in Texas (47% for Austin).

2.5 Suggestions for Improving Future Studies:

We observe significant variation in behavioral impact of AVs emerging from each of the research methods. In this section we highlight important sources of discrepancy that warrant further work to either clarify the source of differences, or to make future exploration more robust by removing undue sources of variability in predicted impacts. As we noted in section 3, control testbeds, driving simulators, and virtual reality are limited in their contribution to better understand the impact of AV on travel behavior. However, VR, can serve as a helpful vignette to provide survey attendants a better picture of the world under AV but not as a method by itself. Accordingly, we discuss below the other three methods explored.

2.5.1 Survey studies:

Several factors contribute to the discrepancy in results from surveys. Primary factors include geographic, cultural/contextual and temporal differences, sources of discrepancy that are of interest and that should be further explored due to the dynamic nature of AV technology diffusion in society. An undesirable source of discrepancy, however, is the inconsistency in the set-up of different surveys. During the literature review, we observed that many studies lacked details on how (S)AV scenarios were defined to respondents. Meanwhile, for projects that include these details, there is inconsistency in how these vehicles, and mobility in the word of AV in general are described. For example, AVs in some studies allow riders to switch to manual driving (e.g. Kolarova et al., 2018) while in others they do not as they do not have a steering wheel or pedals (e.g. Kyriakidis et al., 2015). Relatedly, some researchers use pictures to bring the context closer to respondent, others use videos, text, or some combination thereof. All these can affect all research questions, namely willingness to adopt AVs. It is important for researchers, therefore, to have discussions and address important questions that would enable better comparison among studies and the transferability of results. Important questions to address include: How should an AV be defined? What method is most effective in bringing the context closer to respondents? What is the role of different vignettes (pictures, movies, VR) in describing AVs to participants and how should they be designed and used? It is impossible to have all studies use similar settings, but at a minimum, researchers should include detailed survey design information related to AV definitions and context in publications to allow accurate replication and building on the work already done. It would be helpful to suggest some standard scenarios that various researchers in various locations would repeat. Finally, as more companies test their technology on public roads and some limited ride hailing services using AVs are introduced more people get familiar with AV, it would be helpful to recruit such people for surveys given their closer familiarity with the technology.

2.5.2 Agent-based and travel-demand models:

The main limitation of agent-based and travel-demand models is that they have to rely on assumptions regarding the potential travel behavior changes induced by AV. We found only a single paper (WEF, 2018) that uses results from SP studies and field experiments to inform their simulation assumptions. Anchoring the simulation design on behaviorally valid parameters allows researchers to make assumptions on travel behavior that are more representative of, and specific to, the area under study. Relatedly, none of the studies incorporate heterogeneity in the response to AVs, a main focus of many (SP) studies (e.g. Daziano et al., 2017, Kim et al., 2019, Kim et al., 2020). Finally, most simulation studies that consider a private ownership model fail to include ZOV trips. Going forward, researchers should think more deeply about how ZOV trips should be incorporated in demand models and how these trips will redefine tours and the temporal and geographic constraints in one's daily activity patterns.

When running simulations, researchers typically run multiple scenarios that include a combination of assumptions on changes in supply and demand. The output of these simulations is a direct result of the assumptions of both demand and supply in these scenarios, so the definitions and range of these scenarios directly affect the results. Within the limitations of these approaches, it is still interesting to see the impact of various assumptions on the performance of the transportation network. To better isolate the impact of specific assumptions, it is recommended to run multiple simulations while varying n a single factor (e.g. value of time reduction) and keeping other factors constant and comparing the results for different factors. This has been implemented in multiple studies (e.g. Vyas et al., 2018, Auld et al. 2017) and it would allow us to understand the effect of each assumption on the direction and magnitude of change (e.g. VMT) to understand which policies would have the highest impact.

2.5.3 Field experiments:

Apart from our study in this dissertation, there are no studies that use field experiments for the purpose of exploring the behavioral impacts of AVs. In the future, we propose that researchers develop partnerships with technology companies currently engaged in advanced field-testing of AVs to; 1) get access to (travel) data from field experiment run by tech companies to unravel acceptance and behavioral dynamics around the use of the technology, particularly from participants of such tests as they may have a better understanding of AVs, and 2) help design experiments where the primary purpose is understanding changes in travel behavior, as opposed to testing the technology, which is the companies' primary (only) objective. This will require policy intervention to encourage tech companies to be part of the solution.

2.5.4 Recommended key actions

Every method has its pros and cons and addresses differently the various research questions. In general, an integrated approach has to be developed using the various methods in combinations. Ideally improved insight regarding travel behavior changes under AVs should obtain from (stated preference) survey studies, field test, experiment and evolving evidence as various automation and shared services penetrate the market and fed into simulation and activity-based models to better study the overall implications. One of the main challenges is to develop better ways to provide experience and knowledge to respondent about AV.

The travel behavior research community should coordinate and collaborate with the Human Machine Interface (HMI) community that deal with AV to leverage field tests for behavioral research. Field tests should also consider travel, activity, attitude, behavioral angles. We should collect consistent data over time (longitudinal studies) and across geographies as automation penetrate the market as preferences, knowledge, and awareness will change over time. We should also try to encourage some standard in design of these studies to have some consistency across surveys and experiments.

2.6 Summary Results and Topics That Require Further Research:

The study of behavior surrounding adoption and use of AV is critical to inform future mobility planning, research, and business-models. Yet, despite the rapidly growing body of work, the results in each of the methods are either widely variable, or highly circumscribed. In this section, for each of the behavioral research questions raised in section four we provide a concise summary of the main results. Following each summary, we delineate a future research agenda. We find that research questions and their corresponding results can be divided into four categories: 1) questions with numerous data points, where the *direction of the impact* is consistent across the literature, albeit the magnitude varies considerably; 2) questions with limited data points and consistent, albeit highly variable data points; 3) questions with a few but conflicting data points; and 4) question with a single or no data points.

2.6.1 What is the willingness to adopt AVs?

2.6.1.1 Summary of results

The literature indicates that, in general, people in the U.S. still have reservations about AVs, ones that seem to be fading over time. Concerns stem mainly from the lack of trust in AVs operating properly and the fear of security breaches. The share of the population that is unwilling to adopt the technology ranges from 19% to 68% based on the area and year of study. Similarly, the average willingness to pay for the technology varies considerably based on the context from $1,600 to $14,000, with many respondents (up to 59%) not willing to spend anything ($0).

2.6.1.2 Questions that require further research

Exploring people's willingness to adopt the technology and the factors behind these intentions has been well explored (23 papers), and thus it belongs to category (1) of research questions. However, as more companies test their technology on public roads and more people use autonomous features in their cars and become familiar with the technology, the acceptance of AVs and willingness to adopt them will change. Therefore, researchers should continue to design studies and collect data to pinpoint the dynamic nature of AV adoption, and monitor the evolution of responses over time, for different groups, as a function of social or formal information sources, and across cultures.

2.6.2 What is the impact of AVs on in-vehicle behavior?

2.6.2.1 Summary of results

Few studies (5) have addressed this research topic, and the literature indicates that some people believe they will multitask while riding AVs while others (up to 46%) believe they will not. Lack of trust in the technology and motion sickness are the two main factors that will hinder multitasking in AVs. For those who will multitask, the most popular in-vehicle activities will be talking to other passengers, texting/talking on the phone, and eating.

2.6.2.2 Questions that require further research

The general assumption has been that AV users are more likely to engage in increased in-vehicle activities. Manufacturing companies have already advertised AV concepts that promote in-vehicle activities, like Volvo's 360c AV that includes a coffee table, a desk, and even a bed. However, as the literature indicates, the ability to productively use commute time might not be as attractive as initially believed. More research is required to understand whether people want to or will be able to take advantage of this feature. The limited, albeit consistent results puts this research question in category (2). However, we note that a question that has received no attention is the relationship between in-vehicle time use and the demand for different vehicle configurations. Consumers currently seem to give limited credence to productive time-use in AV's, will this lead to relying on right-sized[9] shared vehicles? Or will people prefer "mobile home" vehicles—i.e. vehicles with a bed, bathroom, work desk, etc.? Answering these questions is key to quantifying the impact of AVs on road capacity, which adoption model (sharing or owning) is going to dominate, activities conducted during commute, etc.

2.6.3 What is the impact on VOT?

2.6.3.1 Summary of results

The ability to multi-task or relax during one's commute is found by most studies to reduce the AV riders' VOT. The decrease varies by mode (AV, SAV, and pooled SAV), and ranges from 5% to 55%.

2.6.3.2 Questions that require further research

Although the reduction in VOT is a key driver for changes in travel-related behaviors, not enough attention has been devoted to this research question (which belongs to category (2)). We only found seven papers that estimate changes in VOT, all of which are SP studies. As estimated VOT for automation typically falls between typical transit and private driving, it appears a natural extension that it is shaped by expectations of time-use on board, which in turn is shaped by local conditions. More effort needs to be put into collecting stated preference data from surveys and revealed preference data from field experiments to quantify changes in VOT and how it differs by

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[9] E.g. choosing a small, single occupancy vehicle when traveling alone to work, and larger vehicle with more space when going camping.

mode, demographic, and trip purpose, for a more accurate integration of these changes into simulation studies.

2.6.4 Changes in travel-related behavior

2.6.4.1 Residential location choices

2.6.4.1.1 Summary of results

When it comes to residential location choice, survey studies indicate that most people do not believe their residential location will be affected by the adoption of AVs. Simulation studies, on the other hand, indicate that lower travel costs will encourage people to move further away from their work location, with some moving closer to the central business district. In a private ownership scenario, people will move away from cities into suburbs, while the opposite is true in an SAV adoption model.

2.6.4.1.2 Questions that require further research

This research question has not received enough attention, and the few studies that address it report conflicting results, and therefore belongs to category (3) of research question. The conflict in part stems from the limited integration between simulation and behavioral studies. More studies should be dedicated to addressing the change in residential location decisions rather than including it as a marginal question in surveys. In addition to exploring them, the reasons and motivations behind these changes should also be investigated.

2.6.4.2 Modality styles and mode choice

2.6.4.2.1 Summary of results

When it comes to ownership preferences, people generally prefer owning AVs over sharing them, with pooled SAVs being the least favorite alternative among autonomous options. People do not believe their car ownership will decrease when they own AVs. For SAVs, 25% of the population are not willing to use them even if they are completely free. Moreover, pricing will play an important role in the demand for SAVs, which will increase substantially as the fare drops. Regarding transit, most studies report that AV technology will reduce transit ridership. Shares are expected to drop by amounts ranging from 9% to 70%, based on the assumptions made by the different studies. However, a policy of increasing operating costs of AVs has the potential to substantially increase transit shares by as much as 140%.

2.6.4.2.2 Questions that require further research

Changes in modality style and mode choice have received a fair amount of attention (22 papers). Moreover, the overall consistency of results puts this research question in category (1). We note that most studies only explore people's preferences for different modes and potential future mode shares, yet little attention has been given to understanding the factors behind these results or the heterogeneity associated with these decisions. Considering the impact this research question will have on determining the future of transportation, additional research is required to understand the factors that will shift people away from auto-dependency and into sharing and multimodality. Just because sharing and pooling is promoted as an effective counter-balance to private use doesn't necessarily mean people will share vehicles, and more importantly, share rides. It is also important to understand which users shared vehicle services will attract—private car users or transit users, and the impact this will have on congestion. With the ongoing COVID-19 pandemic it is an open question how views of hygiene, health and safety of shared and pooled vehicles is evolving.

Further work is needed to examine the cultural, contextual, and generational shifts in how automation and sharing is viewed. Which are the critical service-levels, i.e. cost, waiting time, travel time, or the flexibility that shared services offer? These questions remain unanswered and addressing them will enable decision makers to develop the necessary policies to guide the technology into an uncertain future.

2.6.4.3 Activity patterns and destination choice

2.6.4.3.1 Summary of results

The literature indicates that the convenience of AVs will induce changes in people's short-term travel decisions. The number of trips will increase by 2.5% to 45%, the average trip length will increase by 14% to 20%, and the ability of AVs to autonomously make pickups will substantially reduce escort trips (by up to 20%). A policy of increasing the operating costs of private AVs, however, can reduce the average trip length by up to 16%.

2.6.4.3.2 Questions that require further research

When addressing changes in activity patterns and destination choices, most studies report the change in the number of trips and average trip length. Results on this topic are limited, yet consistent, and thus belong to category (2). However, very little insight has been provided on specific changes in activity patterns and destination choices. Questions raised in section four on the activities that will be performed more/less frequently, changes in the time of day of activities, and whether people will explore new destinations have not been addressed yet. Moreover, heterogeneity in the changes based on people's demographics and lifestyles should also be further explored.

2.6.4.4 Vehicle patterns

2.6.4.4.1 Questions that require further research

Changes in vehicle patterns, being an entirely new research area that did not exist before AVs, is the least explored research question, and therefore belongs to category (4) of research questions. It is the first time the concept of "zero-occupancy vehicles" that can pick-up passengers and run errands arises. Therefore, researchers are facing difficulty in addressing this research area. Nevertheless, considering the impact zero-occupancy vehicles will have on the system, more effort should be put into understanding how vehicles will be used when not occupied by passengers. From reviewing the literature, the two methods that can be used to explore this research question are surveys and field experiments. In the former, respondents can be asked about errands and trips they would most likely entrust to a self-driving vehicle. Respondents can also be asked if they intend to utilize their vehicles to earn extra income (e.g. rent them out) when not commuting, or simply have them idle like they do with today's vehicles. In field experiments, researchers can obtain revealed preference data on vehicle patterns as subjects experience firsthand the reshaping of mobility patterns from the driverless feature.

2.6.5 Vehicle miles traveled

2.6.5.1 Summary of results

For VMT, most studies predict an increase. Similar to previous findings, however, the increase varies considerably across the literature and ranges from a low of 1% to a high of 90% depending on the scenario—shared vs. privately owned—and the assumptions made on changes in travel behavior. Changes in travel-related behaviors discussed thus far will all contribute to the changes in VMT, from changes in in-vehicle behavior, to lower cost of travel (VOT), changes in residential location choice, modality style, user activity patterns, vehicle patterns, and destination choice. In two scenarios, however, VMT is found to drop below current levels—when the operating costs of private AVs are increased (up to 35% decrease in VMT) and when trips are pooled and the demand for pooled SAV is high (up to 20% decrease in VMT).

2.6.5.2 Questions that require further research

The impact of AVs on VMT has been well investigated (25 papers), and the results are consistent, thus this research question belongs to category (1). Despite that, no clear conclusions can be made on this topic. A main takeaway from the literature is that we are highly uncertain about the magnitude of the change in VMT, but that travel behavior and policy will play a key role in determining that magnitude. Therefore, until we have a better understanding of the impact of AVs on the other four research questions, and until we obtain better input to simulations we run, results on VMT change will continue to vary substantially.

Future analysis of vehicle mile effects needs to account for two complicating factors; firstly, there are significantly different behavioral responses to the different levels of automation, second, future analysis needs to consider different user segments rather than average travel effects. Importantly, the mileage-saving effects of vehicle automation are almost entirely captured at levels 1 through 3 via platooning and sharing (Wadud et al 2016). However, because level 4 changes the cost and convenient of "driving" fundamentally, it is also here that we expect the largest increase in VMTs. Moreover, while an overall increase in VMT is problematic, we need to examine the possibility that it enables increased mobility and accessibility for those who are currently deficient in that area (e.g. elderly, people with disabilities, children, etc.).

2.7 Conclusion

In this literature review, we raised five critical research questions regarding the implications of autonomous vehicles on the demand side of transportation: 1) what is the willingness to adopt the technology? and what are the impacts of the technology on 2) in-vehicle behavior? 3) value of time? 4) travel-related behaviors (activity pattern, mode, destination, residential location)? and 5) vehicle miles traveled? We also summarized findings from studies in the literature that explore these questions, and found that results can be divided into four categories: 1) questions that have been explored by many studies, where the *direction of the impact* is consistent across the literature, albeit the magnitude varies considerably; 2) questions with limited and consistent results, albeit the range varies widely; 3) questions that are addressed by a few studies, and where findings are conflicting; and 4) question with a single or no studies that address them. Moving forward, researcher should focus on moving the research towards the first category. This can be achieved by: 1) increasing effort to fill the holes in the literature, and 2) establishing clarity of assumptions used by researchers to enable comparisons and transferability of results.

As part of the literature review, we also reviewed the five main methods used to study the impact of automated vehicles on travel-related behaviors: 1) controlled testbeds; 2) driving simulators and virtual reality; 3) agent-based and travel-demand models; 4) surveys; and 5) field experiments. We presented an overview of each method, its advantages and limitations, and how/if it informs changes in travel-related behavior. Controlled testbeds, driving simulators, and virtual reality are useful for studying safety and human factors but do not inform changes in travel-related behaviors. Agent-based and travel-demand models, on the other hand, are an effective tool to study the impact of policy decisions and changes in travel-related behaviors on the transport system, but do not inform how automation and other technologies will change travel behavior. Rather, these models require assumptions on these changes as input. Finally, surveys and field experiments can help explore changes in travel-related behaviors. Results from surveys, however, are questionable since the context is too remote for respondents to relate to. Whereas for field experiments, technological limitations (using a human to simulate the software of the technology) and geographical constraints can diminish the realism of the simulation and influence travel behavior, introducing biases in results.

The wide discrepancy in results regarding the impacts of AVs on travel behavior highlights the uncertainty surrounding the future of automation and the challenge inherent in addressing these research questions. The goal of this chapter is to promote a conversation among researchers on how to build on the current body of literature to overcome these obstacles. For instance, there is limited convergence on what is intended by adoption, and which service models (ownership, sharing or mobility as a service) are considered. Moreover, researchers using agent-based and travel demand models can use results from survey studies and field experiments as input to their models rather than making assumptions on changes in travel behavior (e.g. value of time, demand, mode share, etc.). Finally, more synergies should emerge between travel behavior researchers on one hand, and cities and companies developing and testing their technology on the other

To conclude, autonomous vehicle technology has the potential to transform our lives, and understanding its implications is key in realizing its benefits and minimizing associated costs. The only way to do so is through a joint effort by researchers, collaborating and working together to build on the intelligence gathered and lessons learned from the current literature and improve the design of research regarding autonomous vehicles.

Chapter 3

Projecting Travelers into a World of Autonomous Vehicles - Estimating Travel Behavior Implications via an Experiment

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Abstract

Automated driving technologies are currently penetrating the market, and the coming fully autonomous cars will have far-reaching, yet largely unknown, implications. A critical unknown is the impact on traveler behavior, which in turn impacts sustainability, the economy, and wellbeing. Most behavioral studies, to date, either focus on safety and human factors (driving simulators; test beds), assume travel behavior implications (microsimulators; network analysis), or ask about hypothetical scenarios that are unfamiliar to the subjects (stated preference studies). Here we present a different approach, which is to use an experiment to project people into a world of autonomous vehicles. We mimic potential life with a privately owned autonomous vehicle by providing 60 hours of free chauffeur service for each participating household for use within a seven-day period. We seek to understand the changes in travel behavior as the subjects adjust their travel and activities during the chauffeur week when, as in an autonomous vehicle, they are explicitly relieved of the driving task. In this first pilot application, our sample consisted of 13 subjects from the San Francisco Bay area, drawn from three cohorts: millennials, families, and retirees. We tracked each subject's travel for three weeks (the chauffeur week, one week before and one week after) and conducted surveys and interviews. During the chauffeur week, we observed sizable increases in vehicle-miles traveled and number of trips, with a more pronounced increase in trips made in the evening and for longer distances and a substantial proportion of "zero-occupancy" vehicle-miles traveled.

3.1 Introduction

"Every new transportation technology affects the geography of communities and the structure of people's lives. Self-driving cars is such a technology. Just like freeways shaped past cities and lifestyles, self-driving vehicles will remake the metropolis once again" (Walters and Calthorpe 2017). More and more automated features are being introduced into new vehicles currently on the market, autonomous vehicles are operating on our roads with a human backup, and fully autonomous vehicles (sans human backup) are operating under controlled environments. Tesla reports 780 million miles have been driven using its Autopilot; Uber and Volvo have shared, autonomous vehicles deployed in Pittsburg; and Waymo is now operating autonomous minivans in a suburb of Phoenix without a human backup. Governments in the US and around the world are racing to develop the necessary legislation that embraces the technology while ensuring the safety of its citizens, and planning agencies are struggling to update policies and plans to best realize a future with AVs.

There is much speculation regarding the impact of autonomous vehicles on the transport system. On one hand, the improvements in safety and efficiency are thought by many to be the answer to our transportation problems, with most images of AV futures implying safe and freely flowing roadways. However, others project a dystopian future where the efficiency improvements, while real, are not enough to counteract the trends of increasing population, increasing urbanization, increasing vehicle-miles traveled per capita, and induced demand. Many believe the key to a utopian future is a shared AV fleet. Each of these futures is purely speculative. While it is not certain which future beckons, there is certainty that human behavior will be central to determining the outcome. And, yet, little is known about how travel will change with autonomous vehicles.

The literature distinguishes between different levels of vehicle automation. Here we are focused on understanding traveler behavior implications for full automation, where vehicles can operate without any human intervention and without a human in the vehicle. This stage has the potential for the most radical traveler behavior changes, and these implications are the least understood today. The introduction of autonomous vehicles is expected to catalyze changes in travel behavior, activity participation, and land use. It is hypothesized to affect the value of travel time (e.g., via increased comfort and multitasking) and therefore the amount of travel. It likely will affect the quantity and type of vehicle purchases as well as the related decisions of whether to own a vehicle or opt for models of shared ownership. In the long run, it can affect decisions such as where to live and work, thereby impacting land-use.

It is difficult to predict the future of mobility after the adoption of autonomous vehicles for the simple reason that they do not currently exist. However, it is possible to project people into a world that includes some of the more salient features of AVs. The biggest difference in using an AV, and arguably the feature that will cause the most change in travel behavior, is not having to be behind the wheel personally driving the car or even to be in the car at all as it travels from one place to another. This feature relieves people from the duty of paying attention to the road, allowing them to make better use of their in-vehicle time. Moreover, it permits sending empty cars (zero-occupancy vehicles or ghost cars) on errands like charging the car, picking up a pizza, or dropping off laundry. Finally, it opens up a major new option for individuals with disabilities, individuals without a driver's license, and elderly who can no longer drive or are not confident anymore in their driving ability and reaction time.

Here, we implement via the use of personal chauffeurs an experiment that aims to create familiarity with this coming technology that, until a few years ago, lay in the realm of science fiction. Our objective in providing subjects with a personal chauffeur is that we are essentially providing the "software" of an autonomous vehicle, relieving them from the duty of personally driving the car or physically being in the car when the car is making trips. This enables people to experience and act directly on how their travel and activities may change if they were to own an autonomous vehicle[10], and it allows us to study such potential shifts. We present in this chapter results from a beta-test of 13 San Francisco Bay Area households.

3.2 Literature Review

Four main approaches are currently being used to gain insight into the potential impacts of autonomous vehicles: controlled testbeds, driving simulators, stated preference studies, and simulation based/scenario analysis studies.

Driving simulators and controlled test beds are extremely useful for studying safety and human factors issues associated with a given trip. For example, Jamson et al. (2013) examined multitasking behaviors and fatigue via a driving simulator. However, they are not as useful for investigating impacts on travel and activity behaviors.

Stated preference studies ask subjects to imagine how they would feel toward, pay for, and use automated vehicles in a hypothetical scenario. For example, Cyganski et al. (2015) and Schoettle and Sivak (2014) examined multitasking intention; Bansal and Kockelman (2016), Milakis et al. (2015), and Zmud and Sener (2017) examined a host of issues regarding autonomous vehicles, including willingness to pay for automation, mode choice, auto ownership, potential to adopt shared autonomous vehicles, and intention to move; and using a discrete choice framework, Daziano et al. (2017) performed an in-depth analysis of willingness to pay for autonomous features, Lavieri et al. (2018) studied adoption and use of the technology, Kolarova et al. (2018) studied the change in value of in-vehicle travel time, and Felix and Kay (2017) studied for which types of trips and purposes people will use automated vehicles. While a valuable technique, particularly to gain initial insight, it is problematic to employ in situations where the context is too far from situations in which the subjects have placed themselves or could consider placing themselves. This is precisely the situation with autonomous vehicles.

Research using agent-based micro simulators (e.g., large-scale urban travel demand models) and network analysis (e.g., optimizing over the number of vehicles needed to serve a given demand) are particularly relevant to our study, as this literature includes predictions of the magnitude of the vehicle-miles traveled (VMT) increase induced by AVs. Because the behavioral impacts of autonomous vehicles are currently largely unknown, such studies have thus far assumed the travel behavior response either by assuming a fixed demand or making assumptions regarding

[10] A complement to our experiment would be to investigate the travel behavior impacts if people were to make use of a shared fleet of autonomous vehicles (rather than private ownership), and this is left for future research.

parameters in a travel demand model. For example, Fagnant and Kockelman (2014) generated demand from a trip-based model under current behavioral conditions, and then performed a network analysis to see how this demand could be served by a shared, AV fleet. Their simulation results indicate that the number of cars necessary to serve the demand is drastically reduced (to about 10%) but that the relocation of vehicles between trips leads to a 10% increase in VMT. Schoettle and Sivak (2015) simulated AV scenarios using NHTS travel diary data, where they assumed that a single household vehicle could shuttle between trips made by multiple household members. They found that in the most extreme cases the ability of the car to autonomously return home would result in a 75% increase in VMT.

Rather than focusing on fixed/current demand, another line of research has modified existing travel demand models to reflect potential behavioral and system changes. Childress et al. (2015) modified the PSRC (Seattle) activity-based model to study the impact of privately owned AVs under different scenarios. Their four scenarios were based on assumptions of reduced parking costs, increased operating costs, decreased value of time, and increased network capacity. Their results varied across scenarios with increases in VMT ranging from 4% to 20%. Fehr & Peers (Biersted et al. 2014) also studied the impact of personal AVs on VMT. After making assumptions on market penetration of the technology, level of service of transit, vehicle cost, and highway capacity increase, the results indicate that with a 50% market penetration, private AVs will result in a 5% to a 20% increase in VMT, and this number rises to 35% with full market saturation. Both PSRC and Fehr & Peers assume fairly marginal impacts on travel behavior in that the basic decision protocols and transport system are fairly consistent with the status quo. The International Transport Forum (2015), in their analysis in Lisbon, pushed the status quo farther in terms of the behavioral assumptions and the transport system configuration. They made assumptions on the demand for the technology, the quality of service of public transit, the trip generation process, parking, car sizes, and the market penetration of the technology. Their results vary by scenario, with their most extreme outcome arising from the case of 50% market penetration of single-passenger autonomous taxis, which leads to a VMT increase of 90%.

These examples illustrate the wide discrepancy across the literature of the predicted increase in VMT: from a low of 4% to a high of 90%. Further, key assumptions regarding the travel and activity behavior modifications are largely unknown and untested. Notably, Childress et al. (2015) point out that "this behavior [decrease of VOT], of course, has not been revealed or even stated by drivers, and at this point is speculation based on other modes of transport." Our objective with this experiment is to provide more directly revealed evidence regarding the potential travel behavior impacts of autonomous vehicles to inform the otherwise untested assumptions of future studies.

3.3 Experimental Design

The key components and flow of the experiment are presented in figure 3. First, both subjects and chauffeurs were recruited and onboarded. Next came the heart of the experiment: the three weeks of tracked travel, with the chauffeur intervention occurring in the middle week. The literature (Gertler et al. 2011) suggests that such a three-week format, particularly since it is a relatively short time period, allows us to treat the two status quo weeks as a control for the treatment week. An online survey was administered before and after the three travel weeks. Each of these components is described in more detail below.

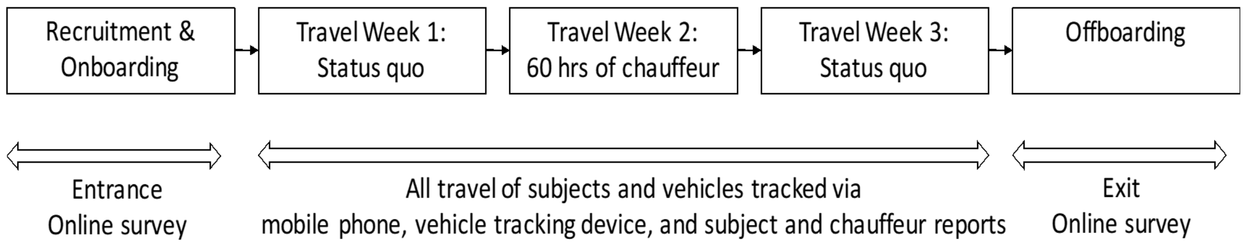

Figure 3: Flow of experiment and primary data collected

3.3.1 Subject Recruitment and Onboarding

Our objective was to recruit a sample that would be illustrative (albeit not necessarily representative) of people who would potentially own autonomous vehicles. Given resource constraints, we chose to target three different cohorts that represent distinct lifecycle stages: Millennials, Families, and Retirees. We hypothesized that the impact of AVs may vary across the cohorts as they have markedly different lifestyles. For example, Millennials may rely more on ride-hailing services than other generations. For Retirees, safety (e.g. driving at night or on congested highways) may be relatively more important factors. For Families, kids and their activities are often a priority.

We recruited subjects via a number of channels. We posted advertisements to a UC Berkeley Facebook group, a Nextdoor neighborhood social network, and a retirement community newsletter. We also recruited via word of mouth from our research group and our subjects. Subjects who responded to our recruitment were screened to ensure that they met all of the following criteria:

- Be 18 years or older,
- Live within the 9-county San Francisco Bay Area,
- Possess a current driver's license and currently drive,
- Own a private car and don't currently use a chauffeur, and
- Possess a mobile phone with location services.

For subjects who met the criteria, we started the onboarding process. We continued recruiting until we reached our target number of 4 subjects within each cohort (and we ended up with 5 retirees). A key to the success of the experiment is that the subject understands what an autonomous vehicle is and its potential benefits, and how a personal chauffeur simulates these. For this purpose, subjects took part in a 30-60 minute one-on-one entrance interview via telephone. The household member who participated in this interview is deemed the "**primary subject**." The primary subjects were informed about the experiment. They were given information on AVs, and they were informed of the potential errands that the technology will be able to run and that the chauffeur will be able to run these errands for them as well. They were informed that they would have access to 60 hours of the chauffeur service that they would allocate based on their needs, and that there is no limit on the number of hours per day. Hours were to be scheduled one week in advance and subjects had the option to modify the schedule one day in advance (or the same day based on the driver's availability). The aim of the interviews was also to have subjects in a futuristic mindset before they are provided with the service, potentially minimizing the time it takes subjects to get used to their new "autonomous vehicle." We also requested that other adult household members formally participate in the experiment so that we could collect survey data from them and track their movements, although this wasn't required.

The subjects were asked to choose a typical three-week period void of special events such as holidays or travel. They were instructed to choose only one vehicle in the household to be used by the chauffeur and not have the chauffeur jump between multiple vehicles. This vehicle is deemed the "**primary vehicle**." Further, they were allowed to loan the service to friends or family, but if doing so, they had to loan the primary vehicle along with the chauffeur. While our experiment does not consider the additional purchase price of an autonomous vehicle, the subjects are covering the full operating costs of their vehicles which is the relevant (marginal) cost considered in personal travel decisions once the vehicle is purchased.

3.3.2 Chauffeur Recruitment and Onboarding

Different chauffeur solutions were investigated, and the decision was to use a designated driver service that provides chauffeurs for hire using customer-owned vehicles (*Dryver*). A unique relationship with the company was established to ensure it could accommodate our experiment. The advantages of our chauffeur service include the use of the subject's car (reducing the costs of the experiment and making costs and the experience more realistic for the subject) and the liability being covered by the company rather than the research team, which eased the approval process from UC Berkeley. Similar to the subjects, chauffeurs took part in a one-on-one entrance interview where they were instructed about the experiment they would be participating in, as well as the technology and all its features that they would be simulating. The chauffeur was with the owner's vehicle at all times during the 60 allocated hours and served at the beck and call of the owner. The cost of the chauffeur service totaled roughly $1,250 per household.

3.3.3 Data Collection - Tracking

All primary subjects and other household members taking part in the study installed a tracking app on their smartphone (*Moves*). The app uses the phone's GPS to passively and continuously record all trips, and distinguishes between ones made by active modes (walk and bike) and by "transport" modes (personal car, transit, Uber/Lyft, friend's car, etc.) without any input from the subject.

A vehicle tracking device (*Automatic*) was installed in the on-board diagnostic (OBD) port of the primary (i.e., chauffeur) vehicle. The device cost $150, raising the total per household cost to $1,400. The vehicle tracker collects data on the origin and destination, timing, and route of each trip. It consistently and continuously records and stores the data, ensuring no loss in data throughout the three-week period. Participating subjects were also asked to complete a log sheet to note any trips made by any form of public transit or by a non-personal vehicle (Uber/Lyft, friend's car, etc.) to compensate for the limitations of the smartphone tracking app. Similarly, chauffeurs were asked to fill out a log sheet to track the number of people in the car and who was being chauffeured (the owner, a friend, a family member, zero-occupancy trip, etc.). Finally, data from all these sources were joined to form a single data set that includes all trips made by the primary subject (including trips made by modes other than the personal vehicle) and all trips made by the primary vehicle (regardless of who is in the car).

3.3.4 Data Collection – Surveys

All primary subjects as well as other adult household members formally taking part in the study first took an online entrance survey that collected information on demographics, typical travel patterns, well-being, and knowledge of AVs and attitudes toward the technology. They also completed an exit survey, which was similar to the entrance survey and included an extra section that asked subjects about their experience with the simulated autonomous vehicle experience.

3.4 Results

We report results from the 13 primary subjects (1 per participating household), excluding any other participating family members from this analysis as their participation was not consistent across the households. While admittedly a small sample, we present what we believe are the first results from an experiment aimed at capturing the impact of autonomous vehicles on activity and travel in a naturalistic setting. Further, this serves as a beta test for a larger experiment, and the small sample has the advantage of being able to supplement the quantitative data with personal interactions with each subject. Our first subjects started the experiment on May 29, 2017, completing the experiment three weeks later. By August 7, 2017, all subjects had finished the experiment.

3.4.1 Subject Socio-Demographics

The beta test sample turned out to be diverse in some aspects but homogeneous in others. The participants collectively represented both genders (5 males and 8 females), different ages (from 19 to 78) and cohorts (millennials, families, retirees), several income levels (from < $25K to $200K+), and different household sizes (from 1 to 5) and relationship statuses. However, the level of education was homogeneous with almost all subjects having at least some level of college education, and most with a college degree. This is not too surprising given that our recruitment effort reached a relatively wealthy retirement community, a relatively wealthy neighborhood in the San Francisco bay area, and UC Berkeley affiliates. The average age of the millennials was 22, the average age of the families was 38, and the average age of the retirees was 73. Two families had minors in their household, one family had a college-student child with her own vehicle, and the other family was a couple sharing one household vehicle. Four of the retirees were single females, and one was a couple. As for the millennials, three of them were single, and one often carpooled with her boyfriend. Relatedly, one of the millennials lived with his parents while the remaining had other millennial housemates.

3.4.2 Impacts on Travel Behavior

Here we present the key findings regarding how the AV simulation experiment impacted travel and activity behavior in our sample. The results are plotted in Figure 4 and Figure 5. Figure 4 presents more detailed VMT results for all 13 primary subjects (in no particular order) to provide a sense for each individual in the sample. In this figure, we focus on the VMT of the primary vehicle (whether or not the primary subject was in the car) in combination with the VMT of the primary subject (whether or not via the primary vehicle). The VMT is broken down into three components: i) VMT by the primary subject, whether in the primary vehicle or not (although nearly all travel by the primary subject was in the primary vehicle throughout the full three weeks); ii) VMT of the primary vehicle when it was driven without the primary subject but with some other non-chauffeur person (e.g. a friend or a family member), and iii) VMT when the chauffeur vehicle was traveling with only the chauffeur (i.e., a zero-occupancy trip in an AV world). Figure 5 summarizes the impacts on a number of key travel dimensions for each cohort and for the sample as a whole. As can be seen in both figures, the two control weeks are fairly similar to each other and distinctly different than the chauffeur week. Accordingly, we focus the analysis on comparing the chauffeur week to the *average* of the pre-chauffeur and post-chauffeur weeks. The key findings are described below.

3.4.2.1 Finding 1: VMT increased for 85% of the subjects (by amounts ranging from 4% to 341%), and the total VMT from the sample increased by 83% overall.

As shown in Figure 4, while total VMT decreased slightly during the chauffeur week for the first subject, and hardly changed (on average) for the second subject, the remaining 11 subjects increased their auto travel. The increases in total VMT during the chauffeur week ranged from a low of 4% for one of the Millennials (from 532 to 554 miles) to a high of 341% for one of the Retirees (from 117 to 516 miles), with an overall increase of 83% for the entire sample (from 3,344 to 6,118 miles).

Our entry and exit surveys provide further insight into these VMT shifts. We asked a wide array of questions to assess views and attitudes toward autonomous vehicles. The responses from the entry survey suggested that subjects would most likely travel more during the chauffeur week. Factors leading to more travel that were ranked most influential by the subjects were: 1) productivity, i.e. people will be able to multitask and make use of their travel time as well as enjoy their commute, 2) zero-occupancy vehicles, i.e. people will be able to send cars out on errands like picking up the groceries, parking, or refueling without having to be present in the car, and 3) convenience, i.e. people will not have to drive and accordingly they are willing to travel on longer leisure trips, or even if under the influence of alcohol and at night when they would be too tired or sleepy to drive themselves.

Our entry and exit interviews also provide further insight. For example, during the recruitment interview, one of the Retirees said that she thought she would not make a good study subject because she spends most of her time inside the neighborhood making short trips. However, when provided with the chauffeur, she increased her auto travel more than three folds. In the exit interview, this subject initially indicated that it was the "novelty" factor that led to such an increase— "I had a chauffeur so I wanted to use it!" However, she followed by saying that with the chauffeur she was able to take longer trips that she had been wanting to take for some time but had not done so when she had to drive herself. So, while there was a novelty factor there was also the release of latent demand related to lowering the burden of driving.

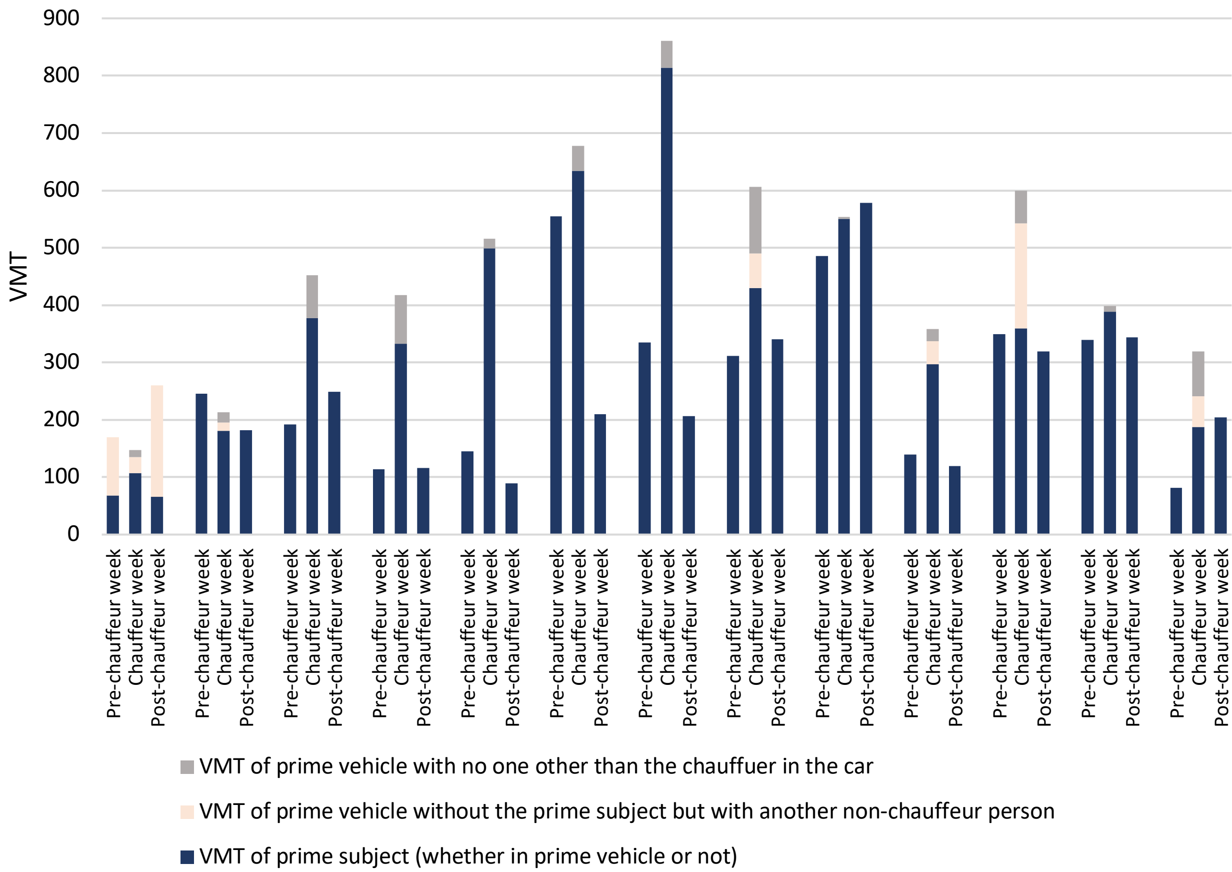

Figure 4: VMT reported for all primary subjects over each of the three weeks

3.4.2.2 Finding 2: All subjects sent the car off without them either for errands and/or to escort family/friends, which made up 34% of the total induced VMT; 61% of which was "zero-occupancy" miles (i.e. errands).

At some point during the chauffeur week, all 13 of our subjects sent their "autonomous vehicles" out on errands, with some subjects doing it more frequently than others. There was a wide range of trip purposes, including looking for parking after being dropped off at a destination, sending the car home to wait to be called for pickup, picking up the laundry or a meal, and picking up friends and family while the primary subject was at work or at home. For one Millennial (a single female) and one Family (a family with two minor children), a substantial portion of the induced VMT was from trips taken while the primary subject was not in the car. For the Millennial, running errands (zero-occupancy vehicle) and loaning the car to friends make up 48% and 21% of the induced demand, respectively. For the Family, running errands and driving the kids around without a parent make up 22% and 69% of the increase in VMT, respectively. Looking at the entire sample, sending the car off without the primary subject (the two lighter colors in Figure 4) accounted for 34% of the total increase in VMT (i.e. 943 of the 2,277 miles induced), 61% of which occurred with only the chauffeur in the vehicle (i.e. 582 of the 943 miles). Confirmation via the exit interviews indicated that most (if not all) of this extra VMT was not simply shifted from another vehicle (either within or outside the household) but indeed induced VMT.

3.4.2.3 Finding 3: Activity patterns changed, with people taking more trips (on average 58% more), traveling more in the evenings (on average 88% more trips after 6 pm), and taking longer trips (on average 91% more trips longer than 20 miles).

The increase in VMT partially results from Finding 2 above, but also results from a shift in activity patterns as summarized in Figure 5. Overall, 58% more trips were taken in the chauffeur week (Figure 5b). Further, there was a 91% increase in trips longer than 20 miles (Figure 5c) and 88% more trips taken in the evening after 6 PM (Figure 5d).

The entrance survey provides more insight into these changes. Related to driving at night, 11 subjects indicated that once they own an autonomous vehicles, they are more likely to participate in more leisure activities after dark because they would not need to drive themselves, and 12 subjects indicated that they would travel more even when they are tired. Moreover, 3 subjects, one from each cohort, indicated that they have a physical condition or anxiety which prevents them from traveling or limits how long they can travel at night. Related to the distance of trips, 11 subjects agreed that they would be more comfortable if they did not have to do the driving, and 12 subjects agreed that they would travel to more distant leisure activities once they own an autonomous vehicle. While increasing the ease of auto travel is hypothesized to impact people's residential choice in the future, only two of our subjects indicated in their exit survey that they believe AVs will result in the relocation of their residence.

3.4.2.4 Finding 4: The Impact on walking was not clearly directional, with 30% of subjects decreasing their walking (on average by 31% of miles walked) and 70% of subjects increasing their walking (on average by 37% of miles walked).

Figure 5e presents the change in miles traveled by walking during the non-chauffeur versus chauffeur weeks as calculated via the smartphone tracking app. (The results are for 10 subjects since the smartphone app did not work for three of the subjects). It is interesting that this is the only result we have thus far uncovered that is not clearly directional. In this case, 7 subjects increased their walking distance during the chauffeur week, ranging from a 10% to an 80% increase; while 3 subjects, one from each cohort, decreased their walking, ranging from a 28% to a 32% decrease. Further, this statistic showed the greatest variability between the two non-chauffeur weeks. The decrease in walking is hypothesized to be due to replacing walking trips with driving trips and also the pick-up/drop-off feature of not having to walk to access the car. On the other hand, the increase in walking is hypothesized to be due to the more active lifestyle that the AVs enabled as represented by the increase in vehicle trips. In our entry survey, when subjects were asked if they are concerned that AVs will decrease the exercise they get from active transportation, only two agreed with this statement, while the rest either disagreed or strongly disagreed.

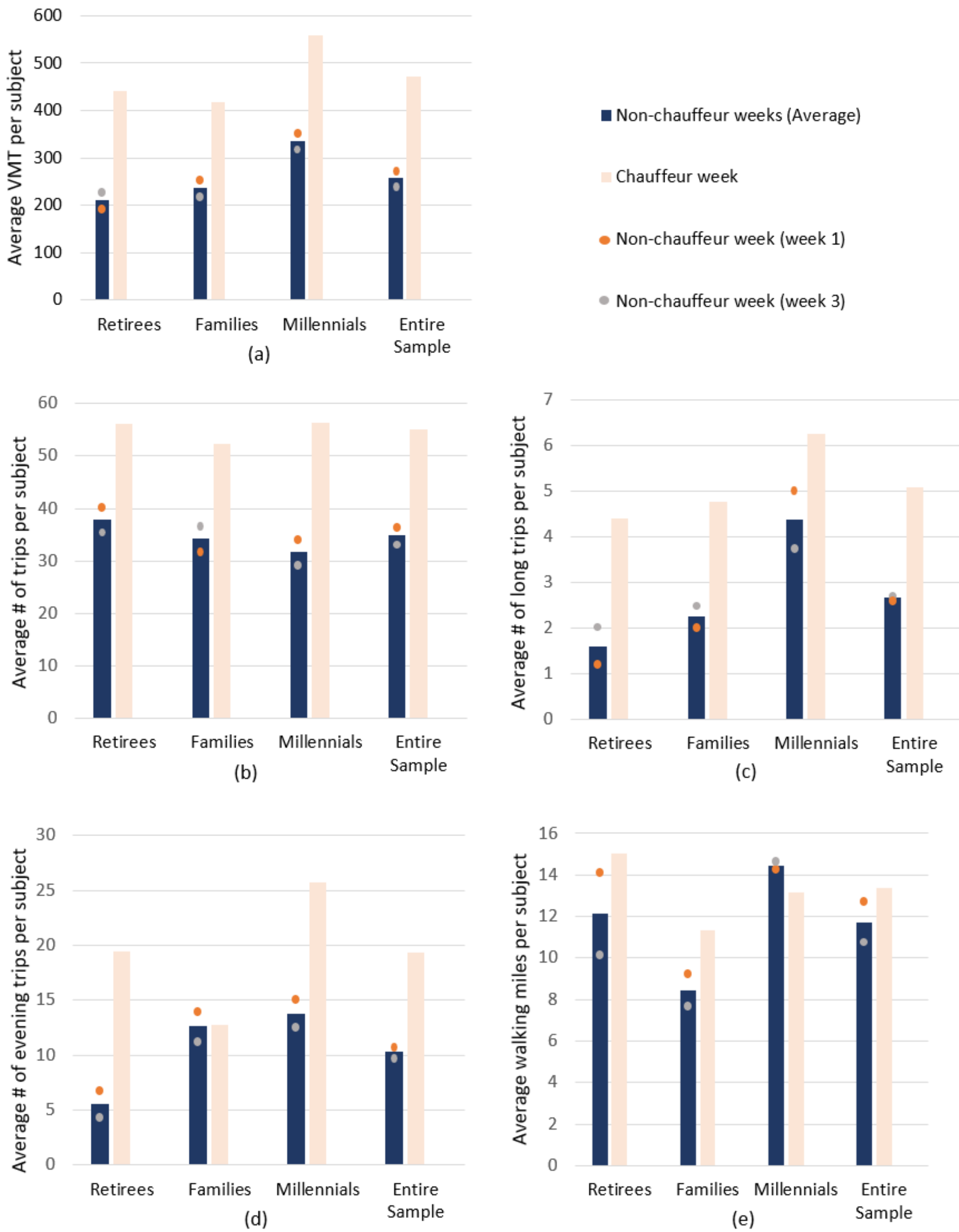

Figure 5: Shifts in weekly travel and activity patterns for the three cohorts

3.4.2.5 Finding 5: There were substantial differences across the cohorts.

While small samples, it is still interesting to note the differences we observe across the three cohorts included in the study. The travel behaviors in the non-chauffeur weeks seem to follow expectations. The retirees drove the fewest miles, although they made a higher number of trips (and therefore shorter trips on average). The retirees traveled substantially less in the evening than the other two cohorts. The millennials traveled the most miles, including (by far) the most long trips. The millennials were also most active in terms of walking, followed by the retirees. The families fell in the middle on all measures except for walking, where they were the lowest.

As with the status quo behaviors, the relative impacts of the autonomous vehicles on the different cohorts are also not surprising. While the retirees traveled the least in terms of VMT, long trips, and evening trips in the non-chauffeur weeks, they increased the most on all three of these measures in percentage terms. Safety, as the retirees highlighted in their exit interview, is of major concern to this demographic as they no longer trust their driving skills as they did before, especially at night. For families, in particular the ones with minor children, the factor that influenced the change in travel behavior the most was the freedom the autonomous vehicle gave the children, which made up a substantial share of the increased travel (Figure 4). All cohorts, however, enjoyed the convenience of having someone else run errands for them while they conducted other activities. The Millennials, on average, had the largest increase in number of trips and were the only cohort, on average, to reduce walking.

3.4.2.6 Non-finding: We cannot say much about mode choice, because our subjects made zero use of bicycles and hardly any use of public transit or transportation network companies (TNCs) during the three-week experiment and zero use of these modes during the chauffeur week.

Significant discussion about autonomous vehicles is related to the potential impact of the technology on mode choice, potentially decreasing use of public transportation and of active modes (biking, walking) (Malokin et al. 2015). We had hoped to provide such insight from our study. Unfortunately, the subjects we recruited were heavily auto-oriented, and thus we were not able to examine such impacts because the use of non-private auto modes (other than walking) was almost non-existent in our sample. We were also hoping to get information on substitution with TNC use (Uber/Lyft) as our subjects did report periodically using such services, but we did not observe such use during our study period. This is not too surprising given the fact that owning a vehicle is a prerequisite to participate. Our entry survey confirmed the auto-orientation. When asked about the mode of transport used to get to work/school, all subjects with such a trip indicated they use some form of personal vehicle, either as a driver or a passenger. Moreover, in the entry survey, subjects were presented with scenarios (going to school/work, dinner with friends, grocery shopping, etc.) where they had to choose between public transit and an autonomous vehicle, and they uniformly chose autonomous vehicles over public transit. Nevertheless, it is noteworthy that while there were a few transit trips recorded outside of the chauffeur week, there was zero use of public transit recorded during the chauffeur week.

3.4.3 Reflections on the Experiment Itself

A critical question is how successful this experiment was in how well it was able to mimic what life may be like with an autonomous vehicle. To get at this, in the offboarding process we asked a number of specific questions in the survey, asked an open-ended question in the survey, and spoke directly with a number of the subjects.

When asked how much subjects agreed with the statement “the experiment closely replicated life with an autonomous vehicle,” four subjects agreed and one strongly agreed, while another four disagreed and two strongly disagreed, and one subject felt neutral. The use of the word “closely” may have been too strong as in our interviews with the subjects after the experiment, almost all subjects said that the experiment helped them get an idea of how life with an autonomous vehicle may change (or not change) their lives. Perhaps “reasonably” would have been a better word choice.

One of the main issues people had was regarding the chauffeur. The presence of a human in the car detracted from the feeling that it was an autonomous vehicle. For example, some subjects felt guilty about sending the chauffeur on errands like taking care of their dirty laundry or having the chauffeur sit in the car doing nothing for long periods of time waiting for the next trip. Another chauffeur-related issue was that some subjects had multiple chauffeurs assigned during their chauffeur week, and there was an adjustment to each chauffeur. While the vast majority of our chauffeurs lived up to the “professional” claim of the driving service, there were issues with chauffeurs including reported aggressive driving, not showing up on time, and in one case causing a fender bender.

Another issue was the 60-hour time budget. An autonomous vehicle will be available 24/7 and not only 60 hours a week. We asked the subjects to submit a plan to allocate their 60 hours a week in advance so that we could schedule the chauffeurs. While they were able to make relatively dynamic adjustments to the schedule (e.g., a few hours in advance), some reported that pre-planning their week took away the spontaneity that autonomous vehicles offer.

Finally, there was a novelty issue. Subjects felt that one week was not enough to really get into a routine and a lifestyle in which they owned an autonomous vehicle. For some subjects, although they already knew they could send the chauffeur on errands, it took them a couple of days to internalize the idea and actually do so.

With all these limitations, however, subjects still felt that they learned something from the experiment, and that they got a better sense of how their life might be once autonomous vehicles become available. In the exit survey, one Millennial summarized his experience as: “with all the limitations of the experiment, I definitely felt the benefits of a self-driving car. I noticed that I reach work less tired, I noticed that I can do work on my way back home and not worry much about traffic jams, and I noticed that my commute overall feels more pleasant.”

Another Millennial highlighted the multitasking potential: “A self-driving car would be super helpful for multitasking! I would use self-driving cars a lot more for thoughtless activities that don't need me present. One thing that I noticed was that I was willing to use my car a lot more frequently to accommodate my friends and family. It also made going out and drinking a lot easier.”

In their exit survey, a Family mentioned what, to them, was the most important benefit of having the autonomous vehicle: “I spend a lot of time in the car driving my kids around to activities. Having a self-driving car would enable me to spend more time on work and would afford my kids more freedom."

Finally, a Retiree reported: "At my age, I am looking forward to the independence a self-driving car will provide as my driving skills decline. I believe self-driving cars will improve safety in driving, a real boon."

3.5 Conclusion

Researchers seem to agree that autonomous vehicles will increase individual vehicle-miles traveled and change travel and activity patterns. However, the predicted magnitude of the VMT increase varies considerably and the ways in which people may change activities (number, location, duration, type, timing, etc.) are largely uncertain. Our objective was to provide insight into these questions by employing an experiment to project people into a futuristic environment via the use of chauffeurs. From the experiment, we are able to provide a new kind of data to shed light on these issues. While our sample is small, it represents real data from real people making adjustments in their everyday lives. We found an 83% overall increase in VMT. The number of long trips (>20 miles) and trips after 6 pm increased by 91% and 88% respectively. Retirees were the cohort with the largest increase in these two trip types (175% and 246% respectively). 21% of the increase in VMT was a result of "zero-occupancy" vehicles, where subjects sent their chauffeur on errands. For active transport, namely walking, there was a bidirectional impact in that 30% of the sample reduced their walking and 70% increased their walking. Comparing the unique impact the chauffeur service had on the travel behavior of the different cohorts, we observe unsurprising differences. The retirees, for example, benefited from the ability to travel at night and on longer trips without having to worry about safety. For families, children were chauffeured to activities without their parents, giving the children more freedom to travel and the parents more time to focus on other activities. These results provide new insight to the growing body of knowledge regarding our future with autonomous vehicles. Future work includes refining the experiment based on this beta test, increasing the size and diversity of the sample, and estimating travel demand models in order to quantify changes in utility under autonomous vehicle scenarios.

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Chapter 4

A Glimpse of the Future – Simulating Life with Privately Owned Autonomous Vehicles & Their Implications on Travel Behaviors

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Abstract

To explore potential travel behavior shifts induced by autonomous vehicles (AVs), we ran an experiment where we provided personal chauffeurs to 43 households in the Sacramento area to simulate life with an AV. Like AVs, chauffeurs took over driving duties and could be sent out to run errands. We recruited households among the participants of the Sacramento Area Council of Governments' 2018 household travel survey. Households were stratified by weekly vehicle miles traveled (VMT) and sampled to be diverse in their demographics, modal preferences, mobility barriers, and residential location. Thirty-four households received 60-hours of chauffeur service for one week and nine households received 60 hours per week for two weeks. Smartphone-based travel diaries were recorded for the chauffeur week(s), one week before, and one week after. During the chauffeur week(s), overall VMT increased by 60%, over half of which came from "zero-occupancy" (ZOV) vehicle trips (when the chauffeur is the only occupant). The number of trips made in the system increased by 25%, with ZOV trips accounting for 85% of these additional trips. There was a shift away from transit, ridehailing, biking, and walking trips, which dropped by 70%, 55%, 38%, and 10%, respectively. Changes in travel behavior varied across the sample; households with mobility barriers and those less auto-oriented had the greatest increase in VMT, while families with kids had the lowest. The results highlight how AVs can enhance mobility, but also bring to light the potential detrimental effects on the transportation system and the need for policy on ZOVs.

4.1 Introduction

While the development of autonomous vehicle (AV) technology is well underway, governments are lagging behind in terms of planning and legislation. Guerra (2015) reviewed the regional transportation plan (RTP) of the 25 most populous U.S. major cities and found that only one included any mention of AVs. Interviewing planners at the 25 metropolitan planning agencies (MPOs), he found that two of the main reasons for the lack of inclusion of AVs in RTPs are that planners do not believe the impact of AVs will be profound and that the impacts are not certain enough to make credible planning efforts. Relatedly, Wong and Shaheen (2020) looked at the actions taken by states across the U.S. in response to AVs and found that policymakers have primarily focused on safety, testing, and infrastructure. However, the potential changes in travel-related behaviors, which is a critical factor in the technology's impact on the transportation system, has not received enough attention (Wong and Shaheen, 2020). In this study, we seek to improve the understanding of the impact of AVs on travel behavior, and consequently the transportation system, helping policymakers to be proactive with their policies.

The literature indicates that existing implementations of autonomous features (levels 2 and 3) in the vehicle fleet are leading to more travel (e.g. Hardman et al., 2019). Our focus is on levels 4 and 5, which have the potential to result in the most radical travel behavioral shifts as they can operate without human presence or intervention in some (level 4) and all (level 5) conditions. The two methods used to explore travel behavior shifts relevant to our study are (i) based on the analysis of survey data and (ii) microsimulations and travel demand models. In survey studies, subjects are usually asked to indicate their preferences, decisions, and potential shifts in their travel behavior under hypothetical AV future scenarios. On the other hand, for studies based on microsimulations, researchers modify existing models to incorporate AV options and simulate an AV future. This requires making assumptions on travel behavior changes caused by the technology. The two methods have been used to explore long-term changes in travel related behavior such us residential and work location choices and short-term changes such as daily activity patterns. For instance, simulation studies consistently find that the introduction of (shared) AVs will lead to an increase in vehicle miles traveled (VMT) (e.g., Childress et al., 2015; Taiebat et al., 2019), the number of vehicle trips (e.g., Vyas et al., 2018; Bernardin et al., 2019), and the average trip length (Thakur et al., 2016; Auld et al., 2018). Moreover, the literature indicates that AV options will likely lead to a decrease in transit ridership (e.g., Kröger et al., 2018; WEF, 2018), largely due to the assumption made on the reduction of AV riders' value of time (VOT), which are backed by findings from survey studies (e.g., Malokin et al. 2019; Zhong et al. 2020).

We contribute to this literature by quantifying changes in short-term travel behavior. Rather than using surveys or simulations, however, we propose a different approach. We build and expand on a previous pilot we ran in the San Francisco Bay Area (chapter 3), and administer an experiment that utilizes personal professional drivers ("chauffeurs") to simulate life with privately owned AVs. Just like an AV, a personal chauffeur takes over driving duties and can be sent out to run errands. The goal of the experiment is to enable study participants to experience the more salient features of an AV, namely the driverless feature, and act directly on how their daily travel and activities may change in an AV future. This allows us to study and quantify such potential shifts and compare our results to findings from the literature. Our results can also inform assumptions being made in AV-focused microsimulations. We are able to highlight aspects of travel behavior that have not received enough attention, such as zero occupancy vehicle (ZOV) trips and the potential benefits to less mobile groups such as the elderly and handicapped.

The remainder of the paper is organized as follows: first we outline the methodology used and describe the experimental design and data collection process. Then we summarize the key findings and explore the impact of the treatment period on the results. We then discuss the policy implications of the findings and conclude with a summary and future research directions.

4.2 Methodology

Building on our previous, smaller 13-household pilot in the San Francisco Bay Area (chapter 3), we carried out an expanded study of 43 households in the Sacramento area, in which we incorporated several improvements over the pilot study. First, to obtain a more diverse sample in terms of demographics, modal preferences, and mobility barriers, we partnered with the local MPO, the Sacramento Area Council of Governments (SACOG), who gave us access to travel survey data for a representative sample of households in the SACOG region, which consists of six counties in California – Sacramento, Yolo, Yuba, Placer, Sutter and El Dorado. We also provided a portion of our households with an extended chauffeur period (two weeks) to explore the impact of the treatment period on the results. Finally, we tracked all members and vehicles in the household and used a different phone tracking app to record a richer dataset that includes trip purpose and more detail on modes (private vs shared), parking, and vehicle occupancy.

The flow of the experiment is illustrated in figure 6 below. First, subjects were screened, recruited, and onboarded. Next, households began recording their detailed travel diary via a smartphone app and a vehicle tracking GPS device. During the first (control) week, travel diaries were recorded under status quo conditions. Then households received one or two weeks of the chauffeur service. In total, 34 households received one week of the service and nine households received two weeks. The two-week chauffeur period helps explore if changes in travel behavior persist as the treatment period is extended and the novelty factor fades. After the chauffeur week(s), travel diaries were recorded for a second control week. Travel diaries were therefore recorded for the chauffeur week(s), one week before, and one week after. A third non-chauffeur week of travel diary was also available for each household from the SACOG's 2018 household travel survey data (SACOG, 2018) and was used as an additional control week. An online survey was administered before and after the three to four weeks of travel tracking to collect data on demographics, regular travel, attitudes and intentions regarding AVs, and (post-chauffeur) reflections on the experiment.

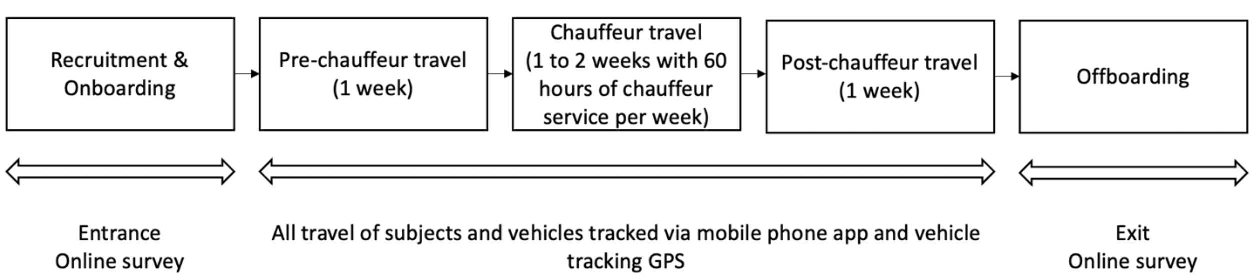

Figure 6: Flow of experiment and primary data collected

Table 12: Detailed set-up for the pilot and full experiments

		Study Area	Sampling	Study Period	# of HHs	Chauffeur week(s)	Tracking	Incentive	Data Sources
Phase I		**San Francisco:** • 47% of HHs have \$100k+ HH income • 40% commute by a mode other than a personal vehicle • 45% of the population identifies as non-white	Used online channels (e.g. Facebook) and word of mouth to recruit a convenience sample	May - August 2017	13	1	Head of HH and "AV" car only	Chauffeur service	• Passive (location data): Automatic, Moves • Passive (walking, biking, or driving): Moves • Entry and exit surveys
Phase II	**Group I**	**Sacramento:** • 30% of HH have \$100k+ HH income • 77% of workers commute by car • 70% of the population identifies as white	Built on SACOG's Sacramento area travel household survey and used stratified and targeted sampling to recruit a diverse sample	Aug - Nov 2019 & Feb - Mar 2020	33	1	All 18+ HH members and all HH vehicles	Chauffeur service	• Passive (location data): Automatic, rMove • Active (mode choice, trip purpose, number of passengers, parking type, etc.): rMove • Active (online shopping and home/work delivery behavior): rMove • Week 0: one-week travel diary from SACOG's 2018 travel survey • Entry and exit surveys
	Group II			Aug - Nov 2019 & Feb - Mar 2020	9	2			

4.2.1 Sampling Strategy and Subject Recruitment

Our sampling strategy targeted a wide array of dimensions related to household mobility and demographics. Our sampling frame was the list of 4,010 households that participated in SACOG's household travel survey, for which we had access to their one-week travel diary data. We further limited our sample frame to vehicle owners, as this was a prerequisite to participating in the study. This population was then stratified according to the household VMT. This dimension was chosen because it potentially reflects the general lifestyle and modality style adopted by a household. Households were segmented into three categories using the one-third quantile of their VMT recorded in SACOG's household travel survey. Within each of the three VMT levels, we targeted respondents with diverse demographics and lifestyles according to their household composition (non-family single and multiple occupancy, families with and without children, non-working elderly aged 60 and above), income, mode use, and residential location (urban, suburban, rural).

We invited 862 households to participate in the study. Households were recruited in the order of their response to our invitation while trying to maintain the diversity of the sample based on the demographic characteristics highlighted above. Households interested in participating took part in a 20-40 minute phone interview where we described the details of the experiment, what an AV is, and how a chauffeur can simulate owning one. They were informed that, during the chauffeur week(s), chauffeurs would take over driving duties and could run errands that AVs will be able to perform; they would be provided 60 hours of chauffeur service per week that they could then allocate based on their needs. Hours were allocated one week in advance and could have been modified up to a day in advance (and even on the same day, based on the driver's availability). Furthermore, chauffeurs were assigned to a single household vehicle that was deemed the household "AV." Any "AV" trips, including lending the service to friends and family were performed using the household "AV." Note that during the chauffeur week(s) households did not receive rides for "free"; even though subjects did not pay for the professional driver service, they still paid for out-of-pocket costs they would incur in an AV future, including all marginal costs for parking, tolls, and gas, as well as the fixed costs of auto ownership.

4.2.2 Data Collection

To understand changes in subjects' travel behaviors, a detailed travel diary and household level data are required. For this purpose, all household members 18 years of age and older and all household vehicles were tracked. For vehicle tracking, the GPS device "Automatic" was installed on all household vehicles. It is necessary to track all household vehicles to explore the changes in VMT for the entire household and the shift in vehicle usage between household vehicles during the chauffeur week(s).

For household members tracking, the GPS-based smartphone app "rMove" was used11. The app collected detailed information on every trip by nudging subjects to answer a trip survey that recorded information on their mode choice, trip purpose, number of individuals traveling with the subjects, parking type, etc. Chauffeurs were also instructed to install the app and answer the survey questions for all trips made during their shifts, allowing us to record detailed information

[11] This is the same app which was used in the SACOG household travel survey. See SACOG (2018) for details.

on trips where the chauffeur was the only individual in the car (equivalent to zero occupancy vehicles (ZOV) in the future).

Finally, to complement the travel diary data, subjects filled entry and exit surveys that provide demographic information, as well as lifestyle questions and perceptions on AVs that could help further explain changes in travel behavior. The exit survey had an extra section that asked subjects about their "AV" experience.

The average per household cost for a chauffeur week in this study was $2,500, almost double that of the pilot ($1,400), limiting the initial sample size for this study to 50, with 7 households that had to suspend the experiment due to the COVID-19 pandemic in early 2020. The increase in cost was mainly due to the change in the chauffeur service provider (required by UC liability requirements), which increased the hourly cost from $20/hour in the earlier pilot to $35/hour to this larger experiment. Tracking all household vehicles (requiring addition Automatic devices) and using the more comprehensive rMove app to collect a richer dataset also contributed to increased experiment costs.

4.2.3 Data Cleaning

With household vehicle data being recorded by Automatic and rMove, there were inconsistencies in some trips that had to be rectified. Inconsistencies were eliminated between the data sources, by a process that carefully investigated all trips recorded in order to add trips missed by one data source and captured by the other, delete trips made by chauffeurs using the household vehicle for purposes that were not related to the study (e.g. going on a break to grab lunch), and combining data collected with the smartphone rMove data from the chauffeurs with those collected from the household members, namely adding "zero occupancy vehicle" trips and "friends and family" trips (see definition for the latter in the next section of the chapter). Finally, the second non-chauffeur week for three households was dropped as it was affected by the shelter-in-place order caused by the COVID-19 pandemic. We note, however, that the shelter in place order only impacted the final sample size, but not the results as the weeks that were affected by the shelter in place order were not included in the analysis.

4.3 Results

In this section, we present the key findings from the experiment. Note these definitions that are used throughout:

- Primary (adult) household members are identified as all members who are at least 18 years old and have access to household vehicles (i.e. do not depend on other household members to travel in a household vehicle such as underaged kids or elderly parents). They are also eligible to record their travel on rMove.
- Friends and family (FAF) are defined as household members that are not primary (e.g. younger than 18) or friends and family members that do not belong to the household. Their travel is not recorded by the smartphone app as this was installed only by the primary household members.
- For every household, the travel behavior statistics that are reported are based on the changes in their travel behavior measures (e.g. VMT) between the chauffeur and non-chauffeur weeks. For instance, if a household traveled 100 and 120 miles in the first and second non-chauffeur

week respectively, and 150 miles in the chauffeur week, then they traveled $150 - ((100 + 120)/2) = 40$ more miles during the chauffeur week.

- All results are based on our sample and are not weighted to the population. (Discussed later in relation to self-selection bias.)

4.3.1 Sample Statistics

Table 13 summarizes the demographics of the population in the SACOG region, SACOG travel survey sample, the subset of vehicle owners in SACOG travel survey sample, households invited to participate in our study, and our study participants. Summary statistics for all samples, except for the overall SACOG region and SACOG travel survey sample, are reported for car owners only, as this was a requirement to participating in the study.

Table 13: Summary of the population demographics

	SACOG Region (ACS 2018)	SACOG HHTS		Invited Sample	Study Sample
		Complete Dataset	Vehicle Owners		
Households	877,911	3,956	3,708	862	43
Persons	2,463,103	8,191	7,827	1,955	76
Gender					
Male	48.4%	45.3%	45.7%	46.7%	38.7%
Female	51.6%	54.7%	54.3%	53.3%	61.3%
Age					
Less than 34 yrs.	31.1%	24.5%	24.0%	30.7%	25.0%
35 yrs. to 54 yrs.	33.5%	31.5%	31.6%	38.1%	46.1%
More than 55 yrs.	35.4%	44.0%	44.3%	31.2%	28.9%
Race					
White alone	65.9%	71.7%	72.8%	71.1%	70.3%
Black or African American alone	6.8%	4.7%	4.0%	4.3%	6.3%
American Indian and Alaska Native alone	0.7%	2.3%	2.2%	2.0%	0.0%
Asian or Pacific Islander	13.8%	12.1%	12.2%	14.3%	18.8%
Some other race alone	6.4%	2.7%	2.7%	1.9%	0.0%
Two or more races	6.5%	6.4%	6.2%	6.5%	4.7%
Ethnicity					
Not Hispanic or Latino	78.0%	92.1%	92.2%	89.8%	92.1%
Hispanic or Latino	22.0%	7.9%	7.8%	10.2%	7.9%
Education					
Less Than Bachelors'	70.1%	66.4%	54.4%	50.2%	12.1%
Bachelors' or more	29.1%	33.6%	45.6%	49.8%	87.9%
Household Income					
Less than $75,000	54.6%	45.9%	43.3%	39.4%	25.6%
$75,000 - $150,000	29.4%	29.8%	31.5%	34.2%	41.0%
More than $150,000	15.9%	24.3%	25.2%	26.3%	33.3%
Vehicle Ownership					
No vehicle available	6.3%	6.3%	0.0%	0.0%	0.0%
1 vehicle available	31.2%	43.2%	46.1%	36.7%	39.5%
2 vehicles available or more	62.5%	50.5%	53.9%	63.3%	60.5%
Employment Status					
Employed	61.3%	66.4%	67.4%	24.6%	68.4%
Unemployed	38.7%	33.6%	32.6%	75.4%	31.6%

	SACOG Region (ACS 2018)	SACOG HHTS		Invited Sample	Study Sample
		Complete Dataset	Vehicle Owners		
Household Size					
1-person household	25.2%	38.6%	36.3%	29.4%	23.3%
2-person household	33.1%	37.0%	38.4%	40.7%	44.2%
3 or more person household	41.7%	24.4%	25.3%	29.9%	32.6%
Number of household members under 18 yrs.					
One or more	33.7%	21.3%	22.1%	27.6%	27.9%
None	66.3%	78.7%	77.9%	72.4%	72.1%

Overall, the characteristics of the participating households are similar to those of the population in the SACOG region and HHTS respondents. The main difference is that our sample includes a higher proportion of females and is more educated and affluent. However, this was not the case for households invited to participate, indicating that females were more willing to participate in the study. The same is true for more educated and higher income households, who account for a higher proportion of participants in our sample as compared to the larger SACOG region. This is most likely an effect of the higher cooperation rate among these groups and the self-selection of certain respondents who are more interested in the research topic (and less concerned about any potential risks the experiment might expose them to). It is possible that these observable demographic characteristics might be correlated with other unobservable characteristics (e.g. lifestyles, attitudes towards the adoption of technology and willingness to trust others) which motivated our sample to participate in this study. Consequently, we chose not to weight our sample based on demographic characteristics to the broader population of the SACOG region as the generalizability of results to the broader population might not be possible and could be potential misleading; this is discussed in more detail in a later section where we explore potential sources of bias in the study.

4.3.2 Changes in Travel Behavior

Table 14 summarizes results from this study, the pilot (chapter 3), and relevant statistics from studies that explore the impact of privately owned AVs on travel behavior.

Table 14: Summary of results

	This Experiment		*Literature*		
	All trips	**Excluding ZOV trips**	**Pilot**	**Remaining Literature**	**Citations**
Average change in VMT	+60%	+33%	-	+1% to +79%	Childress et al., 2015 Auld et al., 2017 Taiebat et al., 2019
"AV" (chauffeur car) VMT change	+114%	+68%	+82%	-	-
% ZOV and FAF VMT of total VMT	20%	-	-	ZOVs account for 30% of vehicle trips	Bernardin et al., 2019
% ZOV and FAF VMT of induced VMT	54%	-	34%	-	-
Change in total miles traveled, by all modes	+44%	+21%	-	-	-
Change in total number of trips, by all modes	+25%	+3%			

	This Experiment		Literature		
	All trips	Excluding ZOV trips	Pilot	Remaining Literature	Citations
Change in average trip length (for all modes)	+17 %	+17%	-	+3% to +47%	Kim et al., 2015a Auld et al., 2018
Change in number of vehicle trips	+39%	+12%	+58%	+3% to +45%	Kim et al., 2015 Bernardin et al., 2019
Change in number of trips at night (after 6 pm)	+20%	+5%	+88%	-	-
Change in 20+ mile trips	+75%	+50%	+91%	-	-
Change in 50+ mile trips	+81%	+61%	-	-	-
Change in transit ridership	-70%	-	-	-9% to -70%	Levin and Boyles, 2015 Huang et al., 2019
Change in walking mode share	-10%	-		-21%	Childress et al. 2015

4.3.2.1 Finding 1: Overall VMT increased by 60%, half of which came from ZOV trips. There were 39% more vehicle trips, 75% more trips between 20 and 50 miles, and 81% more trips longer than 50 miles.

4.3.2.1.1 Vehicle Miles Travelled

The overall VMT increase during the chauffeur week was 60%, which includes all household vehicles as well as non-household vehicles (e.g. Uber, car from work, friend's car). The increase ranged from a low of 3% for a family with no kids to a high of 700% for an elderly individual with another household member with a disability who usually commutes by transit, trips that were substituted by AV trips during the chauffeur week.

4.3.2.1.2 ZOV and FAF Trips

ZOV and FAF trips made up 54% of the induced demand. One source of ZOV trips was non-auto dependent households switching their (commute) mode from transit or biking/walking to "AV" and sending the car back home when parking was an issue. The majority of ZOV trips (66.4%) and ZOV miles (78%) were pick-ups and return home trips, which include returning home after running an errand or after a drop-off to avoid parking or to serve other household members. Running errands made up 17% and 13% of total ZOV trips and miles respectively. Shopping was the lowest use case for ZOVs (7% and 4% of trips and miles, respectively).

Similar to ZOV trips, picking up and dropping off friends and family members constituted most of the FAF trips (66%) and miles (70%). Moreover, driving friends and family to run errands ranked second in terms of FAF trip purposes (17%) and miles (13%). Only one of our 11 households with children in the household recorded any trips with their minor alone in the car with the chauffeur.

4.3.2.1.3 Activity Patterns

Table 14 summarizes the key changes in activity patterns. Interestingly, we found that, during the chauffeur weeks, person trips and miles only increase by 4% and 21% respectively, compared to 25% and 44% in system wide trips and miles respectively (i.e., if ZOV trips are considered). Similarly, system wide, we observed a 20% increase in evening trips (trips where the start or end time is after 6 pm), 76% more trips with length between 20 and 50 miles, and 81% more trips longer than 50 miles. However, if only person trips are considered (i.e., ZOV trips are excluded), these numbers drop to 5%, 50% and 61% respectively. These results indicate that ZOVs were a primary source of travel behavior change as they constituted the majority of the additional trips in the system.

Moreover, during the chauffeur weeks, we observed an increase in the average and median length of person trips by 17% (1 mile) and 23% (0.5 miles) respectively, indicating a decrease in subjects' disutility to traveling to farther locations. Looking at trip purpose, we found that social and recreation trips had the lowest percent increase in the number of trips (5%), but the highest increase in the average trip length (46%), and these results are not affected by the exclusion of ZOVs. On the other hand, pick-up and drop-off trips had the highest percent increase in number of trips (180%) and a 37% increase in average trip length. These numbers drop to 45% and 35% increase, respectively if ZOV trips are not considered.

The entry and exit surveys provide further insight into the changes in subjects' travel behavior. Factors that contributed to these changes are: 1) more relaxed travel, with 90% of respondents indicating that they would enjoy their travel more in an AV; 2) increased productivity during travel with 75% of subjects indicating that their travel would be more productive in an AV; 3) time savings by sending out AVs to run errands with 91% of subjects agreeing with the statement that they would be more productive during an average week if AVs can run errands for them); 4) traveling when tired or under the influence of alcohol, and 5) safety.

4.3.2.2 Finding 2: Households shifted their vehicle usage away from the non-AV household vehicles (53% decrease in VMT) and non-household vehicles (11% decrease in VMT) to the AV vehicle (114% increase in VMT, all numbers compared to the non-chauffer weeks).

During the chauffeur weeks, we saw a shift away from non-household vehicles (e.g. TNCs, car from work, friend's car, etc.) and more dependency on household vehicles. For household vehicles, VMT increased by 66% from 12,067 to 20,085 miles, while it decreased for non- household vehicles by 11%, from 1,152 to 1,016 miles. Moreover, since we tracked all vehicles in the household, we observed the shift in use among household vehicles. During the chauffeur week, we observed a 114% increase in VMT for the "AV" and a 53% drop in VMT for secondary vehicles, with some households completely forgoing the use of the non-AV vehicles. This was possible because the chauffeur could autonomously shuttle between trips to serve multiple household member. Interestingly, when looking at vehicle usage by demographic, we found that the elderly and families without kids had a much higher drop in non-AV use (62% for both) as compared to families with kids (19%).

The shift in the usage of household vehicles could indicate the potential reduction of car ownership in households where members can coordinate their schedules. In their exit survey, one subject indicated that this is how they envision their future: "we also only used one car the entire week as the chauffeur made it easier for both my husband and I to use the car separately during the day, therefore I would envision owning only one car instead of two if in the future we had a driverless car".

4.3.2.3 Finding 3: Subjects shifted away from transit, TNCs, biking, and walking trips which dropped by 71%, 58%, 37%, and 13%, respectively.

One of the most important questions regarding an AV future is the impact on mode choice. For this purpose, we explicitly collected data on mode choice and targeted households that rely on transit, slow modes, and TNCs. During the chauffeur week, households became more auto-oriented and shifted away from other modes. In our sample, transit suffered the most during the chauffeur week, with transit trips and miles dropping by 71% (from 51 to 15 trips) and 90% (from 714 to 71 miles) respectively. During the non-chauffeur weeks, there were mostly two types of transit trips taken by nine of the 43 households—work trips and long-distance trips (e.g. to San Francisco), both of which were substituted for AV trips. For work trips, the chauffeur was sent back home to avoid parking which was scarce and expensive in downtown Sacramento. Similar to transit, TNC trips and miles dropped by 58% and 63% respectively. Since AVs combine the attractive features of a personal car (e.g., privacy) and a TNC trip (e.g., no parking concerns), the latter loses much of its appeal. The same trend is observed for biking, as the number of trips and miles biked dropped by 37% and 38%, respectively.

For walking, even though the overall number of trips and miles decreased by 13% and 17% respectively, the change was not uniform across households: in particular, 58% of households exhibited a decrease in walking miles (by an average of 42%), 28% exhibited and increase (by an average of 92%), and 14% did not record walking trips during the study. For households that decreased walking, the average weekly miles walked during a non-chauffeur week was 8 miles, double that of households that increased their walking trips who averaged 4 miles. Moreover, investigating the differences between groups further, we found that the former group had a much higher increase in VMT (80%) compared to the latter group (40%). This indicates that households that walk more are likely to substitute walking trips by AV trips.

4.3.2.4 Finding 4: The AV particularly benefited the elderly and individuals with mobility barriers (121% and 700% increase in VMT, respectively).

A benefit of AVs is their potential value for individuals with mobility barriers. In the entrance survey, 5 elderly individuals indicated that they have a condition or anxiety that limits how often or how long they can drive at night or on a highway. This was reflected in the fact that the elderly were the cohort that had the highest percent increase in VMT (121%; 101% if ZOV trips are excluded). Relatedly, this cohort exhibited the highest percent increase in the average trip length (37% increase; 45% increase if ZOV trips are excluded). Moreover, the chauffeur service also gave this cohort the freedom to travel more at night (74% increase; 50% increase if ZOV trips are excluded) and on trips between 20 and 50 miles (165%; 218% if ZOV trips are excluded) and longer than 50 miles (267% increase; 167% if ZOV trips are excluded). Two days after starting the chauffeur service, one elderly participant emailed the research team to express her enthusiasm about the service: “I love the chauffeur service. I’ve already gone to two places I would never have driven to on my own and it’s been wonderful.” Similarly, in their exit survey, when asked, after participating in the experiment, how they believe their life will change when AVs are the norm, all elderly subjects shared one of three advantages of AV—safety, the ability to explore new places, and going out at night:

- “I would be more inclined to go out at night as well as more distant locations.”

- “I like the idea of picking up out of town friends, doing an activity and returning them safely home.”
- “If I had a self-driving car, I would go more places, spend more time with friends, and participate in more activities. I often pass up opportunities now because I don’t feel comfortable driving in heavy traffic or at night or in unfamiliar places.”

Our sample also included a particularly interesting household consisting of an elderly member and another member with a disability that prevented them from driving a car. The chauffeur service opened up a new world for this household, increasing their VMT by 700% and their average trip length by 107%. They also traveled more at night, making on average 2 evening trips during the chauffeur week compared to 0.5 trips in a non-chauffeur week. Similarly, they made an average of 5 trips longer than 20 miles and 1.5 trips longer than 50 miles during a chauffeur week, compared to 2.5 trips longer than 20 miles and no trips longer than 50 during a non-chauffeur week.

The elderly household member exhibited a similar behavior to other elderly participants described above and increased their VMT by ~350%. However, the service was particularly life changing for the individual with the disability who went from being a captive transit rider to having the freedom to travel anywhere and anytime via their personal car. During non-chauffeur weeks, the individual relied on transit for all trips (~200 miles per week), primarily for commuting, and had virtually zero VMT. During the chauffeur weeks, they switched to traveling via their AV, cutting their one-hour commute by half and raising their VMT to ~350 miles per week. They also traveled 156 miles (via all modes) for social activities during an average chauffeur week compared to 74 miles for an average non-chauffeur week. To this individual, an important advantage of the AV was not being tied to the transit schedule. In their exit survey, they highlighted this by mentioning that an AV will change their life by allowing them to “go more places and go at different times.”

It is difficult to objectively measure quality of life and how having access to an AV affects it. However, the increase in VMT, average trip length, and night trips highlight how AVs would allow retirees and individuals with mobility barriers the freedom to travel and explore new and farther locations, and at more flexible times of day without having to compromise their safety. These results, supported by subjects’ exit survey responses highlighting the benefits of AVs, suggest that the greater accessibility provided by the chauffeur service (i.e., “AV”), manifesting through farther destinations, is leading to an enhanced quality of life.

4.3.2.5 Finding 5: Changes in travel behavior were the largest for the elderly and single occupancy households (121% and 113% increase in VMT, respectively) and lowest for families with kids (17% increase in VMT). Non-auto dependent households also observed a substantial shift in travel behavior as they transitioned to auto dependency (102% increase in VMT).

Even though we had a relatively small sample, it was interesting to see how the response to the chauffeur service differed across multiple dimensions and lifestyles. During the chauffeur week, the elderly subjects had the highest increase in VMT (121%; 101% if ZOV trips are excluded) followed by single occupancy households (113%; 58% if ZOVs trips are excluded). However, single occupancy households had the highest increase night trips (93%; 41% if ZOVs trips are excluded), trips between 20 and 50 miles (153%; 50% if ZOVs trips are excluded), and trips longer than 50 miles (500%; 300% if ZOVs trips are excluded). On the other hand, families with kids had, by far, the lowest increase in VMT (18%; 10% decrease if ZOV trips are excluded) since this demographic has the least flexible schedules as the kids' activities and needs dictate the household's schedule.

Looking at heterogeneity by VMT category on which our sample was stratified, we found that the lowest VMT category observed the highest percent increase (137%; 110% if ZOV trips are excluded) in VMT, followed by the medium VMT category (93%; 52% if ZOV trips are excluded), and the high VMT category (27%; 5% if ZOV trips are excluded). This is reasonable as the lowest VMT category is the least active in terms of overall miles and VMT. For this group, which is dominated by the elderly and single occupancy households, the advantage of having an AV is manifested in the ability to live a more active lifestyle. On the other hand, households in high VMT category (dominated by families with and without kids) already spend a significant portion of their day on the road (on average 74 miles per day during a non-chauffeur week), so there is little room to add more travel.

We also split the sample into 13 high income households ($150k+), 16 medium income households ($75k - $150k), and 10 low income households (< $75k)12. We found that low income households had the highest increase in VMT (63%; 28% if ZOV trips are excluded) followed by medium income households (54%; 33% if ZOV trips are excluded) and high income households (36%; 13%). We note that results might be driven by the fact that the high-income category was dominated by six families with kids and four without kids as opposed to one retiree and two single occupancy household. Similarly, 10 of the 13 households belonged to the medium (5) and high (5) income categories. We note here that, as clear from the results above, there is confounding between the different dimensions considered, and more information and a larger and more diverse sample is needed to separate the effect for each of these dimensions.

We also explored heterogeneity by residential location. To assign each respondent a home location type, we relied on Salon (2015), who classified all census tracts in California into five categories – central city, urban, suburban, rural-in-urban and rural. For brevity, we collapsed these labels into three categories – urban (urban and central city), suburban, rural (rural and rural-in-urban). Results indicated that suburb residents had the highest increase in VMT (75%; 48% if ZOV trips are excluded), followed by rural residents (47%; 21% if ZOV trips are excluded) and urban residents (34%; 9% if ZOV trips are excluded).

Finally, we look at the response of households based on their auto-dependency. We classified non-auto dependent households as those that relied on a non-auto mode for commute or used non-auto for at least 15% of their trips, which applied to 21 (about half) of our households. The rest (22 households) where classified as auto dependent. In terms of VMT and total mile traveled via all modes, there was a substantial difference between the two groups with non-auto dependent households increasing their VMT and total miles traveled by 102% (68% if ZOV trips are excluded) and 70% (42% if ZOV trips are excluded) compared to a 27% (7% if ZOV trips are excluded) and a 20% (1% if ZOV trips are excluded) increase for auto dependent households. However, in terms of percent increase in total number of trips, the difference is less than 5% (27%

[12] four households preferred not to answer

and 23% for the two groups respectively and drops to 5% and 2% respectively if ZOV trips are excluded). This further highlights the impact owning an AV will have on travel behavior, particularly for households that are multimodal. These households not only became more auto-oriented, but the average trip length also increased by 35% as they switched to AV trips as opposed to no change in the average trip length for auto dependent households.

4.3.3 Discussion of Potential Biases

A primary question about this study is whether our estimates, particularly any reported increases in VMT, are suspected to be higher or lower of what could be reasonable to expect in reality. In this section, we discuss various factors and provide evidence for sources of bias that could affect the estimated results of this study in either direction, including 1) the presence of the chauffeur as opposed to a real AV, 2) the "novelty" factor of having access to a chauffeur, 3) the non-stable conditions across weeks and shifting activities from non-chauffeur weeks to chauffeur weeks, and 4) the 60-hour chauffeur service limit. Additional structural factors to the transportation system (e.g., levels of congestion and introduction of other new technologies, modes, and business models) could affect the true impacts of AV deployment, but these are outside of the scope of the study.

We first address aspects of the study that could lead to downward bias (i.e., underestimation of the impacts of AV deployment) and then investigate those that could lead to upward bias (i.e., overestimation of the impacts of AV deployment).

4.3.3.1 Sources of *downward* bias

4.3.3.1.1 Human Driver Instead of a Real AV

The impact of the presence of the chauffeur was pointed out by many subjects in their exit surveys. For instance, we asked subjects if they would have used the car more often if it were a real AV and 70% of subjects indicated that they somewhat/strongly agree with the statement while 23% somewhat/strongly disagreed, and the rest were neutral. Moreover, 52% somewhat/strongly agreed that the presence of the chauffeur made them, or other passengers feel uncomfortable. This human factor led subjects to avoid making trips in an attempt to escape interactions with the driver. Similarly, the feeling of guilt for "inconveniencing" the driver lead subjects to avoid sending out their chauffeur to run errands which they would have done had it been a real AV. Moreover, one advantage of the self-driving car is productively using in vehicle time, freeing up one's schedule for more activities. The presence of the chauffeur limited this advantage as subjects felt guilty about ignoring the driver or uncomfortable having private conversations in their presence. Below are a few direct quotes from the exit surveys that highlight the behavior:

- "It was very hard NOT to become personally involved with the chauffeur, especially since mine was a young woman. I even canceled one late-night trip because I wanted her early the next morning."
- "I definitely decided not to use the service at night when I get home from work around 03:00 AM. I probably would have used the service for more tasks such as picking up small items from the store etc."
- "It [the chauffeur] just didn't seem like a self-driving car to me. I wasn't comfortable talking to other people in the car or on the phone about personal topics, which I do often."

4.3.3.1.2 The 60-hour Chauffeur Limit

Limiting the chauffeur service to 60-hours per week takes away from the spontaneity a true AV will provide, a sentiment many subjects highlighted. Subjects indicated that in many instances, they wanted to make spontaneous last-minute trips but could not because they did not have the chauffeur booked during these hours. This includes additional (ZOV) trips that subjects will make in the future when they have 24/7 access to their AVs.

- "I feel I would be more inclined to constantly run small errands using a self-driving car, i.e. picking up ice cream at the last minute etc."
- "The time restriction may have impacted our results a little bit, only because with an active teenager and our busy lives it's hard to fully predict when we'll need access to a car."
- "In a few instances, we sent the driver away only to realize we wanted to go somewhere shortly after."

4.3.3.1.3 The Novelty Factor

The novelty factor can actually play a role in either direction as a source of potential bias in the results of the study (as discussed in the next section, for the potential "upward" bias of the novelty factor). On one side, since the chauffeur period is relatively short, there is a learning curve for subjects before getting used to their new lifestyle and using the chauffeur as a real AV. Moreover, there might be effects that take longer to for subjects to experience. For example, the lower burden of driving and enhanced accessibility might encourage AV owners to travel to farther locations and explore new and unfamiliar destinations. This is likely to translate into a downward bias affecting our results. In the exit interview, we asked subjects if "one (two) week(s) with a chauffeur was not enough to get into a routine and adjust to a life where I own a self-driving car". Results indicated that 66% agreed/strongly agreed, 17% disagreed/strongly disagree, and 17% were neutral. The novelty factor particularly impacts ZOV trips as people need time to feel comfortable with their driver and figure out how running errands works best for them, biasing results downwards. Subjects also highlighted this issue in their exit survey:

- "I understand it had to be limited to one week, but it takes a couple of days to get used to it [the chauffeur service]."
- "A week wasn't enough for me to feel like the chauffeur setup was an autonomous vehicle"

4.3.3.2 Sources of *upward* bias

4.3.3.2.1 Unstable Conditions Across Weeks and Shifting Activities to the Chauffeur Week(s)

To ensure that the changes in travel behavior are caused by the chauffeur service and not by confounding factors, conditions across weeks should be stable. In other words, there should be no inherent differences between weeks that would result in biases (e.g. a vacation day during one week that is not present in other weeks). Pre-experiment, we control for this condition by requiring subjects to select a typical three-week (up to four-week) period with no special events such as holidays or travel. Post experiment, testing this condition for all weeks is not possible, so the condition is assumed to hold. However, we can get a better idea of how realistic this assumption is by testing the stability of conditions between the non-chauffeur weeks. We ran a Paired t-test and a Wilcoxon signed rank test (the non-parametric version of the Paired t-test) that compared the total miles traveled via all modes for the two non-chauffeur weeks. Results from both tests indicate that the difference between weeks is not statistically significant (p-values of 0.33 and 0.15 for the paired t-test and the Wilcoxon Signed Rank test, respectively).

Another potential source of bias is subjects shifting activities from the non-chauffeur weeks to the chauffeur week. However, since the difference between non-chauffeur weeks is not statistically significant, it gives us confidence that this effect is minimal, unless subjects shifted the same amount of activities from both weeks to the chauffeur week(s). This is unlikely given that when asked if they "rescheduled some of my activities from the non-chauffeur weeks to the chauffeur week", 52% disagreed/strongly disagreed while 34% agreed/strongly agreed, and the rest were neutral.

Moreover, we used the one-week travel diary from SACOG's travel survey as an additional control since subjects' travel behavior during that week was not influence by having access to the chauffeur service. We dropped 6 households whose household structure changed between the two study periods (e.g., someone moved in or out). Running the same hypothesis tests above, we found that the difference between miles traveled using all modes in the average of non-chauffeur weeks and the SACOG travel survey week was not statistically significant (p-values of 0.40 and 0.37 for the paired t-test and Wilcoxon signed rank test, respectively).

4.3.3.2.2 The Novelty Factor

The novelty factor can also bias results upward as households have the unique opportunity of using a chauffeur service for one (two) week(s) only, thus opting to overuse the service and take advantage of it to the fullest: "I think I was trying to imagine ways to make use of the time that I otherwise wouldn't have done this week even if it were a self-driving car simply because I only had the service for one week." We investigate the novelty factor first by comparing effects on the one chauffeur versus two chauffeur week households and then by examining non-typical trips and extreme behavior.

4.3.3.2.2.1 One vs. Two Chauffeur Week Households

If the novelty factor results in a larger spike in travel behavior change, then we would expect subjects who only had one week of chauffeur service to have a higher per week increase in VMT compared to those who received two weeks (as two chauffeur week households can spread additional activities over the two weeks). Comparing the two treatment groups, we find that households who received two weeks of the chauffeur service actually had a higher percent increase in VMT (80%) compared to the one-week households (56%). However, this may be due to the fact that the two-week households are dominated by low VMT category households. Therefore, even though the overall percent increase in VMT is higher for two chauffeur week households, the overall absolute increase in VMT is almost identical (~180 miles).

Examining the difference between the two weeks for the two-week chauffeur households, we find that six households decreased their VMT during the second week relative to the first (ranging from -6% to -55%), two households increased their VMT (by 15% and 44%), and one had virtually no change in VMT across weeks (-2%). This indicates that the novelty factor potentially biased results upward and that over a longer period the effect may further fade. We note, however, that the main difference between the two weeks comes primarily from a single outlier day. In other words, whether the first or second chauffeur week has higher VMT depends primarily on which of the weeks the household decided to take their "non-typical" long distance trip, for example to go to San Francisco.

4.3.3.2.2.2 Sensitivity Analysis—Non-typical Trips and Extreme Behavior

Another aspect of "taking advantage of the chauffeur service to the fullest" is making trips that one would not usually do, namely long-distance travel. Even though we believe these trips will still be more likely during an all AV era, they might not be typical trips that one would do every week. We explore the impact of "non-typical" trips on VMT increase by excluding them from the analysis. First, we excluded all trips that start or end outside the Sacramento Area (e.g., trips to/from San Francisco) and found that overall VMT increased by 44% compared to 60% when all trips were included. Then, we excluded all trips that are longer than 50 miles and found that the overall VMT is 55% higher during the chauffeur week. Finally, we took it a step further and excluded all trips longer than 25 miles, and still found a 47% increase in VMT during the chauffeur week(s). These results indicate that the increase in VMT is coming primarily from an increase in the number and average length everyday trips rather than less typical "outlier" trips.

During the chauffeur week(s), we also observed some extreme behavior that hints at the potential extreme travel behavior resulting from AV technology in the future:

- The longest ZOV trip was an 83-mile airport pick-up/return home (to and from SFO).
- The longest ZOV errand was 120-mile round trip for a package delivery.
- The longest ZOV food pickup trip was a 45-mile round trip.
- The highest percent of ZOV miles during the chauffeur week (as a percentage of total VMT) for a household was 53%.

If we exclude the outliers of the airport trip, the food pickup, and the package delivery, the ZOV trips as a percentage of the total VMT during the chauffeur weeks reduces from 18% to 16%.

On another note, as discussed earlier, we observed that the individual with a disability showed the highest percent increases in VMT and shift from transit to car travel during the chauffeur week. Excluding this household from the analysis, however, the average increase in VMT during the chauffeur week drops by only four percentage points (from 60% to 56%). Similarly, transit miles and trips would drop from 90% to 86% and from 70% to 61%, respectively if this household is excluded from the analysis.

We cannot be certain whether this extreme behavior outlined in this section is the result of the novelty factor or if these habits will persist in an AV future. Nevertheless, the sensitivity analysis indicated that exclusion of these 'extreme behaviors' still results in substantial magnitudes of travel behavior changes.

4.3.3.3 Self-selection Bias (and Decision Not to Weight Results)

As noted in Table 13, our study sample included higher proportion of individuals with certain demographics (e.g., females and more educated and affluent individuals) as compared to the broader SACOG region. It is likely that additional deviation from the overall population might be present in other unobserved characteristics, such as individuals' personal attitudes towards the adoption of new technologies, preferences for driving a personal vehicle (vs. being a passenger), the interest in and understanding of research experiments, and various components of individual lifestyles which could all play a substantial role in the decision to agree to participate in this study. To a certain extent, demographic characteristics tend to be correlated with some of these attitudes, and previous studies have explored some of these topics, for example showing that high-income individuals and individuals with a higher educational background are likely to be early adopters of the AV technology (e.g. Daziano et al. 2017). Other relationships are less explored, and their impacts on the results of this study not entirely predictable.

In our entry survey, we present participants with a series of attitudinal statements measuring their attitudes towards several topics, including residential location, travel choices, new technologies etc. Responses to some of these statements were found to be correlated with some socio-demographic characteristics. Most notably, half of the participants who do *not* have a Bachelors' degree agreed with the statement that – "*Learning how to use new technologies is often frustrating for me*", whereas only 9% of the respondents who have a Bachelors' degree or higher education agreed with that statement. Similarly, half of the females in our sample agreed with the statement that – "*I'd usually rather have someone else (trustworthy) do the driving*", whereas only one-fourth of men in the sample agreed with the statement.

We believe individuals' personal attitudes about driving, new technologies, etc. played a role in not only affecting their choice to participate in the study, but also how they adjusted their behavior during the chauffeur week(s). There is reason to believe that the correlation of sociodemographic characteristics with self-selection and behavioral change is spurious (or a partial correlation at best). For this reason, we do not attempt to weight our sample based on sociodemographic characteristics to generalize the results to the larger population, as this would assume the observed behaviors to be representative of those in the larger SACOG region—an assumption that is unlikely to hold for the reasons discussed above.

4.4 Conclusion and policy implications

In this study, we ran an experiment to explore potential changes in travel-related behaviors induced by privately owned AVs. We simulated people's lives with a privately owned AV by providing them with a personal chauffeur that, like an AV, took over driving duties and could autonomously runs errands. For our sample of 43 households, we were able to quantify actual changes to VMT, mode choice, participation in activities, and timing of activities under our AV simulation. The results are summarized in Table 14 and discussed throughout the chapter. Here we shift our focus to policy implications, inserting statistics from our experiment in the discussion. A major caveat is that all of these statistics are for our specific sample, however the numbers do provide helpful context regarding possible magnitudes.

The experiment highlighted many of the potential changes that AVs might bring to society and to travel demand, in particular. These include some benefits in terms of mobility and accessibility (for some categories of users in particular, such as individuals with reduced mobility), but also drawbacks and potential for increased car usage, with potentially large negative impacts on society in terms of traffic congestion and environmental implications. AVs will cause changes in travel-related behaviors, and for many, the change is likely to be substantial. Our study clearly shows that, if privately owned AVs are widely adopted, this will lead to more travel as reflected by the 60% increase in the overall VMT recorded during the chauffeur weeks. In such a scenario, it is critical to clearly identify and evaluate the tradeoffs between enhancing quality of life versus environmental and social cost of the additional travel. Policy makers are particularly interested in the topic, especially when it comes to regulating AV deployment and use in order to harvest the potential benefits while limiting the eventual negative consequences.

A clear benefit associated with AV deployment is the enhanced mobility and accessibility that the elderly and subjects with disabilities experienced during the reported experiment which was reflected by this cohort exhibiting the highest percent increase in VMT (150%). At the other end of the spectrum, subjects switching away from public transit and active modes of travel and the extreme reliance on ZOVs (also known as “ghost” trips) are some of the undesirable consequences of AV adoption. The use of public transportation and active modes dropped significantly during the chauffeur week(s) as transit, biking, and walking trips decreased by 71%, 37%, and 13% respectively, partly due to subjects’ ability to avoid the hassle of parking and its fees by sending ZOVs home. As ZOVs made up half of the induced demand, limiting their use to necessary trips is paramount. For example, by restricting ZOV travel to when it is particularly necessary and when owners are willing to pay for the added congestion their empty vehicles are causing.

As policy makers discuss future regulations for AV deployment, they are faced with the difficult task of exploring the policy mechanisms enforceable today, and/or hypothetically available in the future, to promote the socially desirable benefits from the new technology while limiting the negative externalities from its deployment. Fuel costs (and other flexible cost associated with the use of private vehicles) alone are not working as a deterrent to additional VMT. Adequate incentive schemes, road user charges or other policies will be required to reduce induced travel. This might translate in local regulations prohibiting (or strongly limiting, also through pricing) empty “ghost” vehicle trips, at least in central, more congested locations. Dynamic pricing schemes could be enabled to shift demand outside of peak times, or more congested areas, based on time and/or location, or to increase vehicle occupancy. Local stakeholders will be also called to rethink minimum parking requirements and transit agencies might explore ways to integrate their services with AVs, benefiting from autonomous vehicles to provide first/last mile services. Regional agencies and metropolitan planning organizations (MPOs) developing long-range planning will need to consider AV deployment in their future scenarios and envision strategies to mitigate their impacts, including through the coordination of land use development and transportation supply. Finally, state and federal agencies should consider these findings as they consider electric vehicle (EV) targets as a way to contain tailpipe emissions from AV deployment.

The findings from this chapter also point to the need to explore policy options to target specific segments of the population and groups of AV adopters. For example, restrictions on the use of private AVs could be more flexible for the elderly and people with disabilities if their benefits are deemed more valuable. Relatedly, it is critical to understand the response to AVs by different demographics in creating thoughtful policies that maintain an equitable transportation system and do not impact underprivileged households more heavily.

Using the insights gathered from this experiment and from other studies in the literature, it is critical for policy makers to be proactive with regulating the technology rather than reactive.

Changing people's behavior through legislation will take time as behavior change is slow, especially when faced with resistance from users.

The next step in the study is to estimate travel demand models to explore changes in sensitivity to travel time, distance, and the overall attractiveness of AVs compared to other modes to be used in simulations. Moreover, since the dataset includes observed behavior on subject's use of ZOV trips, we can work to incorporate ZOV behaviors into travel demand models, namely tour based models, should be modified to incorporate this new feature as temporal and geospatial constraints will change in an AV future.

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Chapter 5

Estimating Short-Term Travel Demand Models that Incorporate Privately Owned Autonomous Vehicles

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Abstract

Activity-based travel demand models (ABMs) are being used to study the potential impacts of autonomous vehicles (AVs) on the transportation system. This is done by manipulating the parameters of existing models to incorporate AV options. The behavioral parameter assumptions are often based on educated guesses and are, at best, based on stated preference surveys. In this study, we estimated short-term travel demand models using revealed preference data collected from an experiment conducted on 43 households (71 individuals) in the Sacramento area in 2019/20. Our field experiment used personal chauffeurs as a proxy to simulate subjects' lives with a privately owned AV. Smartphone-based travel diaries were recorded for the chauffeur week(s) as well as one non-chauffeur week before and one non-chauffeur week after. We investigated four components of an activity-based model: activity pattern, time-of-day, destination choice, and mode choice. Formulations were inspired by the Sacramento regional model, although kept parsimonious with limited heterogeneity due to the sample size. We compared the model estimated with data from the chauffeur weeks (i.e., AV future) to those during the non-chauffeur weeks (i.e., current conditions). We found that there were no statistically significant differences in the parameters of the individual activity pattern, the time of day, or the destination choice models. For the mode choice model, however, while the constant for auto did not change, the value of time decreased by 60%. As the destination choice model included a logsum from the mode choice model, this resulted in longer average trip lengths even though the parameters (beyond those in the logsum) of the destination choice model did not change. Moreover, while the trip-making propensity of individuals did not change significantly, there was a 25% increase in systemwide trip rates due to the "AV" (chauffeur) being sent on errands. This points to the importance of incorporating zero-occupancy vehicle trips into the activity-based modeling framework. Our findings suggest that these can be added to an ABM framework as additional model components that consist of ZOV home-based tours and ZOV subtours using a standard ABM process. Finally, while demographic heterogeneity was not incorporated here, indications suggest that it is particularly important to do so for mobility-impaired individuals such as elderly and disabled.

5.1 Introduction

Activity-based travel demand models (ABMs) are being used to study the potential impacts of autonomous vehicles (AVs) on the transportation system. This is achieved by manipulating parameters of existing models to introduce AV options and simulate an AV future. Forecasts from these models play an important role in determining policy to regulate AVs. However, there is significant uncertainty as to how to manipulate the models (and parameters) in an ABM to represent future AV travel behaviors. Consequently, behavioral manipulations are currently primarily based on educated guesses, or at best, based on results from stated preference surveys.

In this study, we make use of data from an experiment that uses chauffeurs as a proxy for privately owned AVs in order to estimate short term travel-demand models. Our objective is to use this revealed preference data to estimate the parameters of an ABM that reflect a future scenario where private AVs are prevalent. Shared AVs are outside of the scope of this study. We investigate four different model components of the ABM framework: activity pattern, time-of-day, destination choice, and mode choice. We compare the models estimated on travel data collected during weeks in which the chauffeur was available (i.e., the AV scenario) against travel data collected when the chauffeur was not available (i.e., the status quo situation). We also investigate the incorporation of zero-occupancy vehicle (i.e., ghost) trips into the ABM framework, which is a new travel behavior phenomenon that results from AVs.

The remainder of this chapter is organized as follows: section two summarizes the relevant literature, section three describes the methodology, section four presents our key results, section five includes a discussion of the results, and section six provides conclusions.

5.2 Literature review

To simulate AVs in ABMs, models are modified to incorporate changes that AVs are expected to bring to the transportation system. On the supply side, the most common assumptions include the increase in operating cost of AVs and the increase in road capacity (e.g., Childress et al., 2015). On the demand side, the focus of this chapter, several assumptions are made by different studies. Less common assumption made by a handful of studies include the reduction in parking cost or the ability of AVs to avoid parking (e.g., Childress et al., 2015, Bernardin et al., 2019), the ability of minors to independently ride in AVs (e.g., Kröger et al., 2018), and the increase in the trip generation rate (e.g., Huang et al., 2019). However, the most common assumptions made in ABMs to simulate AVs are the demand for AVs (i.e., market penetration) and the reduction in AV riders' value of time.

The change in rider's value of time has particularly received significant attention in the literature due to its potential impact on travel behavior and the transportation system. Stated preference (SP) surveys are primarily used, and the dominant finding is that the comfort and convenience of AVs will lead to a reduction in VOT, which is projected to range between 5% and 55% (e.g., Krueger et al., 2016; Becker and Axhausen, 2018; Kolarova et al., 2018; Zhong et al., 2020). More recently, however, researchers have challenged the hypothesis that AVs will significantly reduce VOT. For instance, Singleton (2019) argues that the reduction in VOT will be lower than what is currently assumed in the literature, and closer to car passengers than transit riders. The reason is that AV riders will not be able to productively use their in-vehicle travel time as much as transit riders. On the other hand, Rashidi et al. (2020) take it a step further and make the case for why VOT could actually increase for AV riders. Interestingly, several studies have found results that support these arguments. For instance, Bergman (2018), Kolarova et al. (2018), and Kreuger et al. (2019) estimated mode choice models from stated preference survey data where AV options where available to respondents and found that the VOT for AVs are lower than conventional vehicles but higher than transit. Moreover, Gao et al. (2019) conducted a stated preference study and used ride-hailing as a proxy to riding in an AV to bring the context closer to respondents. They find that ride-hailing has a 13% lower VOT compared to conventional vehicles, and this number goes up to 45% when respondents are explicitly reminded that they can productively use their in-vehicle time. However, they report that when the ride-hailing option is presented as a shared AV option, the VOT actually increases by 15% compared to the conventional vehicle option. However, they attribute this increase to the lack of familiarity and comfort with automation at present. Other studies looked at the change in VOT by trip purpose. For instance, from the mode choice model estimated on their stated preference survey data, Kolarova et al. (2019) find that the VOT for commute trips 40% lower in AVs compared to conventional vehicles. This difference, however, disappears when considering leisure trips. Relatedly, Correia et al. (2019) conducted a discrete choice experiment to explore changes in VOT for AV riders when vehicles are designed to accommodate leisure vs. work activities. For AVs with an office interior, they find that the VOT is 26% lower than a conventional vehicle, however, for AVs with a leisure interior, the find a 9% increase in VOT.

Rather than relying on educated guesses or stated preference data, our study is unique because we investigate the potential changes in the parameters of short-term travel demand models using revealed preference data from real world travel decisions made by our study participants.

5.3 Methodology

In this section, we summarize the methodology adopted in this chapter. First, we briefly describe the experiment conducted to collect the dataset used for our analysis. Then, we describe the general methodological framework adopted in the remainder of the chapter. We start by describing the overall structure and flow of an activity-based model. Next we discuss an added complication that AVs bring to the standard activity-based model process—zero-occupancy vehicle trips— and our proposed method to integrate them into that process. Then we identify the four short-term travel demand models that we focus on in the remainder of this chapter.

5.3.1 Data

For our analysis, we used revealed preference travel diary data collected from an experiment conducted on 43 households (71 individuals) in the Sacramento area in 2019/20. In the experiment, households were provided with personal chauffeurs to simulate their lives with personally owned AVs. Just like AVs would do, chauffeurs relieved subjects from driving duties, allowing them to relax during travel or productively use their in-vehicle travel time. They could also be sent out to run errands that AVs will run in the future such as autonomously filling up gas and picking up friends and family. The smartphone tracking app, rMove, was used to record subjects' travel diaries and travel decisions with and without the chauffeur service. This provided detailed information on trips made by participants over the study period, including the origin and destination, time and purpose of each trip, and the mode chosen. Subjects were tracked for three to four weeks with the outer weeks serving as non-chauffeur control weeks (i.e., status quo condition) while the middle week(s) served as treatment chauffeur weeks (i.e., "autonomous vehicle" weeks). For a more detailed description of the experiment and resulting data, the reader is referred to chapter 4.

5.3.2 Activity-based travel demand model

We base our model development on the activity-based model used by Sacramento's metropolitan planning organization (MPO)—the Sacramento Area Council of Governments (Bradely et al., 2009; SACOG, 2020). The SACOG model is typical of ABM models used in practice and it is also the model for the region in which our data were collected. The structure and flow of SACOG's activity-based model is shown in figure 7. As with all ABMs, the model breaks down complicated travel and travel-related behaviors into sub-components that are structured hierarchically with longer term behaviors at the top down to shorter term behaviors at the bottom. The components are linked via conditional dependence when moving down the structure and expectations (typically in the form of logsums) when moving up the structure. The model encompasses long-term and short-term travel decisions at the individual (person) level. Over the long-term, the model predicts travel-related decisions such as work location choice, school location choice, and vehicle ownership. Over the short-term, the model predicts travel decisions such as daily activity patterns, destination choice, and mode choice. The SACOG model is tour-based in that tours (i.e., round trip journeys from home) are the unit of analysis. In this chapter, we focus on the Short-Term Choice piece of the model. The day pattern model predicts the number of tours by purpose and intermediate stop purposes. Next, the primary purpose, destination, and mode of each tour are determined, followed by determination of the details of the intermediate stops and trips. Tours where the primary destination falls outside of the bounds of the Sacramento region are determined exogenously from this framework as are e-commerce behaviors such as teleworking, online orders, and deliveries.

The introduction of privately owned autonomous vehicles into the system (equivalently the chauffeur service in our study) adds a new complication to the ABM framework, as a household vehicle can serve two purposes as simulated by the chauffeurs in our experiment: the first is taking household members to and from their activities, and the second is autonomously making deliveries and running errands (i.e., zero-occupancy vehicle (ZOV) trips). The former can be captured within the existing ABM structure by reflecting the addition of a new mode or modifying the auto mode, where the key modifications/additions relate to the level of service (time and cost), the sensitivity to this level of service, and the AV constant. The latter is an additional component of travel behavior that needs to be incorporated. As observed in our experiment, these trips can either make up their own home-based tours—e.g., the chauffeur/"AV" is sent to autonomously pick up groceries and deliver them home) or as a sub-tour in a household member's individual (person) tour—e.g., the chauffeur/"AV" drops the individual at the restaurant, autonomously looks for cheap parking, and picks up the individual once dinner is over. In this chapter, ZOV trips/tours are compartmentalized as separate from individual trips/tours, similar to how commercial vehicle travel, which includes transportation of goods and services (e.g., deliveries) are modeled separately from resident travel. That is, we exclude ZOV trips (and pure ZOV tours) in our investigation of the day pattern, destination, mode, and timing model components. Further reasoning and implications of this decision (including how they might be incorporated in the framework) are discussed in section six of the chapter.

In the remainder of the chapter, we first present results on four traditional model components of short-term travel demand: the daily activity patterns, destination, mode choice, and time-of-day models. In SACOG's ABM, all four models are logit models and capture a high degree of heterogeneity by tour purpose and individual and household demographics and significant use of conditional dependence and logsums to connect across models. While we base our analysis on the SACOG ABM framework, we work with highly simplified versions of a subset of model components due to the size of our dataset. Our objective is to look for major structural changes that might be required of these models, as well as where it appears there are no significant changes. For example, for mode and destination choice, we estimated simple logit models that captured limited heterogeneity while focusing on changes in parameter estimates for primary variables of interest such as time and cost. Moreover, for the mode choice model, we simplify the choice set into four alternatives rather than the eight used in SACOG's ABM.

After presentation of these four key model components, we return to the discussion of ZOV trips and how they might be inserted into the framework.

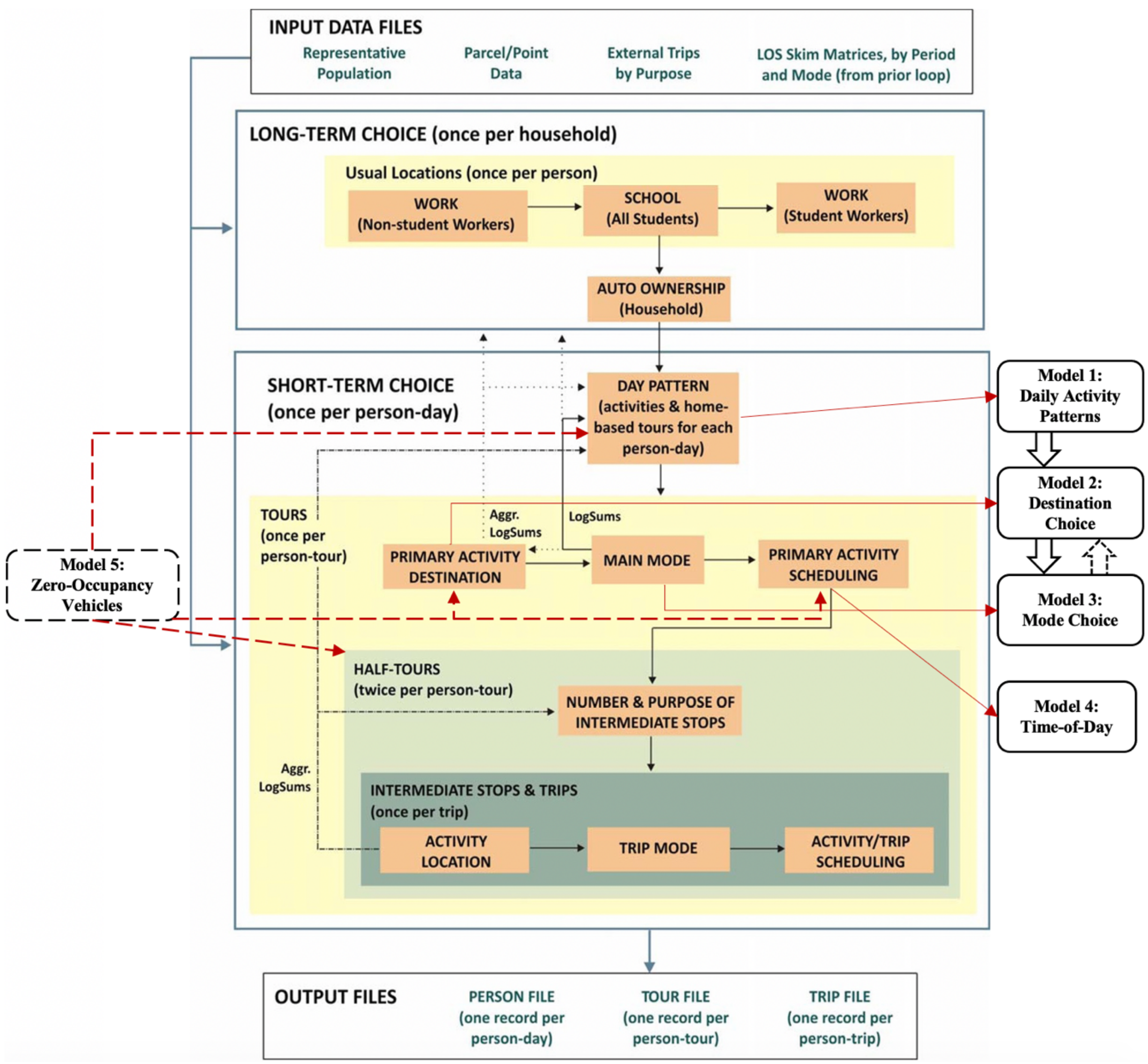


Figure 7: Structure and flow of SACOG's activity-based model—DAYSIM (Adapted from Bradely et al., 2009).

5.4 Results

In this section, we present a summary of our key findings. We first give a brief overview on the study sample then discuss the results for the four models that we investigated. We note that the organization of the discussion does not follow the flow of the models in SACOG's activity-based model illustrated in figure 7. Instead, we first present the results for the daily activity patterns model (model 1) then the time-of-day model (model 4) as the method of analysis for both is the same (hypothesis testing rather than logit model estimation). Next, we present the results for the mode choice model (model 3). Since the destination choice model includes a mode choice logsum term, we estimated the mode choice model first to account for any potential change in the logsum term due to a change in the value of time parameter during the chauffeur week. We then end the section by presenting the destination choice model results (model 2).

5.4.1 Sample

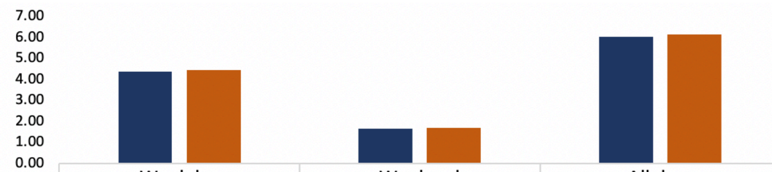
For the sample recruitment, we partnered with SACOG to use the participants of their 2018 Sacramento household travel survey as our sampling frame. Overall, the characteristics of our sample population were close to those of the residents of the Sacramento area. The main difference, however, is that our sample had a higher share of females and was more affluent and educated than the general Sacramento population. For a detailed description of the sample characteristics, the reader is referred to chapter 4.

5.4.2 Model 1: Daily activity patterns

In SACOG's ABM, the daily activity patterns model predicts 1) the decision to participate in non-home activities, and 2) the number of tours made by an individual for the day. For the first decision, binary logit models predict the probability of engaging in a non-home activity vs. staying at home for each of the seven activity purposes—work, school, meal, shopping, escort, personal business, or leisure. Conditional on the decision to engage in a non-home activity, a second logit model predicts the number of daily tours performed for the given activity purpose. Both models are relatively naïve logit models that use constants to predict the number of daily tours, and include variables to capture heterogeneity based on individual demographics (e.g., work/student status, age, gender), household demographics (e.g., income, number of kids in household), and activity purpose. The model also includes mode choice and destination choice logsum terms to account for the effect of accessibility (as measured by the logsum terms) on daily pattern decisions. However, rather than estimating logit models, we used hypothesis testing—Paired t-test and Wilcoxon signed-rank test (the non-parametric version of a paired t-test) to compare the outcomes of the daily activity patterns models and investigate any change in their distribution between the chauffeur and non-chauffeur weeks.

5.4.2.1 Number of days with at least one non-home activity

Here, we look at the number of days subjects decided to engage in at least one non-home activity during the chauffeur and non-chauffeur weeks. Comparing the means of the two weeks using a Paired t-test and a Wilcoxon signed-rank test, we found no significant difference in the average number of days subjects decide to leave the house as illustrated in figure 8 below. In other words, having access to the chauffeur service did not affect subjects' decision to stay home or engage in non-home activities. Breaking down the analysis by trip purpose, we found that the results hold.

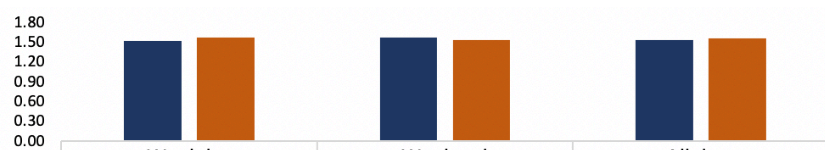


	Weekday	Weekend	All days
Chauffeur week	4.38	1.65	6.04
Non-chauffeur week	4.44	1.69	6.13
Wilcoxon Ranked test (p-value)	0.59	0.67	0.47
Paired t-test (p-value)	0.51	0.47	0.60

Figure 8: Daily activity patterns - average number of days with at least one non-home activity

5.4.2.2 Number of tours per day

After modeling the decision to engage in activities outside of one's home, the next piece of the daily activity patterns model is to predict the number of tours made conditional on the individual's decision to leave their house. Here, we calculated the average number of daily tours (for all purposes) during the chauffeur and non-chauffeur weeks as illustrated in figure 9 below. We found that the difference across weeks is not statistically significant as subjects made, on average, the same number of tours per day. We also found that results hold if we break down the analysis by tour purpose.



	Weekday	Weekend	All days
Chauffeur week	1.53	1.58	1.54
Non-chauffeur week	1.57	1.54	1.56
Wilcoxon Ranked test (p-value)	0.9	0.81	0.9
Paired t-test (p-value)	0.44	0.74	0.75

Figure 9: Daily activity patterns – average number of tours per day

In summary, the results above indicate that, when modeling personal tours in activity-based models for AV studies, parameters in daily activity patterns models do not need to be modified, as having access to an AV does not affect the decisions to participate in non-home activities or the number daily activities performed.

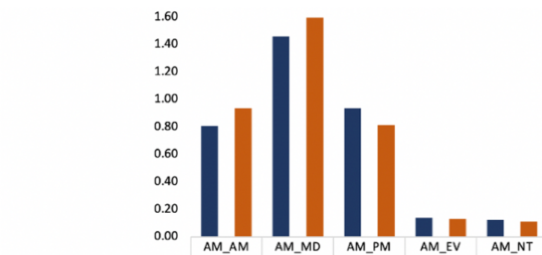
5.4.3 Model 4: Time-of-day of activity participation

After modeling the number of tours an individual makes in a day, a model predicts the departure and return time of each tour. There are several versions of the time-of-day model with different levels of granularity. SACOG's activity-based model uses a logit model to predict the departure and return time for a given tour using 48 half-hour time periods. The combined decision of a departure and return time has a total of 1,716 possible alternatives. Similar to their daily activity patterns models, the time-of-day model is a relatively naïve logit model that uses constants to predict the time of day of tours, and captures the heterogeneity in the decision based on individual and household demographics and activity purpose. Here, we opted for a much simpler version that only uses five time periods as defined in SACOG's activity-based model:

- AM: 7 a.m. to 10 a.m.

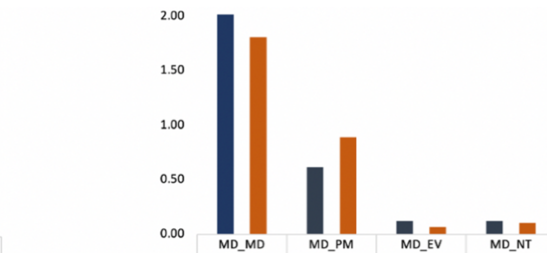
- MD (midday): 10 a.m. to 3 p.m.
- PM: 3 p.m. to 6 p.m.
- EV (evening): 6 p.m. to 8 p.m.
- NT (night): 8 p.m. to 7 a.m.

Figure 10 below summarizes the average number of tours per week for the different departure-return time combinations by our sample population. Comparing the time-of-day choices of our sample during the chauffeur and non-chauffeur weeks, we saw that the chauffeur service had no significant effect on the time-of-day decision for activity participation as subjects made tours during the same time periods across weeks. In other words, our results indicate that there is no need to modify the parameters of a time-of-day model when simulating AVs in activity-based models as AVs will not influence the time-of-day decision for individual activity participation.



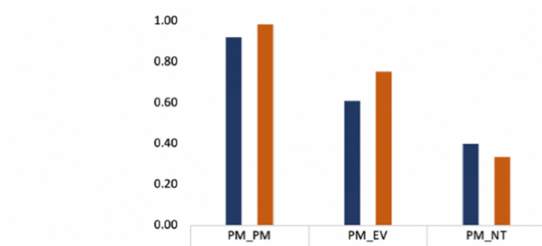
	AM_AM	AM_MD	AM_PM	AM_EV	AM_NT
Chauffeur week	0.81	1.46	0.94	0.14	0.13
Non-chauffeur week	0.94	1.60	0.82	0.13	0.11
Wilcoxon ranked test (p-value)	0.46	0.17	0.17	0.71	0.32
Paired t-test (p-value)	0.43	0.27	0.22	0.87	0.32

(a): Average number of weekly tours with an AM departure time



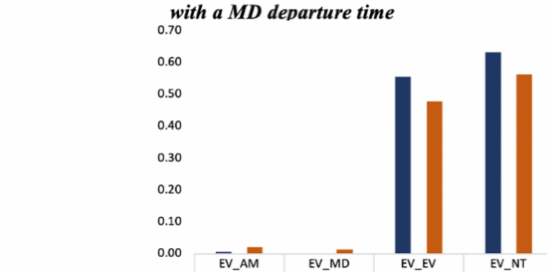
	MD_MD	MD_PM	MD_EV	MD_NT
Chauffeur week	2.02	0.62	0.13	0.13
Non-chauffeur week	1.81	0.89	0.07	0.11
Wilcoxon ranked test (p-value)	0.37	0.02	0.20	0.39
Paired t-test (p-value)	0.24	0.01	0.17	0.54

(b): Average number of weekly tours with a MD departure time



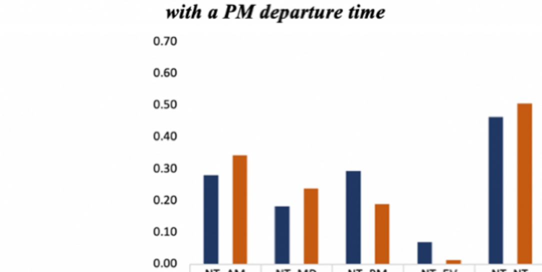
	PM_PM	PM_EV	PM_NT
Chauffeur week	0.92	0.61	0.40
Non-chauffeur week	0.99	0.75	0.34
Wilcoxon ranked test (p-value)	0.64	0.17	0.24
Paired t-test (p-value)	0.59	0.18	0.45

(c): Average number of weekly tours with a PM departure time



	EV_AM	EV_MD	EV_EV	EV_NT
Chauffeur week	0.01	0.00	0.56	0.63
Non-chauffeur week	0.02	0.01	0.48	0.56
Wilcoxon ranked test (p-value)	0.32	0.32	0.69	0.57
Paired t-test (p-value)	0.32	0.32	0.47	0.55

(d): Average number of weekly tours with an EV departure time



	NT_AM	NT_MD	NT_PM	NT_EV	NT_NT
Chauffeur week	0.28	0.18	0.30	0.07	0.46
Non-chauffeur week	0.35	0.24	0.19	0.01	0.51
Wilcoxon ranked test (p-value)	0.25	0.40	0.10	0.41	0.40
Paired t-test (p-value)	0.41	0.38	0.09	0.35	0.59

(e): Average number of weekly tours with a NT departure time

Figure 10: Average number of tours by departure-return time for each week type

We note that our sample size only allowed for testing potential changes in the above travel decisions at the aggregate level. However, individual level analysis suggests that results may be different for some demographic groups. For instance, if we deviate from the analysis above, which aimed at capturing the joint depart-return time decision modeled in ABMs, and look at the total number of evening tours where either the departure or return time is after 6 pm, we find that for the elderly (i.e., non-working individuals above the age of 60) and disabled, the difference is statistically significant (p-value of 0.037 for the Paired t-test) as they made on average 0.34 evening tours per day during the chauffeur weeks compared to 0.21 evening tours per day during the non-chauffeur weeks. This points to an important future research direction and extension to this work which is capturing the heterogeneity in the response to AVs for more accurate manipulations of ABM model parameters.

5.4.4 Model 3: Mode choice model[13]

For a given tour destination, a mode choice model predicts the primary mode used. In SACOG's activity-based model, a logit model is used to predict the primary tour mode from among eight modes—walk, bike, drive alone, shared ride (2 persons), shared ride (3+ persons), walk to transit, drive to transit, and school bus. In our model, we simplify the choice set to four modes—walk, bike, transit, and car. Moreover, our model is estimated using data from all tours combined, while in SACOG's ABM, separate mode choice models are estimates for work, school, and non-mandatory tours (e.g., shopping, meals, leisure). Relatedly, while SACOG's model captures a wide range of heterogeneity at the household and individual level, we opted to estimate a parsimonious model excluding socio-demographic variables. We note, however, that we did investigate model specifications that included socio demographic predictors and found that including these variables did not affect the parameter estimates for our key variables of interest, and thus we opted to report results from the simpler model.

Since we recorded repeated mode choice decision for our sample, we opted to estimate a mixed logit model that accounts for the correlation between the repeated choices made by same individual, also referred to as panel effect. We note, however, that we also estimated a multinomial logit model, which assumes that the observations are independent, and found that the mixed logit model significantly outperform it with 308 lower log-likelihood points. This highlights the importance of capturing the effects of repeated choices when estimating models on panel data. This effect was particularly strong in our sample since we collected their travel data over a long period of three to four weeks. Moreover, the panel effect uncovers unobserved lifestyles that drive the mode choice decisions made by our study participants. Since owning a vehicle was a prerequisite to participate in the study, our sample was highly auto-oriented, and participants' lifestyles were built mostly around the use of personal vehicles. It is expected, therefore that their (repeated) mode choice decisions are correlated and motivated by their lifestyle choices.

For our mixed logit model, we constrained the smallest variance term (the walking alternative in our case) to zero as suggested by Walker (2001). Although with four alternatives all variances are theoretically identified, in practice estimating all four variances is challenging in some datasets, which we found to be the case for our dataset (Walker, 2001). From table 15, we see that the model is behaviorally consistent as parameters exhibit the expected signs. The model

[13] All model estimations in this study were performed using the software PandasBiogeme (Bielaire, 2020).

indicates that biking and walking become less desirable as the number of trips in a tour increase. Similarly, for tours where the origin and destination are in the same TAZ, these modes are more desirable, reflecting the fact that walking and biking are generally used for shorter tours.

To test for a potential change in the car mode's constant during the chauffeur week, we included a car alternative specific constant (ASC), and added an additional constant specifically for the chauffeur week (i.e., $ASC_{car} + ASC_{car\_chauff\_week}$ * chauffeur_week_dummy). We found that the ASC specific to the chauffeur week, with a value of -0.27, was not statistically significant, with a t-stat and p-value of -1 and 0.3 respectively, indicating no significant change in the car constant across the chauffeur and non-chauffeur weeks.

For estimating the value of time, we follow the method proposed by Ben Akiva et al. (1993) and estimated a lognormally distributed VOT, which is done by normalizing the travel time parameter by the cost parameter. We note that if a parameter is lognormally distributed— $\beta \sim LN(\mu_{LN}, \sigma_{LN})$, then its logarithm is normally distributed— $\ln(\beta) \sim N(\mu_N, \sigma_N)$. Moreover, the estimates produced by the model are in fact the mean and standard deviation of the log of the parameter of interest (i.e., $\mu_N, \boldsymbol{\sigma}_N$), and thus need to be transformed to μ_{LN}, σ_{LN}. In our sample, the VOT for car users during the non-chauffeur weeks (e.g., conventional vehicles) was \$9.25 per hour. This value falls within the range, albeit on the lower end, of VOTs used by SACOG in their activity-based model (\$7.25 - \$38.80; SACOG, 2020). Interestingly, during the chauffeur weeks, we see a substantial drop in subjects' VOT by 60%, which supports the hypothesis that AVs will indeed reduce riders VOT.

Other than the reduction in VOT, AVs are also expected to make private vehicles more attractive by eliminating the burden of looking for (expensive) parking in areas where it's limited. We could not explicitly include parking cost as a variable in the model since we did not collect data on parking fees. However, we used tours where the destination is in downtown Sacramento, where parking is a burden, as an instrument to explore the effect of AVs on disutility of parking in mode choice models. Similar to the analysis done for the car ASC, we added a dummy variable in the car alternative if the tour destination is in downtown, and an additional dummy variable if the destination is in downtown and during a chauffeur week to capture any change in the parameter during the chauffeur week. The negative sign on the "destination in downtown" dummy indicates that, as expected, cars are generally a less attractive alternative when the destination is in downtown as parking is a burden. Moreover, the parameter estimate for the dummy variable for the chauffeur week was positive with a value of 0.94, indicating that the disutility of using a car to go to downtown Sacramento decreased during the chauffeur week as parking became less of a concern. However, the parameter was not statistically significant with a t-stat and p-value of 1.36 and 0.17 respectively, meaning that the difference between the parameters for the chauffeur and non-chauffeur weeks was not statistically significant.

Table 15: Mode choice model results – 60% reduction in VOT during the chauffeur week

	ML - VOT ~ LN(μ,σ) (1600 draws)			
	Value	**Rob. Std err**	**Rob. t-test**	**Rob. p-value**
ASC Transit	0.00	-	-	-
(σ transit)	4.10	0.34	11.89	0.00
ASC Car	2.80	0.94	2.96	0.00
(σ car)	2.53	0.27	9.53	0.00
ASC Walk	4.68	1.61	2.91	0.00
(σ walk)	0.00	-	-	-
ASC Bike	-2.16	1.14	-1.89	0.06
(σ bike)	3.16	0.36	8.73	0.00
Dest. in downtown	-2.36	0.66	-3.59	0.00
Orig-Dest. Same TAZ (walk & bike)	1.77	0.74	2.39	0.02
Number of trips in tour (bike)	-0.34	0.18	-1.94	0.05
Number of trips in tour (walk)	-1.48	0.67	-2.21	0.03
Travel cost ($s)	-0.53	0.17	-3.12	0.00
Travel time (hrs) - walk & bike	-3.39	0.57	-5.98	0.00
Travel time (hrs) - transit	-4.96	0.80	-6.24	0.00
VOT - car (non_chauff. week) (μ)	2.10	0.34	6.21	0.00
VOT - car (non_chauff. week) (σ)	0.50	0.10	-4.92	0.00
VOT mean - non_chauff. week	$ 9.25			
VOT std. deviation - non_chauff. week	$ 6.36			
VOT - car (chauff. week) (μ)	0.39	0.98	0.40	0.69
VOT - car (chauff. week) (σ)	1.35	0.40	3.33	0.00
VOT mean - chauff. week	$ 3.67			
VOT std. deviation - chauff. week	$ 13.96			
Average VOT reduction	60.3%			
Initial log likelihood	-2856.52			
Final log likelihood	-665.14			
Rho squared	0.77			
Adjusted rho squared	0.76			

5.4.5 Model 2: Destination choice model

For destination choice, SACOG uses a logit model that captures a high degree of heterogeneity by trip purpose as well as individual and household demographics. Moreover, similar to the mode choice model, they estimate separate models for work, school, and non-mandatory tours. In this section, we estimated a simplified version of SACOG's model that did not include sociodemographic variables and was estimated using data from all tours combined. The equation below is the utility function associated with a given alternative in our estimated models (Ben Akiva and Lerman, 1985).

$$U_i = V_i + \mu' \ln(M_i) + \varepsilon_i = \beta X_i + \mu' \ln\left(\sum e^{\gamma Z}\right) + \varepsilon_i$$

Where:

- U_i is the random utility of destination i
- V_i is the systemic utility of destination i
- M_i is the log-size variable that measure of the "size" of aggregate alternative i which in our case is a single TAZ
- μ' is the parameter estimate for the log-size variable
- X_i is the destination variables (e.g., distance, mode choice log-sum, destination in downtown dummy)
- β is the vector of parameter estimates for the destination variables
- Z is a characteristic of the destination (e.g., population, size, employment)
- γ is the parameter estimate for the characteristics of the destination

Destination choice models generally have a large choice set (1,500 TAZ alternatives in our case) which makes them computationally challenging to estimate. Therefore, it is typical in these models to use sampling of alternatives (Ben Akiva and Lerman, 1985). For our models, in addition to the selected alternative, we randomly sampled 49 alternatives from the 1500 available TAZs. Since we opted for random sampling, no further sampling error term correction was needed (Ben Akiva and Lerman, 1985). Table 16 summarizes the results from the estimated models.

Parameter estimates from the models have the correct signs and are statistically significant. The negative parameter on (log) distance indicates that, as expected, the utility drops as travel distance increases. Moreover, a positive sign on the downtown dummy indicates that downtown TAZs are more attractive compared to other destination. Similarly, destinations with higher populations and employment are more attractive, while the parameter for the area variable was constrained to zero as suggested by Ben Akiva and Lerman (1985). In addition, the mode choice log-sum estimate is positive and falls between 0 and 1, which is required for the model to be consistent with utility-maximizing behavior (Train, 2009). Here it is important to mention that there is a gap in the literature when it comes to calculating the log-sum term for mixed logit models. Theoretical work exists on how to calculate the term for the multinomial logit model (Train, 2009), but not for the mixed logit model. Consequently, for our models we used the "simulated log-sum". Similar to how the probability is calculated for a mixed logit model, we took a random draw from the distribution of each parameter, conditional on this random draw, calculated the log-sum value as if the model was a multinomial logit, repeated the proses several times (400 in this case), and took the average value.

From table 16, we see that in model 1, the parameter estimates for the log of distance and the log-sum variables are larger (in absolute value) for the chauffeur week. However, a loglikelihood ratio test indicated that the parameters for the chauffeur and non-chauffeur weeks were not statistically significantly different and having generic variables is preferred. This result indicates that the decrease in disutility of traveling to farther locations is already accounted for through the mode choice log-sum that captures the reduction in VOT. In other words, if the mode choice model captures the reduction in disutility of longer travel through the reduction of value of time, then no further adjustments to the destination choice model are required once the log-sum variable is included.

Table 16: Destination choice model results – no difference in parameter estimates across weeks

	Model 1				*Model 2*			
	Value	***Rob. Std err***	***Rob. t-test***	***Rob. p-value***	***Value***	***Rob. Std err***	***Rob. t-test***	***Rob. p-value***
Simulated logsum	-	-	-	-	0.26	0.03	8.38	0.00
Simulated logsum (chauffeur week)	0.30	0.04	7.02	0.00	-	-	-	-
Simulated logsum (non_chauffeur week)	0.26	0.04	6.78	0.00	-	-	-	-
Destination in downtown dummy	0.79	0.11	7.46	0.00	0.75	0.11	7.18	0.00
Log of distance	-	-	-	-	-1.09	0.07	-15.90	0.00
Log of distance (chauffeur week)	-1.08	0.08	-13.42	0.00	-	-	-	-
Log of distance (non_chauffeur week)	-1.05	0.10	-10.84	0.00	-	-	-	-
Logsize	0.74	0.04	20.35	0.00	0.74	0.04	20.40	0.00
Population	1.58	0.55	2.88	0.00	1.60	0.55	2.90	0.00
Employment	3.91	0.54	7.23	0.00	3.93	0.54	7.25	0.00
Area (acres) - fixed	0.00	-	-	-	0.00	-	-	-
Number of sampled alternatives	50				50			
Initial LL	-9263.67				-9263.67			
Final LL	-4688.49				-4690.26			
Rho squared	0.494				0.494			
Adjusted rho squared	0.493				0.493			

5.5 Discussion

In this section, we discuss of the key findings presented in this chapter. The discussion follows the same order as the results section above. We begin the section with a discussion on the potential factors that played a role in the (non)findings of the daily activity patterns and time-of-day models. Next we discuss the results of the mode choice model, where we compare our results to the findings from the stated preference literature and review the potential limitations of these findings. Then, we discuss the implication of the destination choice model findings on travel behavior. We end the section by returning to our discussion on zero-occupancy vehicle trips/tours.

5.5.1 Daily activity patterns and time-of-day models

AVs can influence daily activity pattern decisions in two ways. On one hand, the increased comfort during travel can encourage individuals to go out more and participate in non-home activities. On the other hand, the ability to send an AV to autonomously perform activities may encourage individuals to stay home while the AV runs errands for them. Similarly, AVs can influence time-of-day decisions. For example, the ability to productively use commute travel time could influence people's departure and return time to and from work. Moreover, driving at night will be easier, namely for individuals with conditions that prevent them or limit how often they can drive at night, or when individuals are tired or under the influence of alcohol. Interestingly, however, our results indicated that, overall, having access to an AV did not affect our subjects' daily activity patterns and time-of-day decisions. Subjects, on average, engaged in non-home activities the same number of days, performed the same number of daily tours, and were consistent in their time-of-day decisions during the chauffeur and non-chauffeur weeks.

One factor for this behavior could be the short treatment period of one or two weeks, which might not be enough for subjects to change their travel pattern to what it would be in a true AV future. Consequently, changes in travel patterns that were not observed in our study might emerge in the long-run, and the differences between current and future behavior will be greater. Another factor that played a role is that tours with a destination outside Sacramento (e.g., San Francisco) were not considered, but were more frequent (54%) during an average chauffeur week compared to an average non-chauffeur week. Consequently, since inter-regional trips are modeled outside the ABMs framework, modifications should be made to account for the increase in these trips in an AV future. Another major factor for this behavior is the exclusion of zero-occupancy vehicle trips/tours, which is consistent with findings from our previous study (chapter 4). In that study, we found a 25% increase in systemwide trips via all modes during the chauffeur weeks. However, this increase disappeared when ZOV trips were excluded from the analysis. Similarly, we found a 20% increase in evening trips when households had access to the chauffeur service, however, this number dropped to 5% when ZOV trips were excluded. In other words, we found that ZOV trips were a primary source of travel behavior change during the chauffeur weeks, and if compartmentalized and separated from individual (person) trips/tours, the change in individual travel patterns during the chauffeur weeks faded.

5.5.2 Mode choice model

Results from the mode choice model indicated that the alternative specific constant for the car mode did not change across weeks. On the other hand, subjects' value of time dropped by 60% during the chauffeur week, which is closer to the higher end of the VOT reduction range reported by studies in the literature, as summarized in table 17 below:

Table 17: Summary value of time reduction reported in the literature

Study	*VOT reduction*	*Comment*	*Method*
Our Study	60%	-	Revealed preference
Kolarova et al. (2018)	55%	-	Stated preference
Kolarova et al. (2019)	40%	For commute trips only	Stated preference
Becker and Axhausen (2018)	30% - 38%	Pooled AVs - shared AVs	Stated preference
Krueger et al. (2016)	10% - 35%	Pooled AVs - shared AVs	Stated preference
Zhong et al. (2020)	18% - 32%	Rural residents - suburbs residents	Stated preference
Correia et al. (2019)	26%	AVs with an office interior	Stated preference
Kreuger et al. (2019)	5%	-	Stated preference

In their exit surveys, subjects provided further insights into the potential factors behind the reduction in VOT. The responses supported the hypothesis that the two main factors in the reduction of VOT are: 1) reduced stress and 2) the ability to multitask:

- "I do think that access to self-driving cars will help to free up the distraction of driving and allow us to focus more on other things such as conversing with other passengers, checking emails or making calls instead of having to do so at work or at home, resting, etc."

- “The most useful and surprising part was during my commute. I was able to get more work done on a laptop and felt more relaxed when I arrived. I tend to drive fast and also noticed that I didn’t care as much about the speed/commute time or some of the poor driving habits of others.”

- “[I was] More relaxed during morning commute.”

- “I think self-driving cars will help ease some of life stressors and will allow us to do more with our time.”

- “one time I used the chauffeur, I took a nap, I made sure they knew where we were going and then I fell asleep.”

Interestingly, one subject pointed out that they wanted to use their travel time more productively, however, motion sickness limited their ability to do so: “I expected to be able to get more done on my phone such as checking emails or replying to other messages, but I get motion sickness fairly easily and ended up feeling poorly most of the time when I tried to do so”.

We recognize, however, that our results potentially suffer from selection into treatment bias. Even though a lot of effort was put into inviting a representative sample to participate in the experiment, we had little control over who responded and ultimately agreed to participate in our study. Our sample, therefore, might not be representative of all Sacramento residents. The study participants might be individuals who value their time more than the remaining population, and thus were eager to have access to the chauffeur service. Consequently, the reduction in their VOT might be an overestimate of the reduction of VOT of the entire population.

Another aspect of mode choice that we investigated was the effect of the chauffeur service on the disutility of parking in a mode choice model. We used tours with a downtown Sacramento destination, where parking is a burden as an instrument, and found that the disutility of using a car to go to downtown Sacramento decreased during the chauffeur weeks as parking became less of a concern. However, the difference was not statistically significant. It is difficult to say whether this result is true, or if using downtown Sacramento trips as a proxy to parking decisions is not a good instrument, especially given the comments subjects made in their exit surveys regarding this topic:

- “I currently work in downtown where it is expensive to park, so once it [the AV] drops me off I would send to go park somewhere on the outskirts of town where it can find free parking for the day, and then it would pick me up and take me home”

- “One aspect I really enjoyed in the study was not ever having to look for parking. It is definitely something that would make me go out more.”

- “Was very convenient when driving downtown to not worry about parking.”

- “I enjoyed participating in the study and especially liked the convenience of not having to park when I went somewhere.”

Consequently, future experiments should explicitly collect data on parking payments to better quantify the effect of this aspect of AVs on mode choice.

5.5.3 Destination choice model

For destination choice, results indicated that there was no change in parameter estimates between the chauffeur and non-chauffeur weeks. However, the model included a mode choice logsum term (also referred to as expected maximum utility). This term is used as a measure of accessibility (Ben Akiva and Lerman, 1985), which can be defined as a measure of how easily destinations can be reached. During the chauffeur weeks, the VOT dropped by 60%, reducing the disutility of traveling by car and positively affecting the logsum term, thus increasing overall accessibility. This was manifested by an 11% increase in the average tour length of our sample (from 11.17 miles to 12.53 miles) as subjects traveled to farther locations during the chauffeur weeks. We note that the increase was the highest for elderly and disabled individuals who increased their average tour length by 45% (from 11.4 miles to 16.5 miles). This further highlights the importance of capturing the heterogeneity in the response to AVs by different demographic groups which was missing in our analysis due to sample size constraints.

5.5.4 Zero occupancy vehicles

As highlighted earlier, zero-occupancy vehicles will play a primary role in travel behavior change. Therefore, integrating them within the activity-based model framework will be central to making simulation more realistic and representative of the AV future, and for results to be more reliable. Consequently, a major shortcoming of most simulation-based studies that focus on privately owned AVs is the lack of inclusion of zero-occupancy vehicles, which is likely due to the limited knowledge available on how these trips will impact travel decision making on an individual and a household level. By observing how our study subjects utilized their "ZOVs" (e.g., sending their chauffeurs alone to run errands), we recognized that these trips can be integrated as an additional model component within the standard activity-based model process, either as their own home-based tours or as a sub-tour within an individual (person) tour. In this chapter, we showed that zero-occupancy vehicle trips can be compartmentalized and separated from individual trips/tours, just like commercial vehicles and deliveries. However, rather than handling them outside the ABM framework (what is currently done with deliveries and commercial vehicles), our proposed method allows us to integrate zero-occupancy vehicles into the standard ABM process by adding them as a separate model component without major modifications to the standard ABM structure. The advantage of incorporating ZOVs to an ABM process is that it allows for testing the impact of different policies (e.g., pricing) on the use of zero-occupancy vehicles.

We recognize, however, that integrating ZOVs within the ABM framework goes beyond incorporating them as an additional model component. We would also investigate how these trips change temporal and geographic constrains currently imposed on travel decisions in ABMs. For example, in current ABMs, if an individual commutes by bus, the mode choice model for their return trip from work does not include the "drive alone" option. However, in an AV world, this constraint should be relaxed to account for the ability of an AV to autonomously make pickups. Relatedly, once ZOVs are integrated into the ABM framework, another complication to consider is how to model ZOV trips/tours, for example in a destination choice model: how should their utility function be specified? Is the sensitivity to distance zero since no one is traveling in the vehicle?

Answering these questions was beyond the scope of this chapter, however, addressing them is key to improving the accuracy of AV-based simulation studies, and therefore will be the focus of future extensions of this work.

5.6 Conclusion

Activity-based travel demand models are being used to estimate the potential impacts of AVs on the transportation system. This is done by manipulating parameters of existing models to simulate AVs. Since the impact of AVs on travel behavior is uncertain, the behavioral assumptions made rely mainly on educated guesses or findings from stated preference surveys. In this chapter, we estimated short-term travel demand models using revealed preference data collected from an experiment conducted on 43 households (71 individuals) in the Sacramento area. In the experiment, we simulated subjects' lives with a personally owned AV using personal chauffeurs as a proxy. Like an AV, the chauffeur took over driving duties and could be sent out to run errands that AVs will run in the future such as filling up gas or looking for parking. Smartphone app-based travel diaries were recorded for the chauffeur week(s), one non-chauffeur week before, and one non-chauffeur week after. For the analysis, we compartmentalized zero-occupancy trips/tours (e.g., when chauffeurs are running errands) and separated them from individual (person) trips/tours. We then investigated four components of an activity-based model: activity pattern, time-of-day, mode choice, and destination choice. Results indicated that the chauffeur service did not have an effect on daily activity pattern and time-of-day decisions as subjects, on average, engaged in non-home activities the same number of days, performed the same number of daily tours, and were consistent in their time-of-day decisions during the chauffeur and non-chauffeur weeks. This indicated that, when simulating personal tours in an AV future, parameters of these models do not need to be modified. Similar results were observed for the parameter estimates of the destination choice model. On the other hand, for the mode choice model, while the constant for the car mode did not change, we found a 60% reduction in subjects' value of time during the chauffeur week. Relatedly, as the destination choice model included a logsum from the mode choice model, this resulted in subjects making longer tours during the chauffeur weeks, even though the parameters of the destination choice model did not change. This indicated that the decrease in utility to travel to further locations was captured in the reduction of value of time through the mode choice logsum term, resulting in an increase in subjects' accessibility.

Finally, we identified zero-occupancy vehicle trips as a primary source of travel behavior changes. We also proposed a way to incorporate these trips within the activity-based framework, either as their own tours or as sub-tours part of an individual (person) tour. Recognizing the impact of these trips on travel behavior, and the importance of incorporating them in simulations, the next step will be to further investigate how zero-occupancy vehicle trips should be integrated into activity-based model studies.

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Chapter 6
Conclusion

6.1 Research Overview

The field that focuses on the travel behavior implications of AVs is still in its early stages, albeit rapidly growing and advancing. There are a lot of opportunities for improving current studies and for new and innovative work. The goal of this dissertation was to contribute to the field. To do so, we first conducted a literature review to explore the work that has been done thus far. We started by identifying and reviewing the methods currently used to address research questions on travel behavior changes caused by AVs, highlighted their strengths and limitations in contributing to the literature, and proposed ways to improve upon these methods. We then identified critical research questions to be addressed, summarized results from studies that address these questions, and categorized the research questions into four categories based on the level of attention they received in the literature.

Next, after identifying the main, common limitation of current methods—the lack of the right data to address research questions—we proposed a different method that overcomes this limitation. We proposed an experiment in which we simulate participants' lives with a privately owned AV by providing them with a personal chauffeur. Just like a privately owned AV, a personal chauffeur took over driving duties, allowing subjects to relax during travel or to productively use their in-vehicle time. Moreover, subjects were able to send out their chauffeurs to run errands that AVs will be able to run in the future such as filling up gas, picking up groceries, or chauffeuring friends and family. Subjects were tracked for three to five weeks with the two outer weeks serving as control weeks (i.e. status quo conditions with no chauffeur service), and the middle week(s) serving as treatment weeks where households received 60 hours of chauffeur service per chauffeur week. By comparing the chauffeur weeks to the non-chauffeur weeks, we gained insights on potential travel behavior shifts that will occur in an AV future.

We first ran a pilot of the experiment on 13 residents of the San Francisco Bay Area in 2017, then a larger experiment on 43 households in the Sacramento area in 2019/20. Exploring overall changes in travel behavior, the results from both studies were largely consistent. Moreover, results were consistent with findings from the literature, albeit the magnitudes fell into the higher end of the range of results. Overall, households drove (a lot) more during the chauffeur weeks compared to the non-chauffeur weeks. VMT, number of vehicle trips, and average trip length increased substantially during the chauffeur weeks. Moreover, households shifted away from transit, TNCs, and active modes and relied more on their household vehicles, namely their "chauffeur vehicle / AV". The response to the chauffeur service varied substantially across households. Overall, individuals with mobility limitation, namely retirees and individuals with disabilities had, by far, the sharpest shifts in travel behavior (e.g. VMT increase, number of vehicle and night trips). On the other hand, households with less flexible schedules, namely families with kids, had the lowest change in travel behavior. Similarly, households that were not auto dependent also observed a substantial shift in travel behavior as they became more auto-oriented.

Because subjects had the option to send out their chauffeur to run errands like they would in an AV future, we gathered more insights on the impact of zero-occupancy trips on travel behavior, a topic that has not received enough attention in the literature. During the chauffeur weeks, almost all subjects sent out their driver to run errands for them, with ZOV trips making up half of the induced VMT.

Finally, we used our data to explore how to integrate AVs into activity-based models, including model specifications and parameter estimates. We investigated four components of activity-based models: activity pattern, destination choice, mode choice, and time of day. We compared the models estimated with data from the chauffeur weeks to those during the non-chauffeur weeks. We found that there were no statistically significant differences in the parameters of the individual activity patterns, destination choice, or time of day models. However, for the mode choice model, while the constant for car mode did not change, the value of time dropped by 60% during the chauffeur weeks. Moreover, as the destination choice model included a logsum from the mode choice model, average tour lengths increased during the chauffeur weeks due to the drop in VOT, even though the parameters (beyond those in the logsum) of the destination choice model did not change. Moreover, while the trip-making propensity of our subjects did not change significantly, there was a 25% increase in systemwide trip rates due to the chauffeurs being sent on errands. This highlighted the importance of incorporating zero-occupancy vehicles trips into simulation studies. Moreover, by observing how subjects used their ZOV trips (i.e., sending out chauffeurs to run errands) we were able to propose a way to integrate these trips within a standard activity-based model framework. Our findings suggested that ZOV trips can be added either as additional ZOV home-based tours or as ZOV sub-tours within the standard activity-based model process.

In this dissertation, we made several contributions to the literature. First, we collected revealed preference data on potential changes in travel behavior caused by AVs as opposed to the more common (stated preference) survey data. To our knowledge, this is the first such exercise using this chauffeur approach. Second, we quantified the impact of the chauffeur service on areas that have been explored in the literature such as vehicle miles traveled, trip rates, average trip length, mode and choice, albeit with our revealed preference setting. Moreover, beyond these important metrics, our dataset also allowed us to provide unique insights on central topics that have received little to no attention in the literature such as zero-occupancy vehicle trips. Third, we proposed a way to model privately owned AVs by incorporating them within a standard activity-based model framework. We showed that zero-occupancy vehicles trips can be compartmentalized and separated from individual person trips and tours, and then the existing structure and parameters of an activity based-model do not need to be significantly modified, apart from a reduction in the value of time for the auto mode, which we were able to estimate using real world mode choice decisions by our study participants. Finally, we proposed a way to incorporate zero-occupancy vehicle trips into the activity-based model framework as additional zero-occupancy vehicle home-based tours and as zero-occupancy vehicle sub-tours.

6.2 Research limitations:

Despite the advantages and novel insights it provided, the experiment conducted suffered from several limitations, some of which are (currently) unavoidable while others can be mitigated by improving the experimental design. Below we summarize these limitations, their impact on the results, and ways to overcome them in future experiments. We also include direct quotes from subjects' exit surveys that highlight these limitations.

1) Technological limitation:
The biggest limitation of the experiment is the presence of the chauffeur. Subjects react differently when dealing with a machine vs. a human driver for many reasons. First, there is the privacy concern, where the presence of the chauffeur limits the ability to have private conversations during travel:

- "I wasn't comfortable talking to other people in the car or on the phone about personal topics, which I do often."

Moreover, with a real autonomous vehicle, unlike with a human driver, subjects do not have to worry about the vehicle's comfort and wellbeing:

- "It was very hard NOT to become personally involved with the chauffeur, especially since mine was a young woman. I even canceled one late-night trip because I wanted her early the next morning".

Similarly, many subjects felt uncomfortable sending out their chauffeur to run errands:

- "I sometimes felt a little bad about asking him [the driver] to go out and run me an errand or drive to and from Stockton. I wouldn't worry about the feelings of a machine."

Another issues with using the chauffeur as a proxy to an AV is that a chauffeur takes away one seat from the vehicle, potentially affecting travel decisions on some trips where the number of passengers exceeds the number of remaining seats. Moreover, real AVs have the advantage of increased safety and efficiency gains through vehicle to vehicle and vehicle to infrastructure communication, which is not possible to capture via a chauffeur. Finally, chauffeurs, like other humans, get sick and have emergencies that result in them skipping work or having to leave work early/unexpectedly.

The drawbacks caused by the technological limitation are (currently) unavoidable, as the use of fully autonomous vehicles in unrestricted geographical area is not permitted. Therefore, it is not currently possible to overcome limitations associated with the use of a chauffeur to proxy an AV until we can run these experiments using real fully autonomous vehicles.

2) Resource limitations:
The second limitation of this study is the result of limited (financial) resources. Running the experiment was very expensive, with an average cost of $2,400 per household per chauffeur week for the full experiment, not including the additional cost of salaries for the researchers running the experiment, or monetary incentives for the control group we originally planned to recruit.

With a limited budget, the study suffered from a small sample size of 13 households for the pilot, and 43 households for the larger experiment. Moreover, to save on costs, the study period was limited to one week of chauffeur service for most households, with a nine receiving two chauffeur weeks. The relatively short treatment period results in biases caused by the novelty factor. On one hand, it took subjects a day or two to get accustomed to their driver and the chauffeur service, and to use it like they would use a real AV:

- "I understand it [the chauffeur service] had to be limited to one week but it takes a couple of days to get used to it"

On the other hand, having the chauffeur for only one or two weeks means that subjects might want to take advantage of this unique opportunity and use the service more than they would with a real AV:

- "[I] Felt pressured to use the chauffeur to drive more than I would have normally"

Relatedly, and for the same reasons mentioned above, the chauffeur service was limited to 60-hours per chauffeur week. Even though subjects had the flexibility of personally allocating the hours based on their needs, and the ability to adjust hours the same day or a day in advance, having to schedule their chauffeur service, and thus their activities schedule in advance took away from the spontaneity that a real AV offers:

- "One of the advantages of a self-driving car is the spontaneity it affords. Scheduling a chauffeur, even one who was flexible with the plan, limited that spontaneity."

Moreover, the hour limit and the fact that chauffeurs had to go home at the end of the day, meant that subjects were not able to use the service to make overnight trips which could potentially increase as one could sleep in their AV.

Finally, the budget constraints limited the number of chauffeurs to one per household, even for households with multiple vehicles. On one hand, this allows us to study how households coordinate schedules and jointly schedule activities and trips to be able to share the AV. On the other hand, however, it might have forced behavior that is not representative of households' true behavior in an AV future, particularly for households that can afford and will buy multiple AVs in the future to avoid having to coordinate schedules.

The limitations described above can be mitigated by expanding the budget of the experiment. With more resources, the experiment can be run on a larger, more representative sample, and potentially multiple samples in different regions with different lifestyles for a richer dataset. Moreover, to overcome the novelty factor, the experiment should be run over several weeks/months while providing households with the chauffeur service 24 hours, 7 days a week. This ensures that the novelty factor fades with time and households get into their new routine/lifestyle of owning an AV. Finally, with a bigger budget, one should recruit both a treatment group and a control group (i.e. households that do not receive the service and are only tracked under normal life conditions). Having the two groups tracked during the same weeks allows us to control for temporal variations that naturally arise from having weeks different due to unexpected conditions.

3) Context limitation:

The first of the context limitations is the fact that households were offered the chauffeur service at no extra cost. Even though subjects still paid for out of pocket costs, which impact short-term travel decisions, getting access to the chauffeur service for free could be an encouraging factor to overuse the service.

Another potential limitation is that chauffeurs drive the subject's vehicles rather than providing households with another vehicle specifically for the chauffeur service. The advantage of that is making the study more representative of a future where subjects own their personal AV and have to consider the additional miles being put on the car and the insurance and maintenance costs associated with driving one's car. However, this proved to be a deterring factor for many potential subjects who were not comfortable having someone else driving their car or have car insurance that does comply with our study's requirements.

Finally, in this experiment, we only explore the impact of privately-owned AVs on travel behavior, when in the future, individuals will have the option of choosing between buying their own AV, or relying on shared services, or the combination of both. Even though subjects had the option of using currently available shared services during the chauffeur weeks, there was no attempt to simulate potential changes in future shared services such as reduced fares due to lower operating costs. Overcoming this limitation in future studies could be achieved by providing households with personal chauffeurs to simulate personal AVs, as well as subsidizing Uber/Lyft rides to see how that influences subjects' decisions when both alternatives are available in the future. It is worthy to note, however, that a major advantage of shared AVs will be the ability to dynamically relocate vehicles to efficiently serve the demand, minimize user's waiting time, and provide higher levels of service than today's shared services. However, this is another technological limitation that would not be possible to simulate in future studies before fully autonomous vehicles are available.

4) Selection into treatment:

The last limitation of the study is common to many studies that involve data collection—selection into treatment. When recruiting the study sample, a lot of work was put into inviting a representative sample. However, we had little control over who decides to respond to our invitation and ultimately accept being part of the study. Therefore, the sample mainly included subjects that are excited about autonomous vehicles and having access to a chauffeur service. However, as highlighted in Chapter 4, the study underrepresented individuals with lower incomes and lower educational backgrounds. More effort should be put into future experiments to diversify study participants and make sure the sample is representative of the true population. This could potentially be done by oversampling from the underrepresented households, as well as providing additional incentives that target underrepresented groups such as monetary compensation in addition to the chauffeur service or providing the chauffeur service via a rental car to households that do have sufficient car insurance.

6.3 Recommendations for Future Research

As highlighted above, there is room to improve upon the work done in this dissertation, namely in terms of improving the experimental design. Moreover, throughout this dissertation, we highlighted several research questions that were beyond our scope and that should be addressed in future research. Future extensions to this work are summarized below:

1- Run the experiment while overcoming the limitations addressed in the previous section. Overall, the study should be run on a larger, representative, and diverse sample with both a control and treatment groups. Moreover, the treatment period should be extended to minimize the novelty factor, and the chauffeur service should be provided 24/7 to mimic the spontaneity of owning an AV. In addition, the experiment should be run in multiple locations to capture the heterogeneity in response to the technology as people from different cities, states, and countries have different travel behaviors and will respond to autonomous vehicles differently.

2- In chapter 5, we estimated short-term travel demand models to quantify the change in key parameters of interest. However, due to our small sample size, we opted to estimate parsimonious models with limited heterogeneity. Nevertheless, our descriptive statistics indicated that the response to AVs will not be uniform across different demographic groups. Therefore, for more accurate simulations, heterogeneity in the response to the technology should be accounted for. Once the experiment is expanded, and a larger and more representative sample is recruited, more advanced models can be estimated with the intention of capturing the heterogeneity that was missing in our analysis.

3- In chapter 5, the analysis performed and models estimated were only at the tour level. However, in activity-based models, travel decisions are modeled at the tour level as well as at the level of the individual trips that constitute a tour. Consequently, travel decisions at the trip level should be modeled to supplement the analysis done in chapter 5.

4- In chapters 5, we proposed a way to integrate AVs, particularly ZOV trips into activity-based models. The next step would be to test the proposed method by running simulations while explicitly modeling zero-occupancy vehicle trips. This will also require addressing the research questions raised in chapter 5 which include: how will ZOV trips change the geographic and temporal constraints currently imposed in activity-based models? How should we specify the utility equations of ZOV trips/tours in models? Is the sensitivity to travel time and distance zero since there are no passengers?

5- Many studies have focused on understanding individuals' online vs. in person shopping behavior (e.g. Dias et al., 2020). These decisions will change and become further complicated when an additional alternative is introduced—sending out zero-occupancy AVs to perform the shopping activities. This new alternative was available to our study participants, and subjects' daily online and in-person shopping behavior was recorded during the chauffeur and non-chauffeur weeks. This data can therefore be used to investigate the potential shifts in shopping behavior that will arise in an AV world, which can then be used to improve simulation studies.

6.4 Conclusion:

The advent of autonomous vehicles will have profound impacts on our lives. AVs will make our travel safer, more pleasant, and efficient, fundamentally changing how we make travel decisions. Moreover, the increase in mobility and accessibility AVs offer will enhance the quality of life of many, particularly mobility impaired individuals. Nevertheless, properly regulating the technology will be key to realizing its benefits while avoiding unintended negative externalities. To do so, we first need to understand its impacts on the transportation system, and particularly on travel behavior.

Researchers have increasingly focused on understanding the travel behavior implications of AVs. The current literature, however, suffers from two main issues: 1) the impact of AVs on certain aspects of travel behavior has not been explored enough, and 2) for research questions that are well explored, results vary substantially, making it difficult to derive definitive insights for policy purposes. Consequently, there are two key action items moving forward. First, increased efforts should be directed towards under-researched topics, such as the impact of AVs on long-term decisions (e.g. residential/work location choices, car ownership), the impact of zero occupancy vehicles trips, and heterogeneity in the response to the technology by different demographic groups and individuals with different lifestyles and mobility needs. Incorporating these behaviors is key to running more realistic and representative simulations. Second, for well explored research topics, we need to tighten the range of results to be able to derive more definitive insights. It is important, therefore, for researchers to establish clarity of the assumptions used in their studies to enable comparisons and transferability of results, allowing other researchers to build on the knowledge gathered and improve upon it.

Policy makers can also play an important role in advancing the research field. As more companies test their technology on public roads, and in many cases with human subjects involved, policy makers can facilitate partnerships between tech companies and researchers who can use the data generated from the ongoing field experiments to improve our understanding of the implications of AVs on travel behavior. Finally, we call upon policy makers to be proactive with their policies regarding AVs rather than reactive. It is imperative the we start regulating AVs from now. Changing people's behavior through legislation will take time as behavior change is slow, especially when faced with resistance from users.

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