Modeling Users' Behavior Toward Automated Vehicles and Mobility Services Using Revealed and Stated Preference Data

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Abstract

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Chair of the Supervisory Committee:

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Civil and Environmental Engineering

Emerging technologies in transportation, such as automated vehicles (AVs) and mobility services, are expected to impact travelers' behavior and choices. However, due to many uncertainties surrounding these new technologies, the magnitude and direction of this impact remain a mystery. Literature on AVs identifies several crucial questions and issues surrounding automated vehicles and new mobility services including: (1) potential induced demand, (2) trust in technology and its effect on adoption, (3) AVs as a mobility-as-a-service enabler. In this dissertation, I aimed to tackle these issues by quantifying value of travel time as a determinant of induced demand, study trust in AV technology as a key determinant of adoption, and modeling within tour inter-dependencies as determinant of multimodal travel and MaaS adoption. First, I use the data of actual mode choices between ridehailing and free-float carsharing to build models of mode choices to inform analyses of the prospective change in time valuation and travel behavior when riding in future highly AVs. Then, I discuss the design and implementation of a choice survey based on users' revealed trip diary that overcomes shortcomings of revealed preference data. Next, I use the data from the choice survey to build an integrated choice and

latent variable (ICLV) model that quantifies the impact of psychological constructs such as AVs safety perception on trip-based mode choices, specifically choices involving privately-owned AVs and driverless ridehailing services. Finally, I build tour-based mode choice models that allow capturing interdependencies among trips within a tour and explore potential for multimodal trip.

My results from analyzing revealed preference data shows that riding in a car versus driving one reduces the value of travel time (VoTT) by $23/hour which confirms a significant time savings benefit in eliminating the burden of driving for travelers. While AVs potentially provide time saving benefits, based on current public's assessment of the technology's safety, market share of AVs remain small. However, improvements in users' perception of AVs' safety can considerably grow the market share for privately-owned AVs to the point that it hinders market share of driverless ridehailing. Another avenue for AVs to affect transportation system is enabling multimodal travel. Using tour-based mode choice modeling, I found that people preferences to use unimodal tours when using AVs are about the same as any other modes and I identified strong inclination among our sample to use unimodal tours despite the mode of travel.

The findings of this dissertation highlight the potential for increases in VMT and as a result increases in induced demand and GHG emissions, as it is expected that people's value of travel time considerably drops in AVs and market share of AVs grow substantially when users perceive them safe. Also, as highlighted in this dissertation, even with AVs and driverless ridehailing mode inertia is high among users, and solely introducing these new modes would not contribute to multimodal travels. This dissertation illustrates that the adoption of AVs cannot solve many of the pressing transportation issues if they are introduced to the current system without any changes to the system. There is a need for policies and plans in place to make sure the new technologies potential is directed toward a more sustainable future.

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I want to thank Andisheh who started as my colleague in the Sustainable Transportation Lab and turned into one of my best friends. She patiently listened to me for hours when I was trying to figure out my career path. She always guided me like an older sister and cheered me up with her positive attitude and energy.

I was lucky to find a gang of friends who stuck with me through ups and downs. Ebla, Masoud, Shervin, Shakiba, Milad, Moein, Sepideh, Neusha, and Melika; we went through a pandemic together, survived, and grew. We celebrated, cheered, danced, and wept together. I cherish every moment of our friendship.

Above all, I can't express how thankful I am for all the sacrifices that my parents made and for all the love they have shown me all these years. They were my biggest cheerleaders and showed me unconditional support during my PhD program and remind me of the most important things in life. Even though we could not be together as much as we liked, I always felt their support and encouragement throughout my days.

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Introduction

Emerging technologies in transportation, such as automated vehicles (AVs) and mobility services, are expected to impact travelers' behavior and choices. However, due to many uncertainties surrounding these new technologies, the magnitude and direction of this impact remain a mystery. Literature on AVs identifies several crucial questions and issues surrounding automated vehicles and new mobility services including: (1) potential induced demand, (2) trust in technology and its effect on adoption, (3) AVs as a mobility-as-a-service enabler.

Several studies aimed to quantify potential induced demand as a result of AVs adoption. Childress et al. (2015) explored the impacts of automated vehicles by modifying an existing activity-based travel model for Seattle, USA and found AVs may lead to considerable increases in vehicle miles travelled. Jabbari et al. (2019) showed how new technologies impact accessibility and land use by reducing the cost of travel time which can result in people moving further away from central city areas. Levin and Boyles (2015) explored the impact of AV ownership on transit demand by analyzing mode and trip choices through incorporating generalized costs of travel time, monetary fees, and fuel consumption into a multiclass four-step planning model. Authors showed that the number of personal vehicle trips will significantly increase. Correia and van Arem (2016) used the city of Delft as a case study, finding that AVs can satisfy more trips than regular cars, and even though they travel more kilometers, they create a slight increase in congestion. Auld et al. (2017) used a transportation system model, POLARIS, to analyze the interconnections between changes in congestion levels, travel behavior, and activity patterns due to hypothetical privately operated vehicles with connected-automated technologies and found that changes in travel time cost, or value of travel time savings has a substantial impact on VMT. Harb et al. (2018) used a quasi-experiment to explore self-driving vehicles' potential travel behavior impacts. They provided 60 hours of free chauffeur service for each participating household to mimic owning a self-driving vehicle. They tracked participants for three weeks: a week before the study, during the experiment week, and a week after. They found an 83% increase in vehicle miles traveled (VMT) and a 91% increase in the number of trips longer than 20 miles during the chauffeur week. They did not explicitly calculate changes in value of travel time (VoTT); however, an increase in VMT and long-distance trips can be due to lowered VoTT.

Many studies tried to understand how people perceive futuristic modes, the trade-off between attributes of the new modes versus those of the existing modes, and the willingness to pay for the new technology. For example, Haboucha et al. (2017) implemented a stated preference (SP) experiment to study the choice between a regular vehicle, privately-owned AV, and a shared AV for a sample of individuals from Israel and North America. Using a nested logit kernel model, they found significant reluctance towards AV adoption. Megens (2014) conducted an SP study in the Netherlands to determine the preferred levels and circumstances for automation using a discrete choice experiment and found that users only prefer a low level of automation. Liljamo et al. (2018) studied people's concerns regarding AV adoption using an SP experiment and indicated that people's attitudes towards AVs could reflect the general adoption of AVs. Daziano et al. (2017) estimated willingness to pay for automation using a discrete choice experiment to understand how households perceive and value automated vehicle technologies. They found that the average household is willing to pay $3500 for partial automation and $4900 for full automation. They also observed that some households are unwilling to pay anything for either type of automation; however, those who are more familiar with the technology are willing to pay more. A more thorough literature review of existing studies on users' behavior toward automated vehicles and mobility services can be found in the following chapters.

In this dissertation, I am modeling mode choices using two novel datasets: (1) revealed preference data that include actual mode choices between ridehailing and free-float carsharing, (2) stated preference data based on revealed travel pattern to tackle aforementioned issues. In the chapters ahead I quantify value of travel time as a determinant of induced demand; investigate trust in AV technology as a key determinant of adoption; model within tour inter-dependencies as determinant of multimodal travel and MaaS adoption.

In chapter one, I used a unique dataset that includes actual mode choices between ridehailing (riding in a car) and free-float carsharing (driving a car) from a mobility-as-a-service aggregator app. I used this dataset to build models of mode choices to inform analyses of the prospective change in time valuation and travel behavior when riding in future highly automated vehicles (AVs). Using revealed preference data and ridehailing as a proxy to AVs allows an estimate based on established behavior and actual choices of travelers. The sample of app users was located in the United States and had a history of using both carsharing and ridehailing through the aggregator. I analyzed users' choices between these modes using a mixed logit model, controlling for price, in-vehicle time, and out-of-vehicle time (walk or wait time). To the best of my knowledge, there is no other study in the body of literature on this topic that has used such a dataset that includes choice alternatives ridehailing and carsharing.

Some may find stated choice studies not as reliable as revealed choice studies due to respondents not fully grasping the choice situations presented to them, especially in the studies of automated driving. However, revealed preference datasets are usually limited both in size and dimension. The revealed preference dataset I used in chapter 1 uncovers essential information regarding how users value their time riding vs. driving. However, it lacks information about users' socioeconomic characteristics, attitudes and preferences, trip purposes, alternative mode options, and their attributes.

To address the shortcomings of revealed preference data, I designed a choice survey based on users' revealed trip diary. In chapter two, I explain the design of this survey in more details. In this unique survey, in addition to answering questions about their socioeconomic characteristics and attitudes and preferences, respondents provided us with their trip diary for a typical workday. This trip diary was used in real-time to generate personalized scenarios for each participant by collecting data from Google and Uber APIs to create a full choice set of mode options. Users were then asked to make choices for each trip within the tour, helping them imagine their day-to-day life with these new modes to incorporate better behavioral realism. Behavioral realism is critical in the context of automated vehicles and future mobility services since they are not currently available, and users have no experience planning their travels using these modes.

Despite these potential long term merits of AVs, studies have identified several barriers for the public's acceptance and adoption of AVs. Safety of AVs is one of such obstacle that frequently comes up in the literature. Even though AVs are expected to be safer than cars driven by humans, current assessments of people's willingness to use AVs or to ride in driverless ridehailing services are affected by people's lack of trust in AV technology and a recognition that the technology is not yet ready for the market.In chapter three, I used mode choices from the first trip of the choice scenarios explained in the previous paragraph to explicitly model how safety perception and car ownership importance affect mode choices involving AVs and driverless ridehailing services using an integrated choice and latent variable (ICLV) model. I incorporated these two constructs as latent variables into a mode choice model. My goal in this chapter was to quantify the impact of psychological constructs on mode choices, specifically choices involving privately-owned AVs and driverless ridehailing services.

In chapter four of this dissertaation, I expanded the model I created in chapter three and built tour-based ICLV models. According to Ben-Akiva et al. (19), trip-based mode choice models lack "behavioral realism", as one's mode choices for different trips in a tour are usually not independent. This is important specially in the case of understanding multimodal travels and the role AVs can play to support them. The designed experiment allows respondents to either maximize their utility for each trip within the tour and treat each trip independently or think about other latent variables and constraints based on the previous trips when choosing the current trip's mode. I capture these two thought process through by estimating models with and without controlling for prior mode choices.

This dissertation improves on previous literature on users' behavior toward AVs and mobility services by:

1- Closing a gap in leveraging currently established behaviors through both revealed preference data and state-of-the-art choice experiments based on respondents' revealed trip diary.
2- Quantifying the impact of the public's perception of AVs and psychological attachment to cars on adopting AVs and driverless services.
3- Upgrading previous models to tour-based mode choice models to capture within tour interdependencies and improve behavioral realism in modeling and understanding travelers tendencies for multimodal tours.

Chapter 1: Insights from carsharing and ridehailing mode choices for inferring value of travel time in autonomous vehicles using revealed preference data

This chapter of my dissertation is based on a project jointly authored by me, Andisheh Ranjbari, Paul Leiby, and Don MacKenzie (Jabbari et al., 2020a)

Abstract

This study aims to develop quantitative estimates of how the value of travel time (VoTT) may change when time spent driving is replaced by time spent riding in a car. Such estimates can inform analyses of the prospective change in time valuation and travel behavior when riding in future highly automated vehicles (AVs). We form these estimates with revealed preference analysis of actual mode choices between ridehailing (riding in a car) and free-float carsharing (driving a car) using a novel dataset from a mobility-as-a-service aggregator app. Our sample of app users were located in the United States and had a history of using both carsharing and ridehailing through the aggregator. We analyze users' choices between these modes using a mixed logit model, controlling for price, in-vehicle time, and out-of-vehicle time (walk or wait time). The model results indicate an average $23 per hour reduction in VoTT when riding in a ridehailing vehicle compared with driving in a carsharing vehicle.

Introduction

Value of travel time (VoTT) has been described as "the most important number in transport economics" (Daly & Hess, 2019). As the monetary value of the combined disutility and opportunity cost of time spent traveling, VoTT is a significant determinant of travel behavior, affecting both the extent of travel (trip frequency and distance) and mode choice. Estimates of VoTT, or savings in VoTT, are a principal component of the cost-benefit analysis of transportation infrastructure investments (U.S. DOT 2016). This study aims to develop quantitative estimates of how the VoTT may change when time spent driving is replaced by time spent riding in a car. Such estimates can be used to inform analyses of the prospective change in time valuation and travel behavior when riding in future highly automated vehicles (AVs).

One of the main factors that affects VoTT is mode of travel. A study of bicyclists in Stockholm has shown that cyclists have considerably higher VoTT than other modes. The magnitude of VoTT is different when riding on the streets versus riding in bike lanes (Börjesson and Eliasson 2012). For the case of transit, studies have found that VoTT is dependent on how travelers spend their time while onboard (Frei et al., 2015; Varghese and Jana, 2018; Bounie et al., 2019). Frei et al. (2015) found that individuals who participate in active leisure activities (e.g., reading a book, listening to audiobook or podcast, playing printed or digital games) have a more positive attitude toward transit than those who participate in passive leisure activities (e.g., surfing the web, listening to music). Later, Varghese and Jana (2018) investigated the effect of multitasking on VoTT using Mumbai as a case study. Their findings showed that VoTT of individuals who performed multitasking decreased by 26% compared with those who did not. A stated preference study exploring the same topic in Paris found that VoTT drops by 12% when public transportation users feel comfortable using information and communication technology (ICT) (Bounie et al., 2019).

When riding in a ridehailing service or an AV, travelers are expected to experience a reduced mental burden. They will ultimately be free to engage in other activities, such as working, reading, listening to music, or other leisure activities, which may result in the decreased disutility of time spent traveling. Over the past few years, researchers have tried to discern how being driven by others, or by AVs, may affect the VoTT. A number of these studies have found evidence that VoTT in an AV would be lower than in incumbent modes. Since there is minimal actual travel experience with AVs, most studies rely on stated choice or stated preference (SP) data. De Looff et al. (2018) estimated potential changes in VoTT in AVs compared to a conventional car by employing an SP experiment, where respondents were presented with AVs with an office-interior or a leisure-interior environment. The results revealed that VoTT in the AV office-interior is lower than in a conventional car, while VoTT in the AV leisure-interior is the highest. Steck et al. (2018) conducted a choice experiment for driverless taxis and personal AVs and estimated a 31% reduction in the VoTT with full automation. Krueger et al. (2016) also conducted a stated choice survey offering respondents three mobility options, namely shared autonomous vehicle (SAV) with dynamic ride-sharing (DRS), SAV without DRS, and opt-out/alternative which is the user's current option. They found that, for all travel costs, the value of in-vehicle time for an SAV without DRS is lower than that of an SAV with DRS, which is lower than that of the opt-out option. Kolarova et al. (2019) also used the same stated choice survey as Steck et al. (2018) to calculate the VoTT reduction for a privately owned AV and an SAV based on joint mixed logit model results. They found that the VoTT declines by 41% for a commuting trip in an AV compared with driving a conventional car. However, the SAV option is seen as less attractive than the privately-owned AV.

Other researchers have found evidence that the VoTT is higher in an AV than in other modes. Yap et al. (2016) conducted an SP experiment to investigate AVs' potential as a first/last mile mode for transit and found that VoTT in an AV is higher than other modes. While this is inconsistent with the belief that the VoTT in an AV would be lower due to the possibility of doing other activities, the authors suggested that since AVs are not currently available, there could be uncertainties in the outcomes from stated-preference experiments. Gao et al. (2019) reached similar conclusions. Analyzing the results of an SP survey in which respondents chose between ridehailing and driving a personal car for a hypothetical commute trip, they found that the VoTT was 13% lower when riding in a ridehailing service than when driving a personal vehicle. Yet, the VoTT in a driverless ridehailing service was 15% higher than when driving a personal car, which again may reflect a lack of familiarity and comfort with driverless technology at present. When respondents were explicitly primed to think about the ability to multitask in a driverless ridehailing vehicle, a 45% reduction in VoTT was seen compared to driving a personal car, suggesting that people's disutility of travel is lower when aware of the ability to multitask. In another analysis, Wadud and Huda (2019) reported that a quarter of their survey respondents preferred to predominantly watch the roadway when asked how they would spend their time in an AV. They believe this represented a lack of trust in fully automated vehicles, consistent with Gao et al. findings. However, Rashidi et al. (2020) proposed a framework that provides explanations for increasing VoTT in AVs, and cautioned against confirmation bias that dominates the VoTT research to label unchanged or increased VoTT as counterintuitive or associating with hypothetical bias due to the survey design.

Singleton (2019) provides a thorough literature review and summary of recent research on AVs' effects on VoTT. He argues that AV users may not necessarily use their in-vehicle travel time to engage in productive activities; therefore, the VoTT impacts may be lower than anticipated. Further discussing evidence from past research, he claims that the source of reduction in the VoTT would not be from travel-based multitasking but rather from improvements in subjective well-being, i.e., finding enjoyment or meaning from the trip (e.g., stress reduction as a result of not driving). He concludes that further empirical research should be done on the time use and VoTT impacts of AVs using both qualitative and quantitative methods.

All of the studies identified prior to Singleton (2019) above have estimated the VoTT based on SP survey data. De Looff et al. (2018) concludes by asking how reliable stated choices are for predicting future behavior. They assert that respondents may, in many cases, not fully grasp the choice situations presented to them regarding fully automated driving. Hence, using an approach other than a stated choice survey may advance research findings in this area. Harb et al. (2018) used a quasi-experiment to explore the potential travel behavior impacts of self-driving vehicles. They provided 60 hours of free chauffeur service for each participating household to mimic owning a self-driving vehicle. They tracked participants for three weeks: a week before the study, during the experiment week, and a week after. They found an 83% increase in vehicle-miles traveled (VMT) and a 91% increase in the number of trips longer than 20 miles during the chauffeur week. They did not explicitly calculate changes in VoTT; however, an increase in VMT and long-distance trips can be due to lowered VoTT. There are very limited revealed preference studies that provide insights for changes in VoTT of AVs. In their review of potential time-use impacts of AVs, Mokhtarian (2018) highlights the need for leveraging current reality to prepare for the future.

In this chapter, we analyzed recent data on travelers' choices between the options of carsharing and ridehailing services on the same trip, to identify the difference in VoTT between traveler-driven and chauffeured services, which is analogous to the difference between driving a car and being driven by an AV. The general approach is similar to that of Gao et al. (2018), but instead of using stated choices between ridehailing and a personal car, we used revealed choices between ridehailing and free-float carsharing services, by using a novel dataset from a mobility-as-a-service (Maas) aggregator app.

We view the in-vehicle experience in a ridehailing vehicle today as a proxy for that of riding in a fully automated vehicle in the future, when AV technology is sufficiently established and proven that travelers consider it to be similar in safety and functionality to a human ridehailing driver today. Therefore, the difference in the VoTT between carsharing and ridehailing today can provide insights into the difference in VoTT between driving a car and riding in a future fully automated vehicle.

We analyzed the data using discrete choice models to estimate the difference in the disutility and implied monetary VoTT between carsharing and ridehailing, controlling for price, waiting time, and walking time.

Data

The novel data for this project were provided by Migo, a Seattle-based mobility-as-a-service (MaaS) aggregator. The Migo app presents the traveler with a set of simultaneous mode options for their intended trip, along with cost, time and other attributes of each option, and can observe some aspects of their choice behavior. Thus, this data set allows examining actual choices by individuals between simultaneous riding and driving options, both car-based, for the same trip. Migo has historical data on travelers' trips and mode choices over a multi-year period, including information on UberX, Lyft, and car2go trips. UberX and Lyft are solo ridehailing services where the traveler is picked up in a car and dropped off, and car2go is a free-float carsharing service where the traveler walks a short distance, gets in a car, drives to her destination, and leaves the car. In addition to trip-related information such as traveler location, travel time and price, Migo app also stores information on app usage events, such as app opening time, tap on services, link-out to service providers' app. We worked with Migo to translate their event-based data (e.g., app openings, taps, link-outs) into a trip-based dataset (e.g. trip origins, destinations, distances, times). Data extraction was performed by Migo staff, and the resulting dataset included:

- traveler ID (anonymized)
- traveler location (anonymized by introducing uniformly distributed random noise, up to 100 meters, to the latitude and longitude coordinates)
- origin and destination locations (anonymized by introducing random noise)
- distance between traveler location and entered origin (based on actual origin and destination before random noise was introduced)
- for car2go: walking time (to the closest available vehicle), in-vehicle time, and price
- for UberX and Lyft: waiting time, in-vehicle time, and price
- whether the traveler booked UberX, Lyft, or car2go in the Migo app, or linked out to the booking page in the respective service provider's app, and time of booking/linking out.

For car2go, actual booking is not integrated into Migo and therefore the data can only tell us whether the user linked out to the point in the car2go app at which booking is finalized. For UberX and Lyft, both link-out and booking data exist.

To have a meaningful comparison, we only included data for travelers who had used both car2go and one of the ridehailing services (either UberX or Lyft) at least once in their lifetime use of Migo. Sessions that did not produce a booking or link-out were removed from the dataset by Migo, since they do provide information on the mode choice response.
We received data on 168 travelers and corresponding 2082 sessions. The dataset includes trips happening during 8 months spanning from July 2018 to February 2019. Ten of the 168 travelers were outside the US and were removed from the dataset. Figure 1 shows the geographical distribution of the remaining 158 travelers within the Migo dataset.

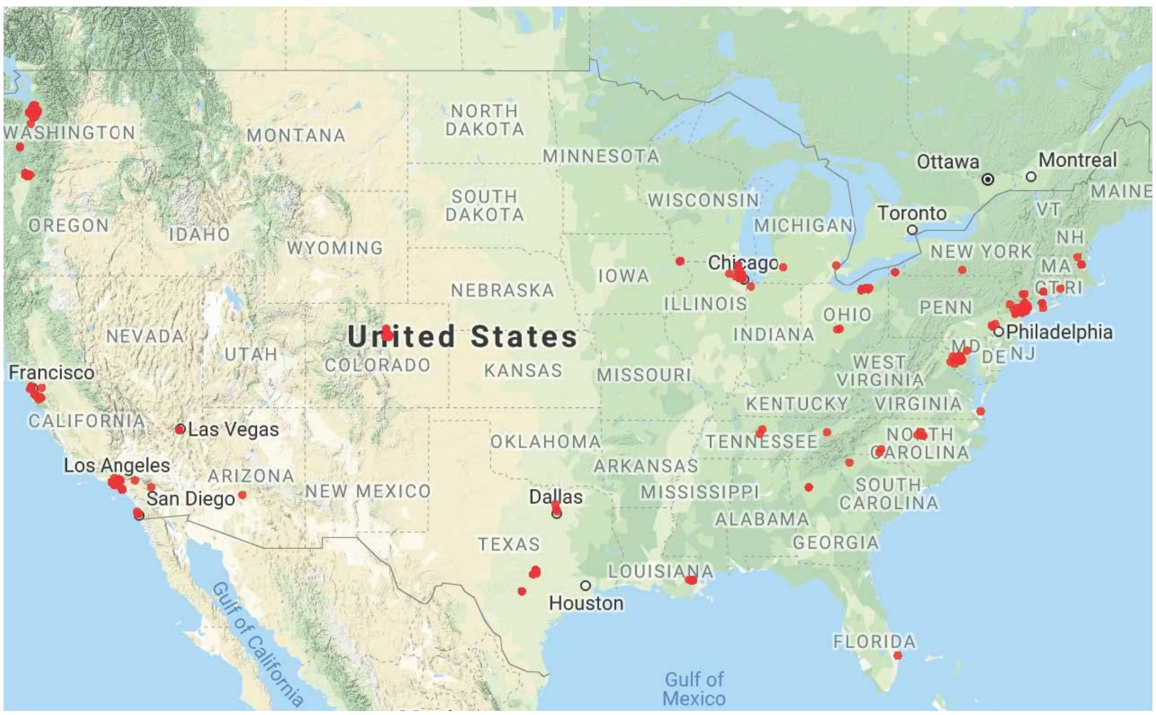

Figure 1 The geographical distribution of the travelers in the Migo dataset before data cleaning (158 travelers)

In order to prepare the dataset for modeling, we cleaned the dataset in several steps. First, we removed sessions with missing data, except when in-vehicle travel times or car2go prices were missing. When in-vehicle travel time was missing, we used origin and destinations, and date and time of the trips and collected in-vehicle travel time from the Google Maps API. We also removed sessions in which either the car2go option or both ridehailing options were unavailable for that trip (Figure 1 shows initial data that includes trips happening in areas where car2go or ridehailing services were not operating).

127 observations were missing car2go prices. We used regression models to impute car2go price structures based on the travel times using the origin cities' existing data. Regression results for cities with missing data are shown in Table 1. We used the imputed car2go prices in the mode choice modeling.

Table 1 Regression model for imputing car2go prices

City	Estimate	Standard Error	R^2
Seattle, WA			
Travel time	0.43	0.01	0.75
Intercept	3.79	0.15	
Denver, CO			
Travel time	0.38	0.03	0.78
Intercept	3.28	0.49	
Washington DC region			
Travel time	0.36	0.01	0.93
Intercept	3.61	0.21	
Chicago, IL			
Travel time	0.29	0.01	0.67
Intercept	2.59	0.23	
New York City, NY			
Travel time	0.40	0.02	0.85
Intercept	3.41	0.65	
Portland, OR			
Travel time	0.35	0.02	0.94
Intercept	3.31	0.49	

Next, we removed sessions with unreasonable in-vehicle travel time and/or price. We assume that an in-vehicle time more than double the Google travel time, or a price larger than $4 per minute for UberX and Lyft or larger than $3 per minute for car2go represent errors in the data, and we removed such sessions.

Finally, we removed sessions for which the distance between the traveler's current location and the entered trip origin is more than 1200 meters. We assume that these do not represent a trip that the traveler is about to make. The cleaned dataset included 103 travelers and 863 sessions.

Summary Statistics

Table 2 shows how many times each mode was chosen as well as the number of unique users that chose each mode. For each observation, users had a carsharing mode (car2go) and a ridehailing mode (either UberX or Lyft) among their available options. Travelers had chosen both carsharing and ridehailing services at least once during their lifetime of using the Migo app; however, they did not necessarily use both carsharing and ridehailing during the study period, or their use of one or more services might have been removed during the data cleaning process (for example, data cleaning could have removed a trip that showed a traveler had used car2go but lacked essential data on walking distance or waiting time).

Table 2 Chosen modes by number of observations and number of unique users

Chosen Mode	Number of Observations	Number of Users
car2go	98	52
UberX	457	60
Lyft	308	51

Summary statistics for UberX and Lyft wait times, car2go walk time, in-vehicle travel times (IVTT), and prices for all the modes are presented in Table 3. As shown in Table 3, there is little-to-no variation in IVTT for different modes. This is because the car2go travel times displayed by the Migo app were based on travel times between user's origin and destination rather than travel times between the nearest car location and the user's destination. Thus, the IVTTs for car2go, UberX, and Lyft end up being the same because origin, destination, and speeds are assumed to be the same for those services.

Table 3 Summary statistics of variables

Variable	Minimum	1st quantile	Median	Mean	3rd quantile	Maximum
car2go walk time (min)	1	3	5	6.88	9	32
UberX wait time (min)	1	2	3	3.15	4	14
Lyft wait time (min)	1	1	2	2.33	3	15
car2go IVTT (min)	1.53	8.89	11.78	13.31	16.19	123.27
UberX IVTT (min)	1.53	8.92	11.78	13.31	16.19	123.27
Lyft IVTT (min)	1.53	8.92	11.78	13.31	16.19	123.27
car2go price	3	6	9	8.67	10	49
UberX price	1	8	11	14.09	15	171
Lyft price	5	9	11	14.8	17	158

Note: Wait times, walk times, and prices were shown to users, and reported by Migo, as whole numbers.

Figures 2 and 3 show the distributions for wait time (for UberX and Lyft) and walk time (for car2go). For all services, the distributions appear to be within reasonable ranges. Moreover, the wait time values for the two ridehailing services are fairly similar, though Lyft's estimated waiting times average about 1 minute less than UberX's.

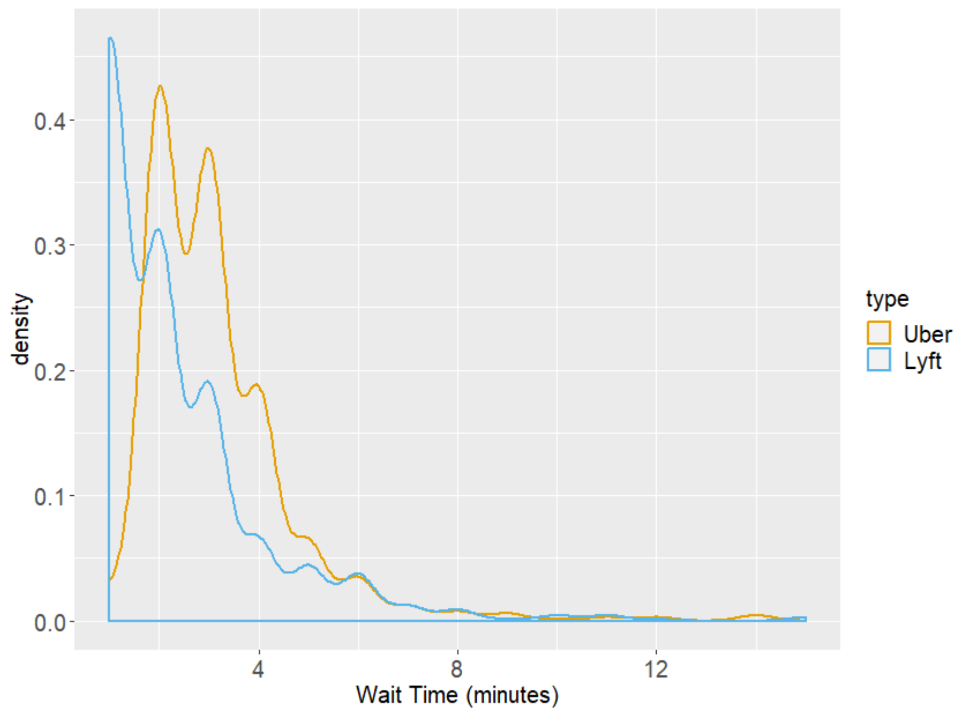

Figure 2 Wait time distrubution for UberX and Lyft

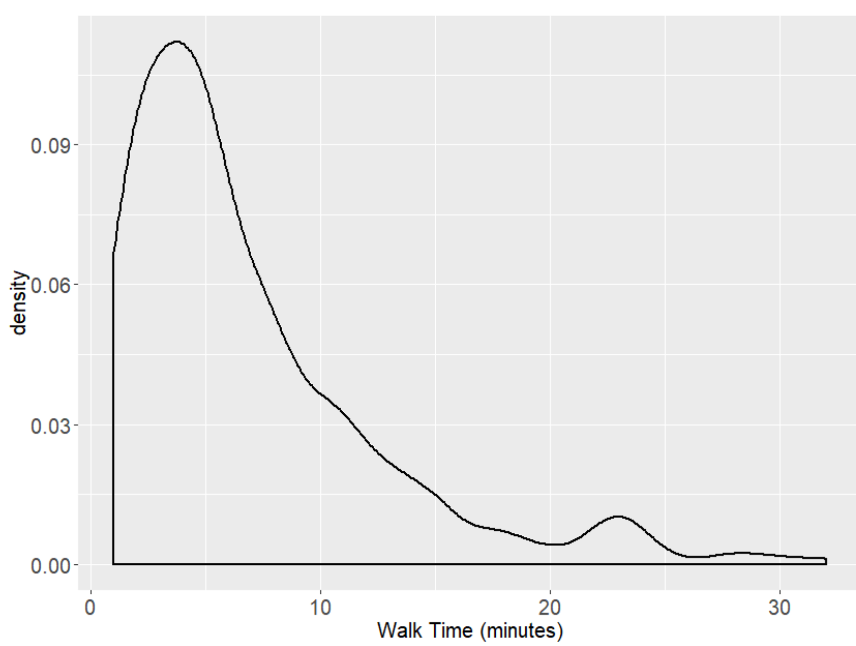

Figure 3 Walk time distrubution for car2go

Analysis

We analyzed the data using a discrete choice model to estimate travel time's marginal disutility in carsharing (car2go) and ridehailing (UberX and Lyft) modes, controlling for waiting time, walking time, and price. We modeled choices using a mixed logit model with error components structures. We originally intended to model observed choices using the following utility functions:

$$V_{car2go,t} = \beta_{price}P_{car2go,t} + \beta_{IVTT,car2go}T_{car2go,t} + \beta_{walk\ time}\ WK_{car2go,t} \quad (1)$$
$$V_{Uber,t} = \beta_{price}P_{UberX,t} + \beta_{IVTT,ridehailing}T_{UberX,t} + \beta_{wait\ time}\ WT_{UberX,t} + ASC_{UberX} \quad (2)$$
$$V_{Lyft,t} = \beta_{price}P_{Lyft,t} + \beta_{IVTT,ridehailing}T_{Lyft,t} + \beta_{wait\ time}\ WT_{Lyft,t} + ASC_{Lyft} \quad (3)$$

V_{jt}:	observable portion of the utility for mode *j* in choice situation *t*.
ASC_j:	alternative specific constant for mode *j* (ASC_{car2go} fixed to zero).
P_{jt}:	cost of using mode *j* in choice situation *t*.
T_{jt}:	in-vehicle travel time of mode *j* in choice situation *t*.
$WK_{car2go,t}$:	walk time from origin location to the nearest car2go in choice situation *t*.
WT_{jt}:	wait time for UberX or Lyft in choice situation *t*.

This specification would have allowed us to compare the disutility of travel time in car2go driving versus in ridehailing options by directly comparing $\beta_{IVTT,car2go}$ and $\beta_{IVTT,ridehailing}$. We had expected to observe different IVTTs for car2go compared with UberX and Lyft, since variation in the closest vehicle location would lead to different starting locations and, therefore, different travel times. However, as explained earlier, it turned out that there was little to no variation in IVTT between the different modes in any given choice situation in the dataset (Table 3). So, we treated IVTT as a situational attribute rather than a mode-specific attribute, as below, with car2go as the reference mode with respect to the time term.

We used a mixed logit model with error components, because it is more stable, and provides a more general substitution pattern compared with multinomial and nested logit models. We followed the procedure discussed by Brownstone and Train (1999) to incorporate the correlation between UberX and Lyft and control for repeated observations. Brownstone and Train described that the substitution pattern imposed by the nested logit model is not realistic in many settings, and it does not allow the data analysis to find whatever substitution pattern actually occurs. As a result, they proposed a mixed logit model with error components as a more general alternative. We added the term, $\sigma\ \varphi_i$, to the utility functions of ridehailing modes:

$$V_{car2go,it} = \beta_{price}P_{car2go,t} + \beta_{walk\ time}\ WK_{car2go,t} \quad (4)$$
$$V_{Uber,it} = \beta_{price}P_{Uber,t} + \beta_{IVTT}T_{Uber,t} + \beta_{wait\ time}\ WT_{Uber,t} + ASC_{Uber} + \sigma\varphi_i \quad (5)$$
$$V_{Lyft,it} = \beta_{price}P_{Lyft,t} + \beta_{IVTT}T_{Lyft,t} + \beta_{wait\ time}\ WT_{Lyft,t} + ASC_{Lyft} + \sigma\varphi_i \quad (6)$$

Where φ_i is an independently and identically distributed (iid) draw from a standard normal distribution and σ denotes the standard deviation of the normal deviate that generates that error component. For estimation purposes, a value of φ_i is drawn for each respondent from a quasi-random number generator for the standard normal distribution, and then the conditional probability with σ for φ_i is evaluated. We repeated this process for 500 Halton draws, and the conditional probabilities are averaged to calculate simulated probability. We used PandasBiogeme package (Bierlaire, 2020) to estimate the model. The results of the mixed logit model with error components are presented in Table 4.

The coefficient for IVTT of ridehailing modes is positive and statistically significant with a value of 0.123. The estimated coefficient for UberX and Lyft wait time is positive but statistically insignificant based on the 95% confidence level. The coefficient for car2go walk time is significant and has the value of -0.41, indicating that having to walk to a car2go vehicle greatly decreases its utility. The error component on ridehailing is large and highly significant, indicating a strong correlation in the utility of UberX and Lyft.

Table 4 Results of mixed logit model with error components

Parameters	Value	Standard error	*t*	p-value
Alternative specific constants				
Car2go	-	-	-	-
UberX	0.841	1.28	0.66	0.51
Lyft	0.609	1.25	0.49	0.63
Cost	-0.318	0.09	-3.56	0.00
In-vehicle travel time				
Car2go	-	-	-	-
UberX/Lyft	0.123	0.06	1.99	0.05
Wait time				
UberX/Lyft	-0.062	0.08	-0.78	0.44
Walk time				
Car2go	-0.416	0.15	-2.71	0.01
Error component				

Ridehailing	-6.690	2.37	-2.82	0.00

Initial log likelihood:	-1065.758	Akaike Information Criterion:	1307.240
Final log likelihood:	-646.620	Bayesian Information Criterion:	1340.563
Rho-square:	0.387		

Based on the estimated coefficients for travel time and cost parameters, the VoTT ($/hr) can be calculated as stated in the following equation:

$$VoTT = \frac{\beta_{time}}{\beta_{cost}} * 60 \qquad (7)$$

The coefficient of IVTT reported in Table 4 represents the effect of IVTT on choosing ridehailing modes relative to car2go. In other words, it represents how the difference in utility between ridehailing and car2go changes as IVTT increases. Therefore, we can only calculate the *difference* in VoTT ($\Delta VoTT$) of individuals when using ridehailing modes versus car2go. Using coefficients from the estimated model:

$$\Delta VoTT = \frac{0.123}{0.318} * 60 = 23.20\ \$/hr \qquad (8)$$

Discussion

The analysis results indicate that the differences in VoTT between ridehailing services and carsharing is about $23 per hour for Migo users in the US. This number may seem high, considering literature (mainly stated preference studies) studying similar concepts and reporting a range of 13-40% reduction in VoTT for traveling by ridehailing or AV relative to driving a conventional car (e.g., Gao et al., 2019; Steck, 2018; Kolarova, 2019). However, the data we used in this study is unique and not similar to any prior studies. Therefore, it is worthwhile to understand who the users in our sample are.

Migo's data is constructed based on users' interaction with the app, and these interactions represent trips they took. Therefore, the more trips the users take, the more likely they are to be represented in this sample. So, our sample leans toward frequent ridehailing/carsharing users. Table 5 shows the observed frequency of ridehailing/carsharing use our sample. 44% of users took more than one ridehailing/carsharing trip per month, and since users could also book trips outside the Migo app, their actual use of these services might be higher.

Table 5 Observed frequency of ridehailing/carsharing use in the Migo sample

Frequency of service use in Migo data	Number of users	Percentages
Once per month	58	56.3%
2-3 times per month	23	22.3%
1-2 times per week	8	7.7%
More than 2 times per week	14	13.6%

Income level plays an important role in how travelers perceive VoTT. Since we did not have income information for users of the Migo app, we referred to the U.S. National Household Travel Survey (NHTS) data (U.S. Department of Transportation, 2017) to find the average income levels of frequent ridehailing/carsharing users. To do that, we first calculated the percentage of ridehailing/carsharing users for each income bin, broken out by frequency of service use (carsharing and ridehailing combined) (Table 6). Then, using mean income values for each bin, we calculated an average income for each usage frequency category, by fitting the income data to a lognormal distribution. This approach helps estimate the average income more accurately compared to using midpoints of the income bins.

The median household income in the U.S. was $63,179 in 2018 (U.S. Census Bureau, 2019a). However, looking at the estimated average income values in Table 6 (the bottom row), all carsharing/ridehailing users have a household income exceeding $100,000. Moreover, users with higher frequency of use have a higher average income. So, our sample (leaning toward frequent users) consists of individuals with higher than average income.

Table 6 Percentage of NHTS carsharing and ridehailing users by frequency of service use and income category.

Income Bin	Mean Income for the bin (from NHTS data)	Users broken by Service Use Frequency				All users
		once per month	2 or 3 per month	1 or 2 per week	more than 2 per week	
Less than $10k	$7,276	1.18	1.32	1.04	0.66	4.20
$10k-$15k	$12,600	0.73	1.23	0.40	0.27	2.64
$15k-$25k	$19,959	1.38	1.83	0.98	0.73	4.92
$25k-$35k	$29,798	1.51	1.73	0.89	0.73	4.87
$35k-$50k	$41,948	2.23	2.59	2.17	0.92	7.91
$50k-$75k	$60,976	3.03	4.25	4.22	1.85	13.34
$75k-$100k	$86,106	3.24	4.74	3.42	1.39	12.79
$100k-$125k	$111,239	3.02	4.35	2.77	1.18	11.31

$125k-$150k	$136,353	2.13	3.72	2.50	1.01	9.36
$150k-$200k	$170,988	3.27	3.42	3.23	1.03	10.95
More than $200k	$282,469	3.76	5.48	5.13	3.34	17.71
Estimated Average Income (via fitting to a lognormal distribution)		$113,669	$115,773	$125,285	$129,979	$119,645

Furthermore, for modeling purposes, we only included trips for which both ridehailing and carsharing modes were available. This criterion limits study observations to specific cities listed in Table 7, and these cities have a higher median income than the national average. This is again consistent with our sample consisting of individuals with higher than average income. Table 7 shows median income in these cities and the number of users from each city in the sample (for users who had trips recorded in multiple cities, we considered the city with highest trip frequency as their "home" city).

Table 7 Median household income in sample's home cities

Home City	Number of users	Number of trips	Median household income (USD) in each city in 2018 (US Census Bureau, 2019b)
Seattle	37 (35.92%)	516 (58.3%)	$87k
New York City	24 (23.30%)	53 (6.0%)	$78k
Chicago	16 (15.53%)	171 (19.3%)	$70k
Washington DC region	11 (10.68%)	95 (10.7%)	$102k
Denver	7 (6.79%)	32 (3.6%)	$79k
Portland	6 (5.82%)	16 (1.8%)	$75k
Austin	2 (1.94%)	2 (0.2%)	$71k

The unweighted average annual income across the cities represented in our sample is \$80.2k, or \$41/hour (based on the rough calculation of 49 weeks of work per year at 40 hrs/week (US DOT, 2016)), which is higher than the national average. Moreover, frequent carsharing/ridehailing users are more heavily represented in our sample, and those users tend to be wealthier than non-users and infrequent users, having an average annual income of \$120K (from Table 6, All users) and a direct income of roughly \$61/hour nationally.

In light of these factors, the \$23/hour difference in VoTT between ridehailing and carsharing for Migo users is more understandable. Considering frequent users' average wage rate of \$61/hour, a \$23/hour reduction in VoTT would represent 38% of the hourly wage.

Conclusion

In this chapter, we developed quantitative estimates of how the VoTT for car travelers changes when time spent driving is replaced by time spent riding in a car, through comparing VoTT between ridehailing and carsharing modes. Since ridehailing and AVs free the travelers from burden of driving compared to conventional vehicles, ridehailing offers a useful proxy for AVs. We used a novel dataset of ridehailing and carsharing users from a MaaS aggregator app, Migo, documenting actual choices by individuals between paired simultaneous riding and driving options, both car-based, for the identical trip, but differing in cost and waiting or walking time. Using this revealed preference dataset, we built a mixed logit model with error components to measure the difference in VoTT between ridehailing and carsharing modes. We estimated that there is a \$23/hour reduction in VoTT when riding in a vehicle versus driving a vehicle.

The \$23/hour difference in VoTT may at first appear high. However, our sample leans toward frequent ridehailing/carsharing users and users in big cities, who have higher than average income. The \$23/hour difference represents 38% of the mean hourly wage of frequent ridehailing users. This finding confirms that there is a significant time savings benefit in eliminating burden of driving for travelers.

One of the main caveats of prior studies with stated preference surveys is that surveyed individuals have little to no experience with AVs, and their responses are affected by their expectations and perceptions of experiences in AVs. Some studies even found higher VoTT for AVs despite the intuition that AVs free travelers from the burden of driving. Using revealed preference data and ridehailing as a proxy to AVs allows an estimate based on established behavior and actual choices of travelers. Our finding is consistent with the intuition and some of the SP studies' conclusions that in AVs, VoTT declines.

Our findings here are based on a useful, but limited-size dataset, and the sample is restricted to urban, mostly high-income travelers. Inferences regarding VoTT in AVs are also dependent on the suitability of ridesharing as a proxy for automated vehicle travel. We found that, at least for a portion of society that our sample represents, the VoTT drop for riding rather than driving is considerable. This may be due to the ability to use in-vehicle travel time productively to work or participate in other activities (making a phone call, reading a book, listening to music/podcast, etc.), or due to reduced mental burden.

Our data cannot reveal exactly what the underlying reason for the drop in VoTT is but learning more about that reason may be important for the interpretation of rideshare proxy results. AVs could provide an even greater opportunity for engaging in other activities while riding a car than ridesharing, but would not be as likely to deliver further reductions in mental burden.

Chapter 2: Design of a personalized tour-based mode choice survey

This chapter of my dissertation is based on a paper jointly authored by me, Andisheh Ranjbari and Don MacKenze (Jabbari et al., 2020b).

Abstract

In this chapter I discuss the design process of a personalized tour-based mode choice survey. Using this survey, I collected data that I used for my PhD dissertation project. The choice experiments included in this survey are based on revealed trip diary of survey participants. Therefore, I took advantage of RP data to design choice scenarios and collect data as realistically as possible.

Survey design

We designed a survey that consisted of four sections: 1) socio-economic questions, 2) trip diary, 3) choice experiments, and 4) psychometric measures. Section one included questions about the respondents' socio-economic characteristics, and their household. In section two, the respondents filled out a trip diary for each trip that they made during their typical or most recent working day, including the approximate origin and destination addresses and the purpose of the trip. Approximate addresses were used in real-time to retrieve travel time, wait time, and cost data the Google Distance Matrix and Uber APIs. In section three, API data was used as base values to generate personalized choice scenarios for the respondents. Section four included the psychometric questions prioritized by Ge et al. (2019).

To create personalized choice scenarios, we analyzed each respondent’s trip diary in real-time. First, we identified their main tour of the day and chose the destinations to be included in the choice experiments. Using the chosen destinations, an experimental travel day was created. We extracted from the Google and Uber APIs base values of cost and travel time for each mode and trip, and to understand the sensitivity of individuals to different attributes of modes, we varied the attributes across the scenarios. Figure 4 demonstrates the survey design scheme, and the aforementioned steps are described in more detail in the following subsections.

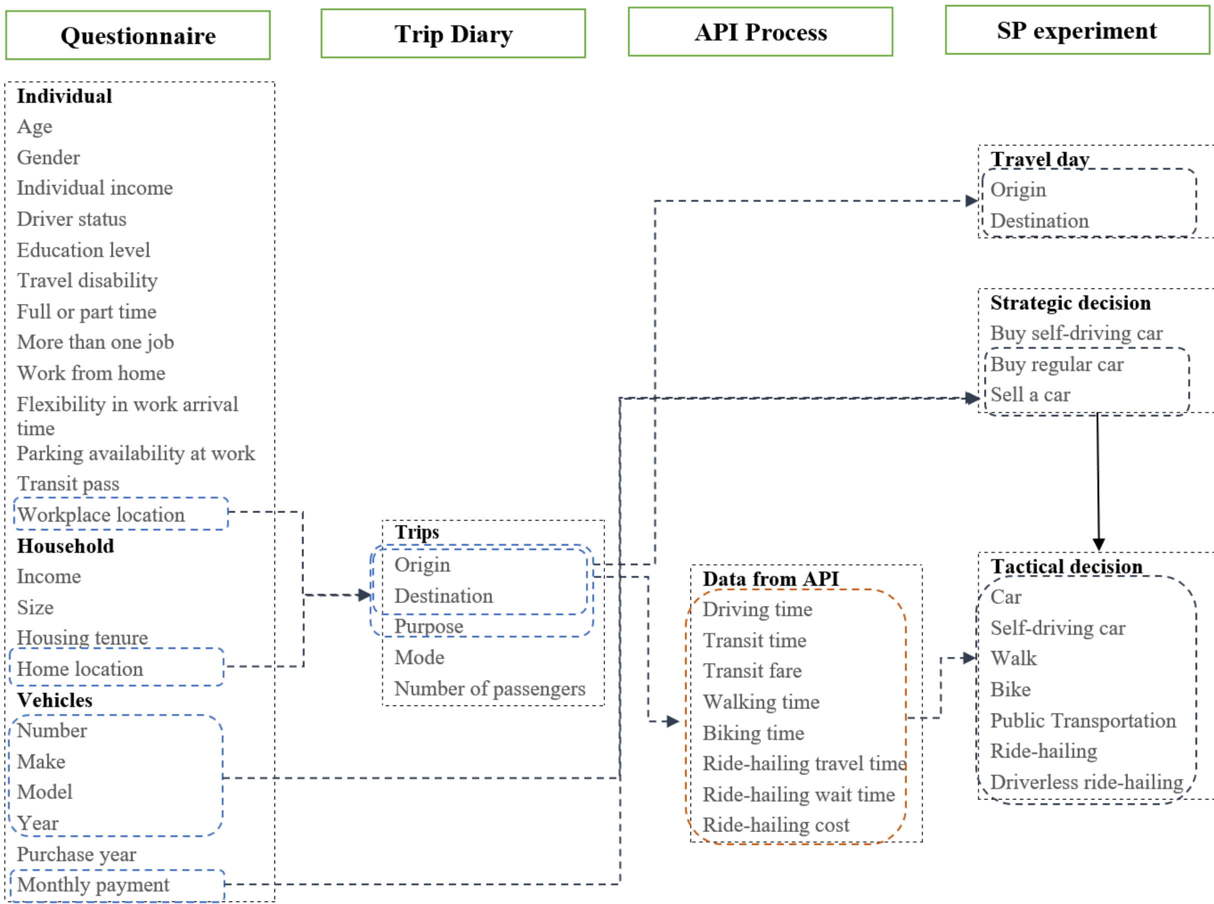

Figure 4 Survey design scheme: blue boxes highlight user data that was used for API data collection or SP experiment generation; orange box shows data collected from APIs; grey boxes show what parts of the choice experiment is based on user/API data.

Choice experiments

We extracted base values for most of the trip and mode attributes in choice scenarios from the Google and Uber APIs, as will be explained momentarily. For the attributes that were not collected through APIs, we assumed the following base values:

- Transit waiting time of 10 minutes; Transit wait time is derived based on average weighted transit wait times in 2017 National Household Travel Survey, which is 9.6 minutes (Guzman, 2017).

- Parking fee of $2.00 per hour; Auchincloss et al. (2015) used 2009 survey of public parking agencies and found that on average, on-street meters charges $1 per hour. Considering this value in 2009, we decided to use $2.00 per hour for our survey.

- Monthly car payment of $500 (for self-driving cars; and regular cars when individual does not own a car). Experian data from first quarter of 2019 (U.S. Census Bureau, 2019) shows an average monthly payment of $554 for new cars.

We collected travel time for all the modes (driving, ride-hailing, transit, walking and biking) and travel cost for transit from the Google Distance Matrix API; and collected wait time and travel cost for ride-hailing trips from the Uber API. Since for ride-hailing option there is no intermediate stops, we assumed ride-hailing in-vehicle travel time is the same as the driving time collected from the Google API.

Transit options may not be available for some trips. Those trips were flagged, and the transit option was presented as *unavailable* in the choice scenarios. In some other cases, the transit option is available for a trip, but the Google API does not provide a cost estimate for it. For such cases, the cost of $1.40 is assumed for the transit trip (Bureau of Transportation Statistics, 2017). For ride-hailing options, we used the time and price estimates for the UberX service, which is a private service by Uber in which users do not share rides. Since in the UberX service there are no intermediate stops to pick up/drop off other passengers, we assumed ride-hailing travel time is the same as the driving time that was collected from the Google API. The Uber API provides a high and low-cost estimate, and we chose to use the high estimates for all scenarios throughout the survey. To use the Uber API, origins and destinations need to be in geographic coordinates format, and we used the Google Geocoding API to convert addresses to geocodes.

Each respondent faced six personalized choice scenarios based on the trip diary and API data. Respondents were asked to make travel-related decisions (e.g. purchase a self-driving car, purchase/sell a car, choose a mode) for a hypothetical individual who was very similar to them in terms of age, gender, and vehicle ownership. This approach is inspired by Le Vine et al. (2011). Polman (2010) found that individuals are more inclined to justify choices made on behalf of others than the ones they made for themselves. Prior to showing the scenarios, we also presented respondents with a service description for the less common modes, such as ride-hailing, self-driving car, and driverless ride-hailing. Here are the descriptions with the same order and wording as presented in the survey:

- Self-driving car is a car that can drive itself or be driven by a human.
- Driverless car is a self-driving car with no human backup driver.
- Ride-hailing services are services such as Uber and Lyft, that connect passengers to local drivers to give them a ride.
- Driverless ride-hailing services are services that connect passengers to driverless vehicles to give them a ride. It cannot be driven by the passenger.

In all six scenarios, respondents saw the same typical travel day and were asked to choose their preferred mode for Jane's/John's trip. If they chose a car (regular or self-driving) for their first trip, they had to stick with that mode for the rest of the day, whereas, for any other mode, they could change their mode for each trip within the given day. The choice set included seven modes: regular car, self-driving car, ride-hailing, driverless ride-hailing, transit, bike, and walk.

In the first two scenarios, respondents were asked to imagine a situation where Jane/John did not own a vehicle nor had the option to purchase one. Therefore, they needed to choose one of the walk, bike, transit, ride-hailing, and driverless ride-hailing options. Figure 5.a shows an example of this choice scenario. The purpose of these two scenarios was to help respondents become familiar with the choice tasks, and those two scenarios are not used in the analysis.

The third and fourth scenarios presented a situation in which Jane/John did not own a vehicle but had the option to purchase a regular car and/or a self-driving car. Their strategic decision of whether to purchase a car affected the available mode options for each trip. For example, if they decided to purchase a self-driving car, the self-driving car option became available for all trips; otherwise, it was greyed out (meaning that the respondent could not choose it), but the respondent would still see its attributes (See Figure 5.b and 5.c).

In the fifth and sixth scenarios, the respondents were asked to imagine that Jane/John owned a certain number of cars. The cars that Jane/John owned were the same as those reported by the respondent in section 1 of the survey, with the same monthly payment. The respondent had the option to sell a car, purchase a new car, or purchase a self-driving car. Similar to the previous two scenarios, strategic decisions impacted available mode options for each trip (Figure 5.d). If they only owned one car and they decided to sell it and not purchase a new one, the car option would be greyed out for them. If a respondent did not own a car, we still asked them to imagine that Jane/John owns one, with a monthly payment that was generated through the experimental design explained earlier.

Figure 5 Example of choice scenarios: a) first and second scenarios: No-car situations b) third and fourth scenarios: Not buying any cars c) third and fourth scenarios: Buying a regular car, d) fifth and sixth scenarios: Selling the car(s)

To identify the sensitivity of respondents' choices to different attributes, we multiplied the base values of attributes (collected from APIs as explained above) by multipliers shown in Table 8. The set of multipliers used in any choice situation was determined by an experimental design. The product of the base value and the multiplier was then included in the choice scenarios.

Table 8 Experimental attribute levels

Attribute	Levels
Transit Travel Cost	0.6, 0.8, 1.0, 1.2, 1.4
Ride-hailing Travel Cost	0.2, 0.6, 0.8, 1.0, 1.2, 1.4
Parking fee	0.0, 0.6, 1.0, 1.4
Travel time	0.6, 0.8, 1.0, 1.2, 1.4
Wait time	0.6, 1.0, 1.4
Monthly payment	0.6, 0.8, 1.0, 1.2, 1.4

A recent work has shown that, when prior values are not available, the random design "performs as well as any other design" (Walker et al., 2018). In their paper, Walker et al. (2018) tested the robustness of different experimental designs. Their findings show that efficient designs will perform best if the prior parameters are close to the truth, but they are sensitive towards misspecification of priors. They explain that efficient designs should only be used when excellent priors are available. They also found that regardless of priors, the random design performs as well as any other design. In the context of the current study, some of the alternatives in the choice set do not exist today and we lack appropriate priors. We decided to proceed with the random design. The full factorial design consisted of over 1 billion combinations of attribute levels (which also made it computationally difficult to perform any design except random design). We randomly selected combinations of levels from the full factorial matrix and created blocks of 6 sets of combinations for each respondent's choice experiment.

Survey implementation

We used an Amazon Web Services to implement the survey. To make the survey accessible for respondents, we purchased a domain from the Amazon Route 53 service and connected it to the EC2 instance. To make sure respondents' data were transmitted safely from their browsers to our servers, we also acquired a certificate from Amazon to encrypt the data. We then used Amazon's Mechanical Turk (MTurk) to recruit survey participants.

MTurk is an online crowdsourcing platform, and workers registered on MTurk get paid through the platform for the jobs that they complete and are approved for. There are several criteria that requesters (e.g., researchers) can apply to find workers (e.g., respondents) who best fit the job.

For the purpose of this study, we needed workers from around the US. After conducting a pre-test and exploring data quality, we decided to recruit workers with an approval rate of 95% or higher and a minimum of 100 previously completed jobs. Workers were required to be over 18 years old to participate in the survey. Considering the expected average time to spend on the survey (20 minutes) and an hourly wage of $15 per hour, we paid each worker $5 for completing the survey.

Moreover, the team's previous experiences using MTurk for national data collection indicated that launching a survey simultaneously for all time zones could result in an overrepresentation of respondents from a specific time zone, as the proportion of workers active in the MTurk platform varies over time. To mitigate this, we launched the survey in four batches, one for each of the four time zones in the Continental U.S. (Eastern, Central, Mountain, Pacific), with the local launch time being the same in each time zone. We collected data from 1000 respondents, and the sample size for each time zone was set proportional to the total population of states in that time zone (Hawaii and Alaska were considered in the Pacific batch).

After data collection was complete, the data was cleaned. To check the quality of responses, we repeated two of the psychometric questions and reversed the order of the Likert scale choices. Responses meeting any of the following criteria were flagged and responses with two or more flags were omitted from the sample.

- Responses to the repeated psychometric questions that differed by more than one point on the six-point Likert scale.
- Number of children they entered exceeded the number of household members.
- Purchase year of their car was more than one year before the model year of the car.

Individuals who did not provide their approximate address or entered an address that did not exist (and as a result API data for them were not accurate), were removed from the sample. We also removed individuals whose trips were too long (driving time more than 2.5 hours) or too short (driving time less than 5 minutes) to be of interest in this work.

Chapter 3: How Do Perceptions of Safety and Car Ownership Importance Affect Autonomous Vehicle Adoption?

This chapter of my dissertation is based on a paper jointly authored by me, Joshua Auld and Don MacKenzie (Jabbari, Auld, and MacKenzie, 2021)

Abstract

In this study, we explicitly modeled how individuals' perceptions of automated vehicle (AV) safety and the importance they place on car ownership affect mode choices involving conventional and automated vehicles in the context of privately owned cars and ridehailing services. We adopted psychometric questions to capture these two latent variables and designed a stated preference survey based on the participants' actual travel patterns. Then, we quantified the impact of these latent variables on mode choices using an integrated choice and latent variable (ICLV) model. We found that both latent variables have a statistically significant effect on mode choices. The results show that car ownership importance has the most potent effect on privately owned cars (conventional car and self-driving car), followed by driverless ridehailing and conventional ridehailing. We also found that changes in safety perception are equivalent to sizable changes in price. We further investigated the impact of improvements in safety perception through four scenarios. The scenario testing results show that as the distribution of perceived safety is compressed toward positive safety perception, the market share of AVs spikes and dominates regular cars. Our results demonstrate that based on our respondents' current understanding of AVs, even if AV prices were comparable to regular cars, we cannot expect widespread use of AVs. However, improvements in AVs' safety and, consequently, consumer safety perception can considerably expand AVs' market share, and may offset the high cost of using the technology.

Introduction

Over the past decade, the potential benefits of automated vehicles (AVs) and services have been explored by many researchers (For example, Fagnant and Kockelman, (2015); Wadud et al., (2016); Litman, (2020)). These benefits include but are not limited to, reducing human error-induced crashes, relieving congestion, enabling travel by persons with reduced mobility (e.g., elderly, disabled), lowering energy consumption, and reducing carbon emissions. Despite these potential long term merits of AVs, studies have identified several barriers for the public's acceptance and adoption of AVs. Safety of AVs is one of such obstacle that frequently comes up in the literature. Even though AVs are expected to be safer than cars driven by humans, current assessments of people's willingness to use AVs or to ride in driverless ridehailing services are affected by people's lack of trust in AV technology and a recognition that the technology is not yet ready for the market. For example, an international survey of 1,722 residents of six countries found that the majority of respondents are highly concerned about "equipment or system failure" and "self-driving cars not performing as well as human drivers" (Schoettle and Sivak, 2014). Another paper studying public acceptance of AVs found that out of 467 study participants, 82% ranked "personal safety and the safety of those around you while operating an autonomous car" as the most critical topic affecting their adoption of AVs (Casley et al., 2013). Xu et al. (2018) found that perceived safety of AVs can predict intentions to use and willingness to ride in an AV, while Nazari et al. (2018) and Mushtaq et al. (2018) confirmed that safety concerns adversely impact public acceptance of shared and regular self-driving cars.

Additionally, despite similarities between the in-vehicle experience of AV mobility services (e.g., driverless ride-hailing) and privately owned AVs, studies show that the public perceives them differently, and willingness to use them varies among different groups of individuals. For example, an online survey of 556 residents of Austin metropolitan showed that most of the respondents prefer to own an AV rather than use AV services such as driverless ride-hailing (Zmud et al., 2016). Another study found that younger, more educated, technology savvy and urban residents are more likely to use AV mobility services than older individuals and residents of suburbs and rural areas (Lavieri, 2017). Krueger et al. (2016) surveyed 435 residents of Australia's metropolitan areas and found that people who use multiple modes in their daily lives are more likely to use AV services. Very few studies have explored the underlying reasons for these differences. One study found that individuals who express greater concern for the environment are more likely to use shared autonomous vehicle services (Haboucha et al., 2017). In this study, we hypothesized that willingness to use mobility services is affected by psychological attachment to car ownership.

In this work, we use an integrated choice and latent variable model (ICLV) to explicitly model how two latent constructs – perception of AV safety and car ownership importance – affect mode choices involving AVs and driverless ridehailing services. Then we simulate the market share of each mode under various scenarios, defined by shifts in prices and safety perceptions. This study provides empirical evidence for the crucial role of latent constructs, specifically safety perception and car ownership importance, when analyzing AV modes' adoption. It therefore contributes to our understanding of the impact of user preferences and attitudes on adoption of autonomous driving.

In the past few years, more studies have investigated latent variables, such as people's perceptions and attitudes toward AVs and services, to better understand AV adoption motivations and barriers. For example, Haboucha et al. (2017) explored the motivations of travelers to adopt AVs and modeled mode choices between regular cars, privately owned AVs, and shared AVs. They identified five latent variables using identifier questions from prior literature and found three of them statistically significant in the mode choice model: (1) Pro-AV attitudes; (2) enjoyment of driving; and (3) concern for the environment. As expected, their results show that people who enjoy driving are more likely to use a regular car than an AV, and individuals with pro-AV attitudes are more inclined toward AVs. Concern for the environment was a more robust predictor for shared modes. Lavieri and Bhat (2019) explored which individuals are willing to share an AV with strangers in the future using a multivariate integrated choice and latent variable approach. Their model included three latent variables: privacy-sensitivity, time-sensitivity, and interest in the productive use of travel time. They concluded that individuals who are more interested in using travel time productively are more likely to choose ride-hailing services. They also found that travelers dislike shared rides more because of delays than because of the presence of strangers. Wicki et al. (2019) investigated the willingness to pay to use self-driving bus services. They incorporated technology-related attitudes to explore the tradeoffs between "technological skepticism" and the potential benefits of the service. They found that the technology acceptance latent variable is a strong predictor of self-driving bus usage. Rahimi et al. (2020) analyzed people's attitudes toward shared mobility options and autonomous vehicles using a structural equations model. They identified eleven latent variables and explored their relationships with socioeconomic characteristics and correlations between the attitudes.

Ge et al. (2019) reviewed the transportation literature and concluded that processes of selecting questions to measure psychological constructs are inconsistently applied, and in many cases, questions are somewhat arbitrarily defined. Therefore, they conducted an extensive literature review to identify the critical psychometric measures influencing mode choices and specifically, adoption and use of autonomous vehicles. They considered three psychological concepts (norms, perceptions, and attitudes) and nine qualitative utility constructs that shape individuals' travel behavior to develop a comprehensive list of latent variables. They performed a factor analysis on a nationwide sample to obtain a minimum set of latent variables and questions to measure them.
In this study, we adopted questions identified by Ge et al. (2019) for the safety of AVs and car ownership importance latent variables. Then we investigated and quantified the impact of psychological constructs on mode choices, specifically choices involving privately-owned AVs

and driverless ridehailing services. To improve behavioral realism, we designed a novel stated preference choice experiment based on each user's revealed preference data as explained in chapter two. We asked respondents to choose from a choice set that included both traditional modes (e.g., car, bike, transit, and walking) and unconventional modes (e.g., ride-hailing, privately owned self-driving car, driverless ride-hailing service) since such a mixed choice set is more likely in the next few decades (Schoettle & Sivak, 2014). An ICLV model was built using Biogeme software (Bierlaire, 2020) to analyze the data.

In the following sections, we first discuss the collected data and characteristics of our sample. Then we talk about the applied methods and results. The paper concludes with a discussion of the results and suggestions for future work.

Data

For this part of study, we used scenarios 4 to 6 as described in chapter two. We used the first trip of each tour for modeling. For this part of the study, 757 respondents (out of 1000) were eligible, and their corresponding data were used for analysis.

89% of our sample indicated that they are full time employees. The sample's household income distribution is shown in Figure 6. Both mean and median income fall into the $40,000-$59,999 category. In 2018, median household income for the United States was $61,937 (U.S. Census Bureau, 2019a).

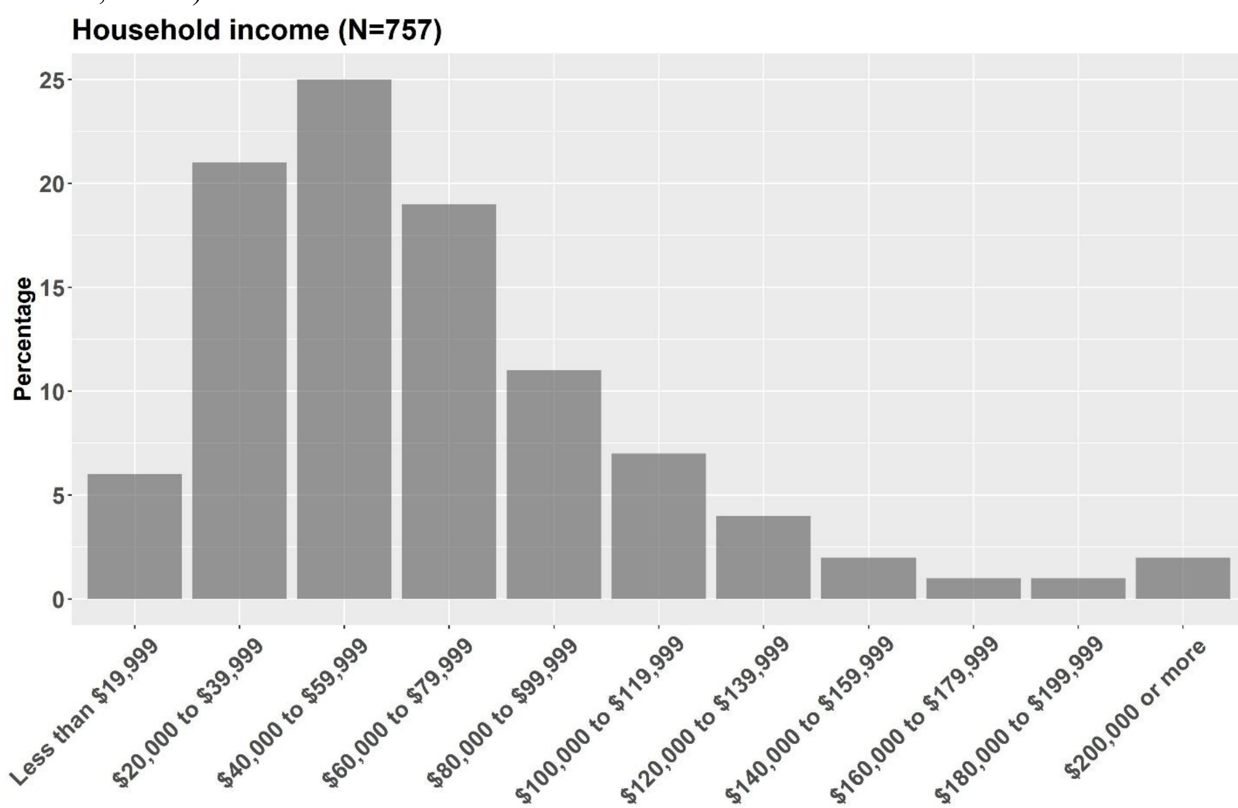

Figure 6 Sample's household income

Our sample consists of 46% females, 53% males, and 1% who chose other. Compared to the U.S. population (51% females, 49% males) (U.S. Census Bureau, 2019b), our sample represents more men. Figure 7 shows the educational attainment of the sampled individuals which is skewed toward higher education than the U.S. population (U.S. Census Bureau, 2019c).

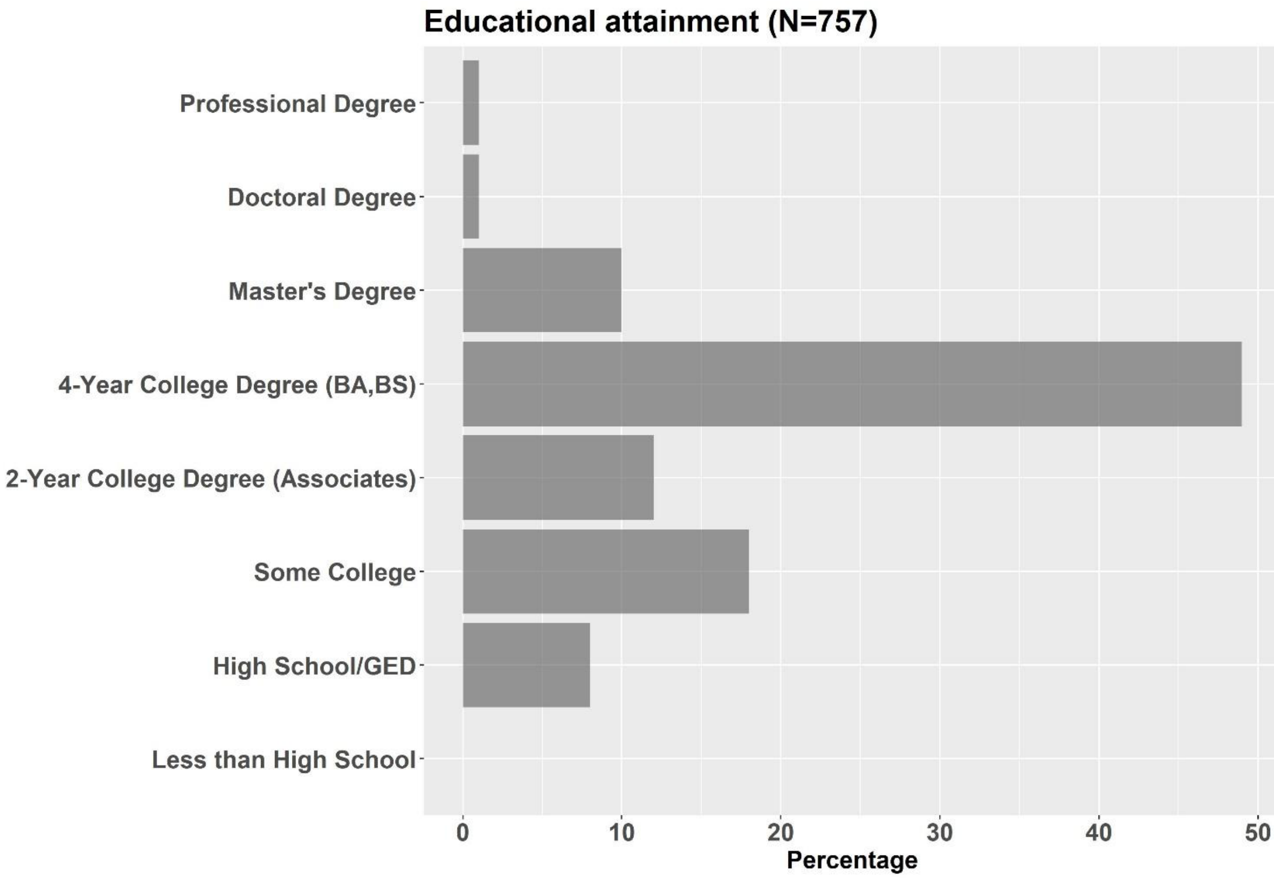

Figure 7 Sample's educational attainment

Table 8 shows the age distribution of our sample. The mean and median age are 35 and 33 years old, respectively. The median age of individuals 18 and older in the U.S. is in the 45-49 years old range (U.S. Census Bureau, 2019d). Our sample is biased toward younger individuals compared to the national population.

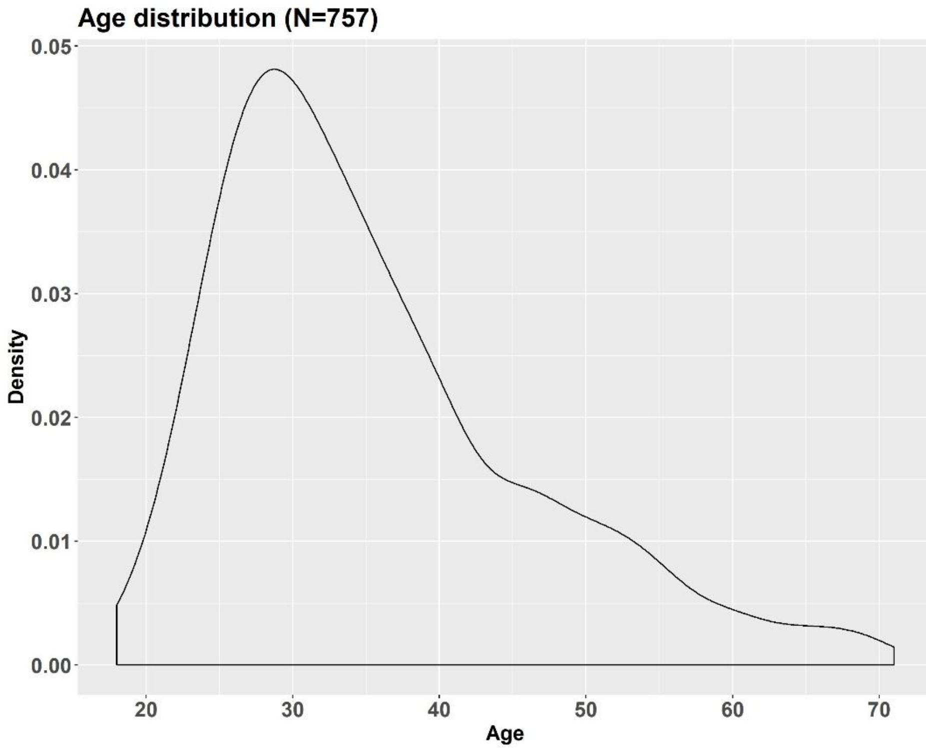

Figure 8 Sample age distribution

Table 9 Number of cars owned by surveyed households

Number of Cars	Number of Households
0	75
1	399
2	226
3	43
>3	14

We used the first trip of the travel day for modeling. Each person participated in up to four choice scenarios, and we had 2848 observations recorded for 757 individuals. Mode selection for all the observations is shown in Table 10 below:

Table 10 Chosen modes.

Selected Mode	Count
Car	1258
Self-driving car	638

Driverless ridehailing	207
Ridehailing	223
Transit	121
Bike	297
Walk	104

The distribution of trip purposes for the first trip of the workday are shown in Table 11.

Table 11 Trip Purposes

Purpose	Count
Work	671
Pick up/Drop off	17
Family/Personal Errands	16
Social and Recreational Activities	9
Other	6
Not recorded/Missing	31

The driving travel time distribution is summarized in Table 12.

Table 12 Driving travel time distribution in minutes

Minimum	1st quantile	Median	Mean	3rd quantile	Maximum
1.0	6.5	13.5	17.0	22.3	158

Methods

Traditional discrete choice models treat the decision-makers as an "optimizing black box" and have focused on observable variables such as attributes of alternatives, socio-economic characteristics of decision-makers, market information, and past experiences as inputs that can determine choice (McFadden, 1986). However, findings from studies in the social sciences have shown that latent constructs such as attitudes, norms, and perceptions can override the influence of observable variables of disaggregate behavior (Vij & Walker, 2015; Bamberg & Schmidt, 2001; Gärling et al., 2003; Anable, 2005). Figure 9 illustrates the decision-making process. Terms in rectangles can be observed or measured by proper experiments. Terms in ovals are unobservable latent variables. Perceptions, generalized attitudes, preferences, decision protocols, and behavioral intentions are essential constructs in the modeling of cognitive decision process (McFadden, 1986). Although these latent constructs cannot be measured directly, latent variable modeling techniques hypothesize that their effects on measurable variables can be observed and measured (Walker & Ben-Akiva, 2002).

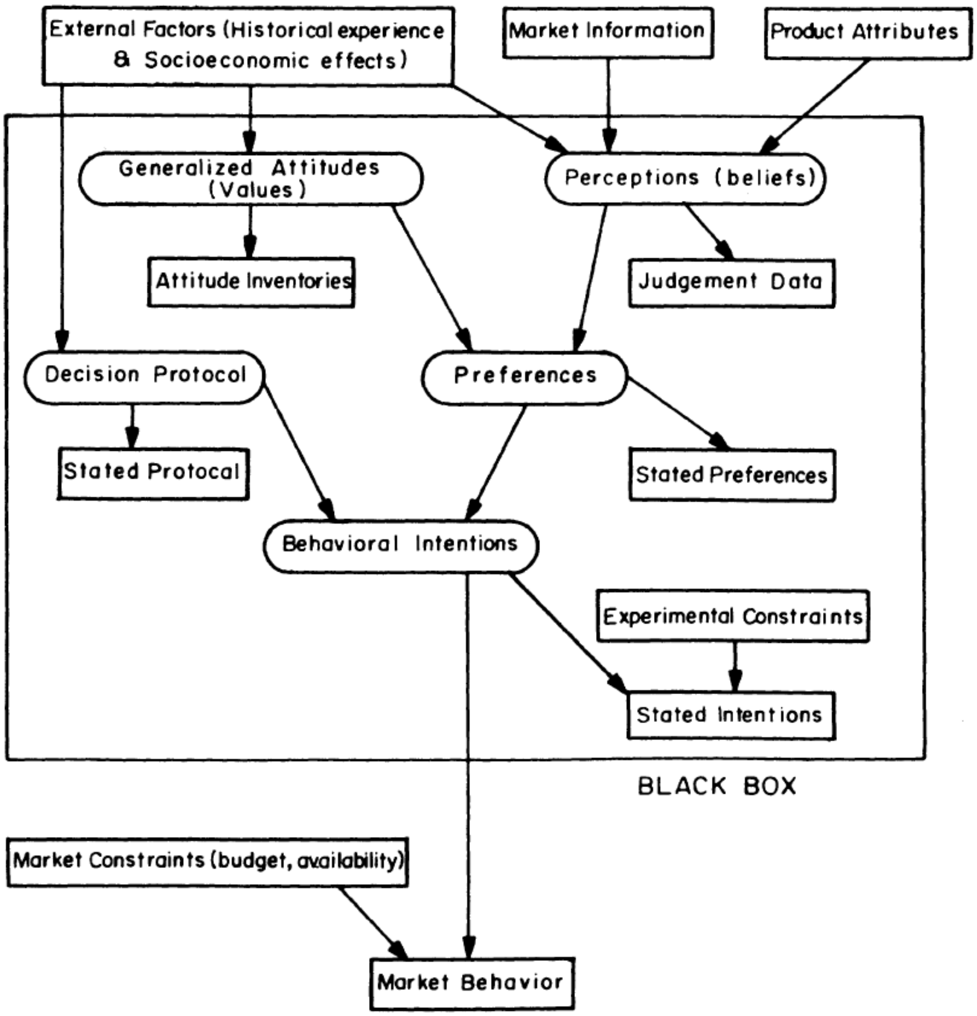

Figure 9 Path diagram for the customer decision process (McFadden, 1986)

ICLV models are an extension of traditional discrete choice models that fall under the broader umbrella of hybrid choice models (HCMs). ICLV models explicitly incorporate psychological factors such as attitudes and perceptions into choice model, and model the cognitive processes underlying the formation of a choice (Vij & Walker, 2015; Walker & Ben-Akiva, 2002). ICLV models include a choice model formulation that contains unobserved psychometric measures (e.g., attitudes and perceptions) incorporated through latent variables, along with observed variables. Perception variables capture how decisionmakers perceive attributes of different alternatives. Attitudes reflect decisionmakers' tastes, needs, goals, and capabilities that have been shaped over time and are impacted by both experience and factors such as their socioeconomic characteristics (Bolduc and Daziano, 2010).

Bolduc and Daziano (2010) described the estimation techniques and implementation of ICLV models using empirical data. They showed that estimating ICLV models using simulated maximum likelihood can be successfully implemented. They concluded that the ICLV model provides an "unbiased, consistent, and smooth estimator of the true probabilities." Their case study showed that the ICLV model could be adopted for practical situations and improve understanding of consumer profiles and new technology adoption.

Vij and Walker (2015) evaluated the ICLV modeling framework's statistical properties and compared them to a reduced form choice model without latent variables. They found that ICLV models do not offer improvements in terms of goodness-of-fit and the consistency of parameter estimated over the reduced form choice models. However, ICLV models allow identification of structural relationships between observable variables that could not be identified using choice models without latent variables. They also found ICLV models are potentially more efficient in estimating parameters than reduced form choice models without latent variables.

Applications of ICLV models in transportation and specifically mode choice studies have been growing over the past two decades. For example, Morikawa et al. (2002) included comfort and convenience latent variables in their study of mode choice. They found integrating latent variables improves goodness-of-fit, and both latent variables are significantly positive. Johansson et al. (2006) included latent variables for attitudes towards flexibility and comfort, and for being pro-environment, in their mode choice model. They found that both influence mode choice decisions. They concluded that in addition to economic incentives, there are other ways to attract individuals to different modes of transportation. Ding et al. (2017) compared the ICLV model with the traditional model and explored the influence of attitudes toward active modes on mode choices. They found that the ICLV model outperforms traditional models in terms of fit and explanatory power, and attitudes toward active modes play an essential role in the nonmotorized mode choice. Bouscasse (2018) has conducted an extensive literature review of ICLV models' applications in mode choice modeling. They concluded that even though forecasting is difficult when using ICLV models, ICLV models are useful for informing policy development and recommendations.

Figure 10 depicts the ICLV framework we adopted for this study. There are two main components: (1) a discrete choice sub-model and (2) a latent variable sub-model. Each of the sub-models includes a structural and a measurement component (Vij & Walker, 2015). Under the random utility maximization (RUM) framework, the standard choice model is a latent variable model itself. Utility is a latent construct that measures an individual's satisfaction conditional on attributes of each alternative. Structural equations describe the latent variables in terms of observable exogenous variables, and measurement equations link latent variables to indicators. For the latent variable sub-model, indicators can be responses to psychometric questions. For the choice model, the indicator is the decision maker's choice (whether revealed or stated) (Vij & Walker, 2015, Bolduc & Daziano, 2010).

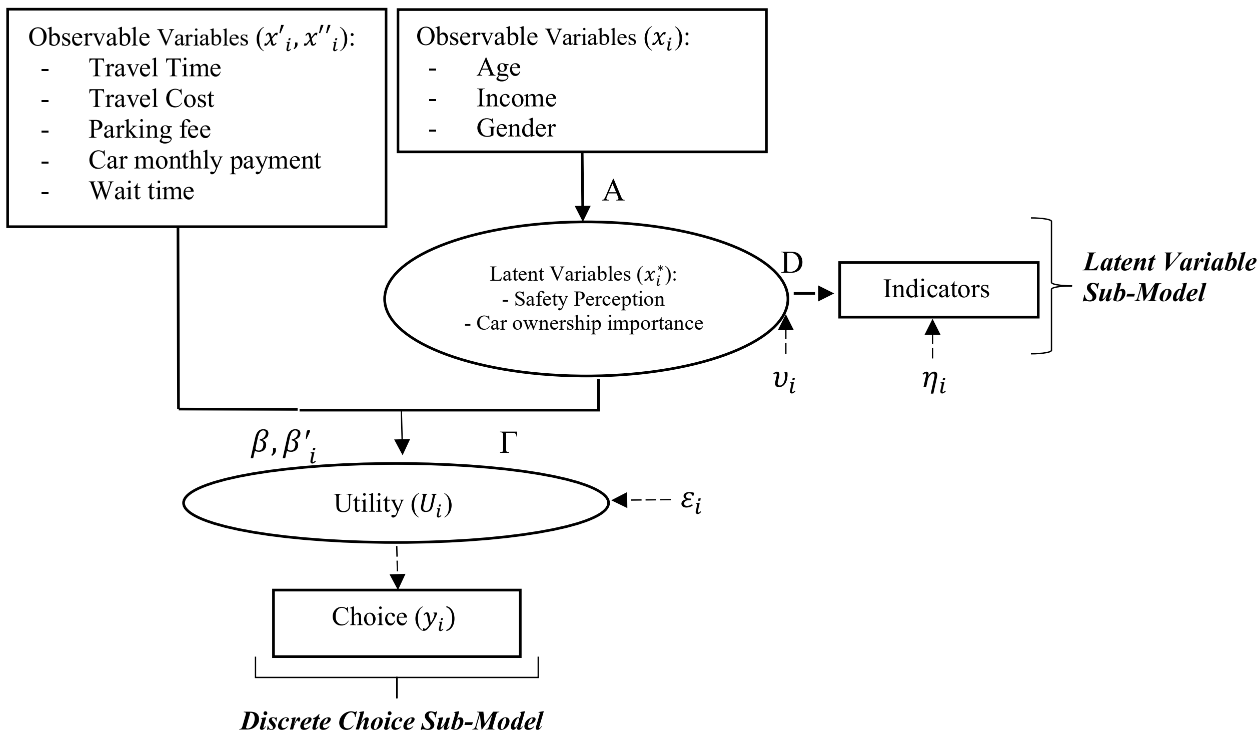

Figure 10 The ICLV framework (adapted from Vij and Walker, 2015)

We adopted Vij and Walker's (2015) ICLV model representation and used a mixed logit model as the discrete choice sub-model.

Structural equations

$$U_i = \beta x''_i + \beta'_i x'_i + \Gamma x_i^* + \varepsilon_i \quad (9)$$

$$x_i^* = A x_i + \upsilon_i \quad (10)$$

Measurement equations

$$I_i = Dx_i^* + \zeta_i \quad (11)$$

$$y_i = \{1\, if\, u_{ij} \geq u_{ij'}\, for\, j' \in \{1, \ldots, J\}\, 0\, otherwise \quad (12)$$

Where U_i is the vector of utilities of each of the *J* alternatives for the decision-maker i, x_i, x'_i and x''_i are the vectors of observable explanatory variables and $x_i^*$is the vector of latent variables, β and Γ are the matrices of unknown model parameters corresponding to observable and latent variables, respectively. β'_i is the matrix of random coefficients corresponding to observable variables for person i representing that person's tastes. ε_i is the vector indicating the error terms associated to utilities, assumed to be iid extreme value; *A* is the matrix of parameters that indicate the structural relationship between the latent and observable variables. υ_i is the vector of stochastic component of that relationship from a normal distribution.

The measurement model links the latent variables to indicators. I_i corresponds to a vector of indicators used to measure the latent variables for the decision-maker i. *D* is the matrix of unknown parameters that indicate the relationship between indicators and latent variables, and ζ_i is a vector of measurement equations error terms that are normally distributed; y_{ij} is the choice indicator (Vij and Walker, 2015).

Since we used a Likert scale to collect data on our indicators, the probability of a given response can be calculated by the ordered probit. For the case of multinomial ordered probit with L responses, equation 3 is updated as below (such as 6-point Likert scale, L = 6):

$$I_i^* = Dx_i^* + \zeta_i \quad (13)$$

$$I_i = \begin{cases} 1 & if\, \gamma_0 < I_i^* < \gamma_1 \\ 2 & if\, \gamma_1 < I_i^* < \gamma_2 \\ L & if\, \gamma_{L-1} < I_i^* < \gamma_L \end{cases} \quad (14)$$

More details on theoretical concepts can be found in Vij and Walker (2015) and Bolduc and Daziano (2010).

Results

We conducted a confirmatory factor analysis and confirmed the relationship between indicator questions and latent variables developed by Ge et al. (2019) in our data. In our model each individual can have up to four choice scenarios and we captured the repeated observation nature of the data through random effects on travel time variable. For each individual, we considered their first trip of the day mode choice for modeling.

We found the perceived safety of AVs and car ownership importance to be statistically significant, and they improved the explanatory power of the model. Perceived safety of AVs was included in the utility functions for the self-driving car and driverless ridehailing modes. For car ownership importance, we estimated three coefficients: one for privately-owned options, one for driverless ridehailing, and another one for the regular ridehailing option.

To estimate the random effects, we used 2500 Halton draws taken from a normal distribution. Results corresponding to different parts of the model are presented in Tables 6, 7, and 8.

Table 13 ICLV model results

Variable		Estimate	Std error	*t*-test	*p*-value
Car					
Monthly Payment/Monthly Income		-3.08	0.41	-7.56	<0.001
Parking fee/Daily Income		-6.60	2.84	-2.32	0.02
Travel Time (hr)	mean	-2.00	0.32	-6.29	<0.001
	std. dev.	2.27	0.42	-5.41	<0.001
Alternative-specific constant		0.98	0.27	3.63	<0.001
Car ownership importance		1.22	0.14	8.53	<0.001
Self-driving car					
Monthly Payment/Monthly Income		-3.08	0.41	-7.56	<0.001
Parking fee/Daily Income		-6.60	2.84	-2.32	0.02
Travel Time (hr)	mean	-2.35	0.43	-5.49	<0.001
	std. dev.	3.21	0.52	-6.22	<0.001
Alternative-specific constant		0.16	0.28	0.55	0.58
Safety of AVs		0.46	0.04	12.30	<0.001
Car ownership importance		1.22	0.14	8.53	<0.001
Driverless Ridehailing					
Cost/Daily Income		-5.21	0.69	-7.60	<0.001
Wait Time (hr)		0.01	0.02	0.86	0.39
Travel Time (hr)	mean	-1.55	0.53	-2.95	<0.001
	std. dev.	0.17	0.53	0.37	0.75
Alternative-specific constant		-0.83	0.30	-2.79	<0.001
Safety of AVs		0.46	0.04	12.30	<0.001
Car ownership importance		0.81	0.17	4.68	<0.001
Ridehailing					
Cost/Daily Income		-5.21	0.69	-7.60	<0.001
Wait Time (hr)		0.01	0.02	0.86	0.39

Travel Time (hr)	mean	-4.42	0.89	-4.99	<0.001
	std. dev.	2.44	0.68	3.60	<0.001
Alternative-specific constant		0.16	0.28	0.58	0.56
Car ownership importance		0.57	0.17	3.34	<0.001
Transit					
Cost/Daily Income		-5.21	0.69	-7.60	<0.001
Wait Time (hr)		0.03	0.02	1.21	0.22
Travel Time (hr)	mean	-2.97	0.55	-5.42	<0.001
	std. dev.	1.92	0.35	5.46	<0.001
Bike					
Travel Time (hr)	mean	-10.80	1.28	-8.41	<0.001
	std. dev.	-6.50	0.74	-8.82	<0.001
Alternative-specific constant		2.63	0.29	8.93	<0.001
Walk					
Travel Time (hr)	mean	-55.80	13.10	-4.26	<0.001
	std. dev.	30.90	7.18	-4.31	<0.001
Alternative-specific constant		5.08	0.59	8.58	<0.001

Initial log likelihood: -18684.46
Final log likelihood: -13303.33
Adjusted Rho-square: 0.285
Akaike Information Criterion (AIC): 26708.66
Bayesian Information Criterion (BIC): 26944.49

We assumed a linear structural regression equation for the chosen latent variable. We created two age categories: Millennials and Generation Z (18-38 years old at the time of the survey) and older respondents (39 years old and older). We included two income categories: over sample median (over $60,000) and below sample median (below $60,000). Table 14 shows the estimated structural model. We found that income is not statistically significant for either safety perception or car ownership importance. Individuals older than 38 years old perceive self-driving cars as less safe than younger individuals, and they perceive car ownership as more important. Also, male respondents perceive self-driving cars as safer and place less importance on car ownership than their female counterparts.

Table 14 Structural model results

Structural Model	estimate	Std err	t-test	*p-value*
Safety Perception				
Age (Older than 38 years old)	-0.68	0.15	-5.01	<0.001

Income (Over $60k)	-0.12	0.13	-0.95	0.34
Gender (Male)	0.84	0.13	6.47	<0.001
Intercept	0.33	0.11	2.97	<0.001
Error component	1.64	0.07	23.70	<0.001
Car ownership importance				
Age (Older than 38 years old)	0.17	0.07	2.41	0.01
Income (Over $60k)	0.09	0.07	1.32	0.19
Gender (Male)	-0.14	0.07	-2.16	0.03
Intercept	1.01	0.07	14.20	<0.001
Error component	0.83	0.04	20.70	<0.001

The coefficients on the first indicators of both safety perception and car ownership importance were set to 1, and coefficients in other indicators are estimated relative to the first one. All the estimates have a positive value because higher-ranking responses correspond to a higher perception of self-driving car safety. Table 8 shows these estimates.

Table 15 Measurement model results

Indicators	Estimates	Standard Error
Safety Perception		
I am ______ self-driving vehicles can drive as well as human drivers in general. (1- Extremely doubtful, 2- Doubtful, 3- A little doubtful, 4- Sort of confident, 5- Confident, 6- Extremely confident)	1.00	-
Driverless cars generally will be ______compared with most drivers on the road. (1- Much more dangerous, 2- More dangerous, 3- Somewhat more dangerous, 4- A little safer, 5- Safer, 6- Much safer)	1.04	0.04
Widespread use of self-driving vehicles would result in ______crashes. (1- A lot more, 2- More, 3- Slightly more, 4- Slightly fewer, 5- Fewer, 6- A lot fewer)	1.07	0.04
Driverless cars generally will be ______than I am as a driver. (1- Much more dangerous, 2- More dangerous, 3- Somewhat more dangerous, 4- A little safer, 5- Safer, 6- Much safer)	0.90	0.04
I ______trust self-driving car technology to keep me safe when I am riding in one. (1- Definitely would not, 2- Probably would not, 3- Maybe would not, 4- Maybe would, 5- Probably would, 6- Definitely would)	1.10	0.04
Car ownership importance		
Owning a car is a(n) ______part of being an adult. (1- Not important at all, 2- Not important, 3- Not so important, 4- Somewhat important, 5- Very important, 6- Extremely important)	1.00	-
Owning a car I can use anytime is ______. (1- Not at all important, 2- Not important, 3- Not so important, 4- Somewhat important, 5- Very important, 6- Extremely important)	1.83	0.07
Driving my own car is ______ . (1- Not empowering at all, 2- Not empowering, 3- Not so empowering, 4- Somewhat empowering, 5- Very empowering, 6- Extremely empowering)	1.32	0.06
The flexibility of driving by myself is ______. (1- Not at all important, 2- Not important, 3- Not so important, 4- Somewhat important, 5- Very important, 6- Extremely important)	1.65	0.07
The ability to make spontaneous stops when I drive my own car is ______ to me.	1.40	0.06

(1- Not at all important, 2- Not important, 3- Not so important, 4- Somewhat important, 5- Very important, 6- Extremely important)

The above results show that perception of AV safety and car ownership importance both have a direct, positive, and statistically significant impact on the utility of self-driving cars and driverless ridehailing services. The estimated effect of car ownership importance for privately owned options (regular car and self-driving car) is 1.6 times higher than for driverless ridehailing. This means that individuals who place more importance on car ownership are more likely to choose a privately owned car or self-driving car relative to driverless ridehailing, and driverless ridehailing over other modes (e.g. regular ridehailing, transit, bike, and walk). Even though the in-vehicle experience in the driverless ridehailing service and self-driving car is likely to be similar, larger psychological dependency on cars favors privately owned vehicles more than any other mode.

As individuals perceive AVs as being safer, they are more likely to choose them as their mode of transportation. We looked at the equivalent monetary value of safety perception on the choice of self-driving cars and driverless ridehailing services for an individual with a \$60k income. A one unit improvement in the safety perception latent variable, holding all else equal, increases the utility of these modes by 0.46 units of utility.

$$\Delta\, utility = \beta_{Safety\ perception} . \Delta\, Safety\ perception \tag{15}$$

$$\Delta\, utility = 0.46 \times 1$$

For the case of a privately-owned self-driving car, this is similar to the change in utility that would result from decreasing the monthly car payment by about \$750:

$$\Delta\, utility = \beta_{\frac{Monthly\ payment}{Monthly\ income}} . \Delta \frac{Monthly\ payment}{Monthly\ income} \tag{16}$$

$$0.46 = -3.08 . \frac{\Delta Monthly\ payment}{60{,}000/12} . \Delta Monthly\ payment = -\$746.75$$

For driverless ridehailing, a one unit improvement in safety perception provides the same utility benefit as decreasing cost of the trip by \$14.51:

$$\Delta\, utility = \beta_{\frac{Ride\ cost}{Daily\ income}} . \Delta \frac{Ride\ cost}{Daily\ income} \tag{17}$$

$$0.46 = -5.21 \cdot \frac{\Delta Ride\ cost}{60{,}000/365} \cdot \Delta Ride\ cost = -\$14.51$$

For both of the modes, the influence of a one unit change in safety perception is considerable. However, since safety perception is a latent construct, a one-unit change does not have an intuitive meaning. To better contextualize the meaning of this latent variable, Figure 11 illustrates how a one unit increase in the safety perception latent variables changes the distributions of the associated indicators.

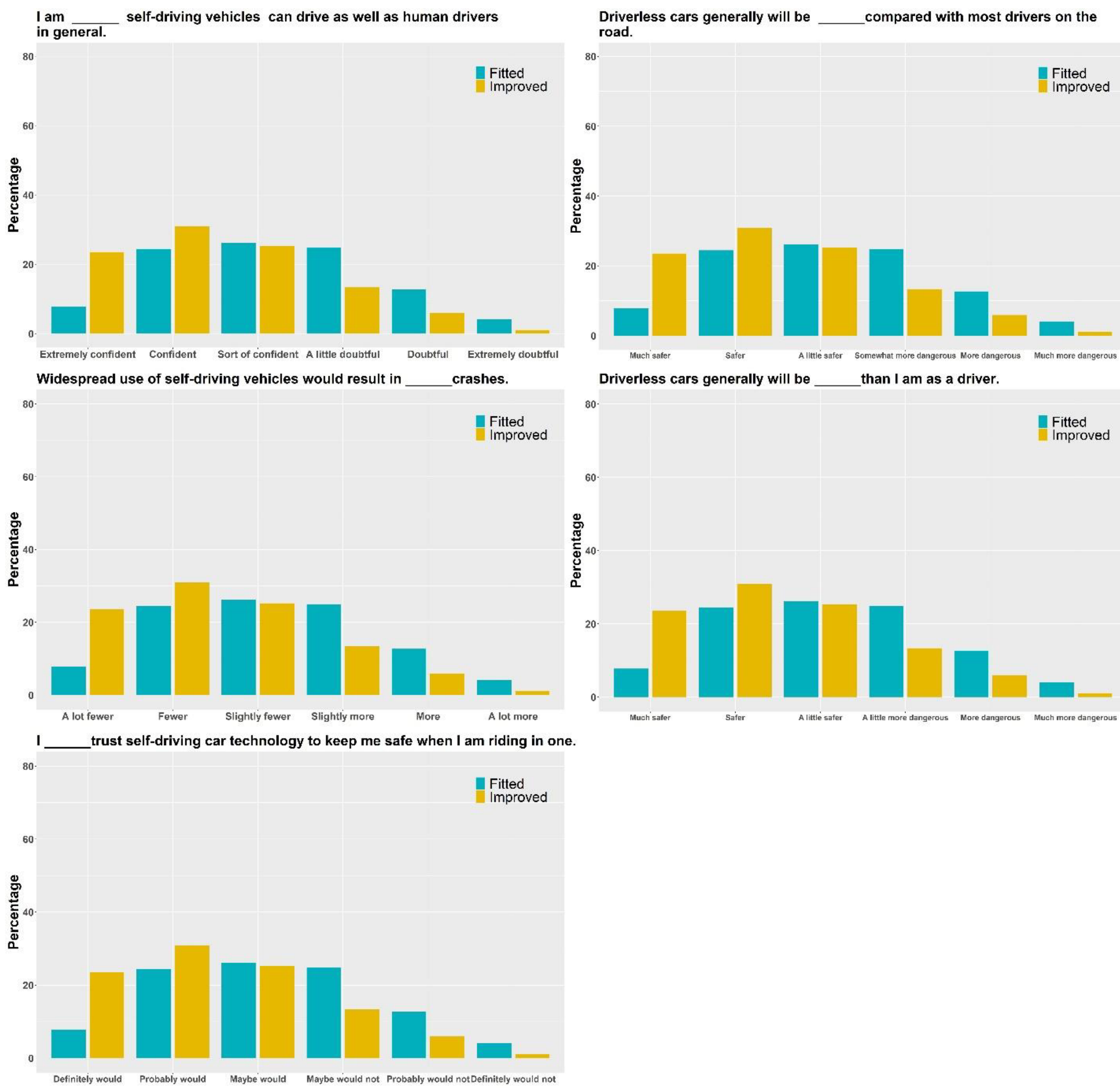

Figure 11 Fitted values of indicators in our sample vs. indicators after a uniform, one-unit increase in safety perception latent variable for all respondents.

Next, we explored four different scenarios, to demonstrate the potential impact of change in safety perception on the market share of driverless ridehailing.

For the base scenario, we used attributes' base levels and individuals' collected API data. The base level for self-driving car monthly payment and individuals who did not own a car was \$500 and for individuals who owned a car we used their self-reported monthly payment.

For the first scenario, we decreased the monthly cost of owning a self-driving car by 50% to \$250. In the second scenario, we assumed that the cost of riding in a driverless ridehailing service decreased by 75% due to much lower labor costs. In the third scenario, we improved safety perceptions of some of the individuals by reducing the estimated safety perception distribution's variance. We achieved this distribution by reducing the difference between each person's fitted safety perception and the highest fitted safety perception value by half. Figure 12 illustrates fitted safety perception density and how it changed in the improved version. Figure 13 shows expected responses to attitudinal statements when safety perception improves under this scenario and compares them with actual responses. Under scenario 3, everyone perceives AVs' safety positively.

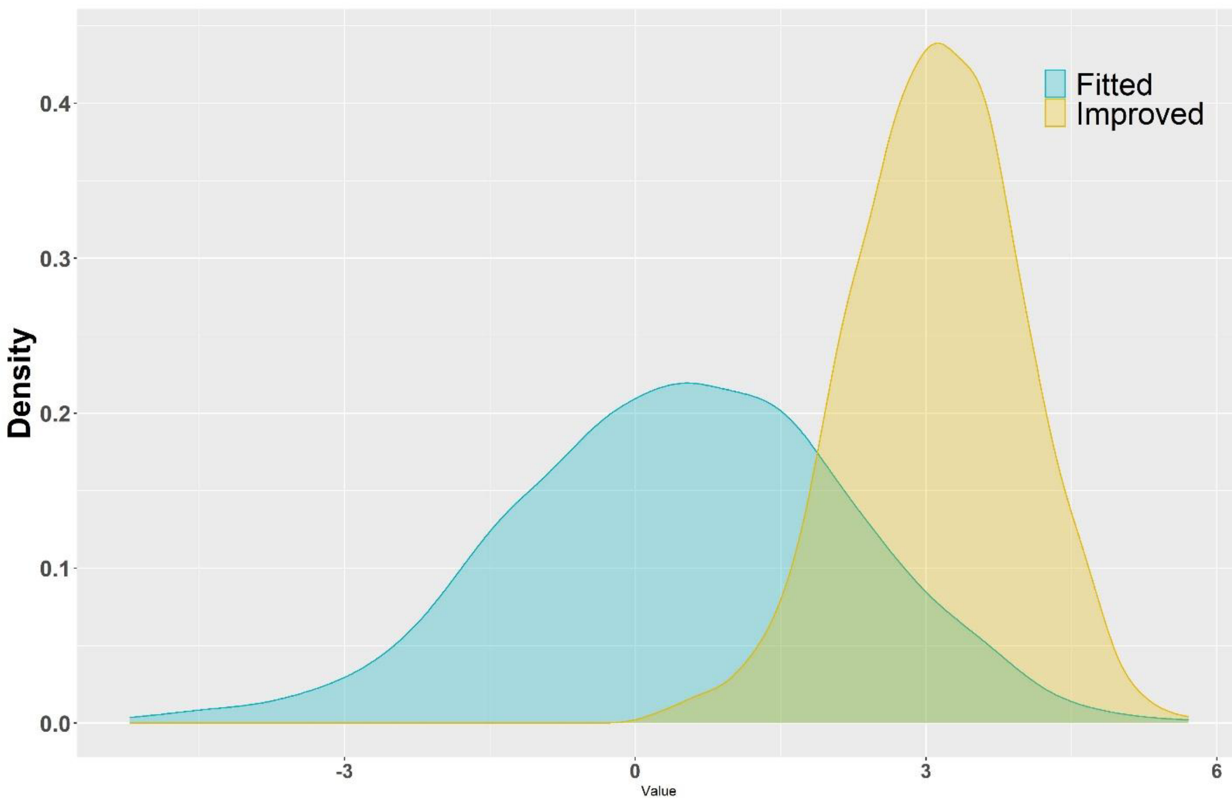

Figure 12 Fitted safety perception vs. improved safety perception densities

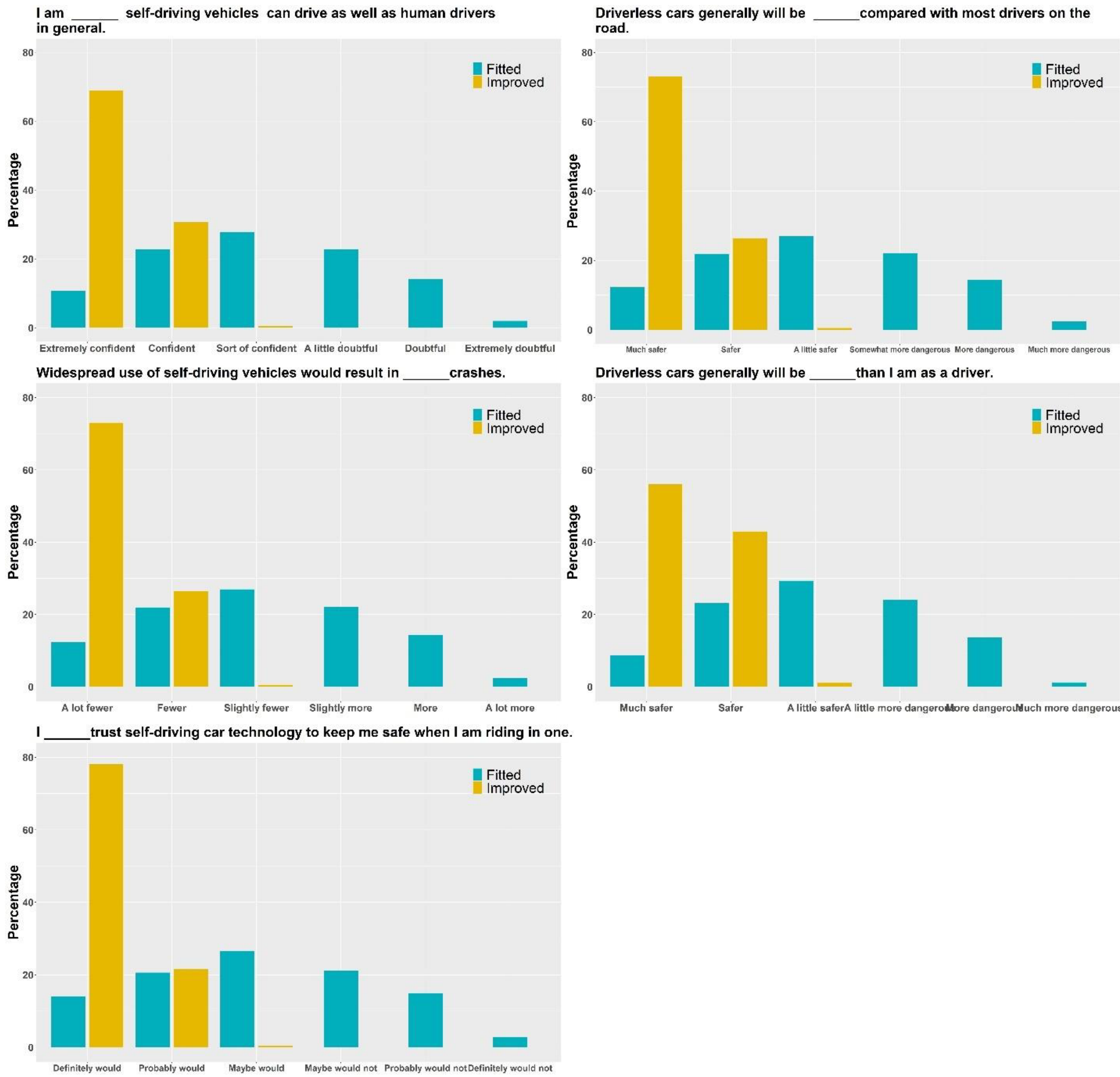

Figure 13 Expected responses after improved safety perception (scenario 3 and 4) vs fitted responses

In the fourth scenario, we explored how a simultaneous decrease in driverless ridehailing cost and better safety perceptions affect the market shares. Table 16 shows the market share of each mode under different scenarios.

Table 16 Market share under different scenarios

	Car	Self-driving car	Ridehailing	Driverless ridehailing	Transit	Bike	Walk
Base Scenario	68.6%	15.4%	0.1%	0.7%	1.4%	11.0%	2.6%
50% lower self-driving car price	65.1%	19.0%	0.1%	0.7%	1.4%	10.8%	2.6%
75% lower ridehailing fares	63.0%	11.5%	0.1%	12.1%	0.9%	9.6%	2.5%
Improved Safety Perception	32.5%	50.8%	0.0%	3.6%	0.8%	9.5%	2.6%
Improved Safety Perception & 75% lower ridehailing fares	29.7%	49.7%	0.0%	8.3%	0.5%	9.0%	2.6%

In scenario 1, market share of self-driving car increases by 3.6% due to halving the monthly payment while keeping the monthly payment for regular car the same as the base scenario. When the cost of driverless ridehailing drops to 25% of the current cost of ridehailing services, driverless ridehailing market share increases by 11.4%, mostly taking travelers from privately owned options. In scenario 3, when the perception of AV safety improves, self-driving cars dominate the market by taking approximately 50% of the market, and regular cars' market share drops to less than half of its base scenario share. This scenario highlights the magnitude of safety perception's effect on the market shares. When safety perception improves, more people switch to AVs from their regular cars. In the last scenario, when we reduce driverless ridehailing cost, self-driving car market share remains about the same relative to the third scenario, but the market share of driverless ridehailing doubles relative to the third scenario. In this scenario, driverless ridehailing market share is still lower than the second scenario, even though both cost and safety perception have improved; this means that the overall utility of driverless ridehailing does not surpass the utility of the self-driving car.

These scenarios demonstrate that under current conditions, even if AV prices were lower, we would not expect self-driving cars to take over the private car market. They highlight the role safety perceptions can play on the demand for private AVs. If AVs' safety improves and the public's perception of safety improves with it, consumers may ascribe higher utility to self-driving cars and driverless ridehailing services. Personal AVs' safety has the potential to compensate for their high costs. Consumers may be willing to pay more to use this technology if they perceive it as safe. For driverless ridehailing, their mode share would grow if AVs enabled a 75% reduction in fares, even if the safety perception remained the same as today. With safety perception improvements, more people would opt for privately owned self-driving cars, resulting in smaller mode share for driverless ridehailing services. This may have implications for policy making as prior research has found that as more households opt for privately owned self-driving cars, vehicle miles travelled (VMT) increases considerably as AVs significantly change the travel behavior of owners (Auld et al., 2019; U.S. Department of Energy,2020).

Discussion

A limited number of prior studies have linked mode choices to the perceived safety of AVs using hybrid choice modeling. One recent paper (Kolarova, and Cherchi, 2021) explored the effect of trust in automated technology on value of travel time savings (VTTS). In that study, the authors used a similar method (ICLV framework) to capture the latent variable's impacts on mode choices. They found that trust in the AV technology significantly affects the VTTS for AV modes and, ultimately, mode choices. In addition, the authors highlighted the importance of individual attitudes on preferences for AVs, which is consistent with our findings. Another study (Yap et al., 2016) adopted a similar approach to explore preferences for using automated vehicles as last-mile public transport trips. The authors included trust in AVs as a latent variable in their mode choice model and found it to have a positive and statistically significant effect on the utility of choosing an AV as egress mode.

While our scenarios help to gauge the importance of safety perceptions, they beg the question: How achievable are the assumed improvements in safety perceptions? A 2014 survey (Beck et al., 2018) of an online consumer panel in Sydney, Australia, helps to contextualize these scenarios. In that work, more than 90% of respondents responded between "neutral" and "strongly agree" that "Overall I feel safe when on-board an aircraft" (Figure 14). Although the question wordings and response scales are not the same, comparing Figures 13 and 14 suggests that our scenarios involving improved safety perception represent a world in which AVs are seen as similarly safe or safer than air travel was seen in 2014.

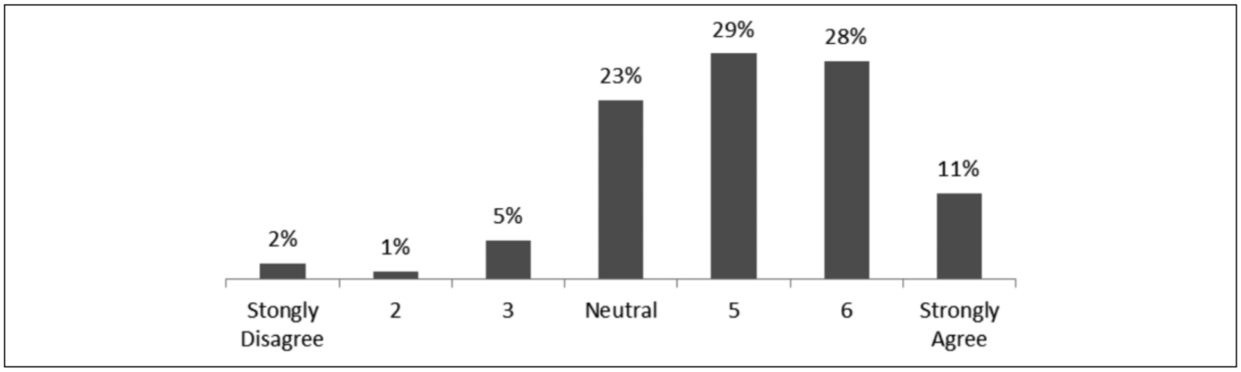

Figure 14 Agreement with the statement "Overall I feel safe when on-board an aircraft" in a 2014 survey in Sydney, Australia (from Beck et al., 2018).

This in turn points to the questions: How might safety perceptions be improved in practice? Is there a role for policy, or marketing campaigns? Or will perceptions improve naturally if AVs build a track record of safe performance? Again, this paper does not address these questions directly, but the literature does provide some clues.

Fischhoff et al. (1978) studied perceived risk, acceptable risk, and perceived benefit for 30 activities and technologies. They also studied nine descriptive attributes of risk and found them to fall under two basic dimensions, which they labeled "technological risk" and "severity." Figure 15 shows the location of activities within their two-factor space. Notably, their respondents perceived commercial aviation risks as more severe than those of motor vehicles, even though statistics show that odds of dying in a motor vehicle crash are far greater than odds of dying in a passenger aircraft incident. They also associate commercial aviation with involuntary and uncontrollable items that have consequences for masses of people, but perceive motor vehicles as voluntary activity with consequences at the individual level. Riding in a fully automated car is similar to driving a conventional motor vehicle in terms of having consequences at the individual level and which may be less than catastrophic. However, AV travel shares some characteristics with commercial aviation such as riders not having control over the vehicle. We might therefore expect self-driving cars sits somewhere between motor vehicle and commercial aviation in this two-dimensional space.

Cognitive biases mean that improving the objective safety performance of AVs may not, on its own, lead to commensurate improvements in perceived safety. The availability heuristic (Tversky and Kahneman, 1973) is a cognitive bias in which a person's subjective assessment of the probability of an outcome is affected by the ease with which a representative case can be recalled. Anchoring effects mean that individuals tend to remain attached to initial assessments and update their assessments insufficiently (Tversky and Kahneman, 1974). Together, these biases suggest that early, high-profile incidents involving AVs may lead to fairly resilient perceptions of the technology as being unsafe. Regulation of AV testing in a way that mitigates catastrophic harms and the risk of early, high-profile incidents may therefore help to improve perceptions of AV safety.

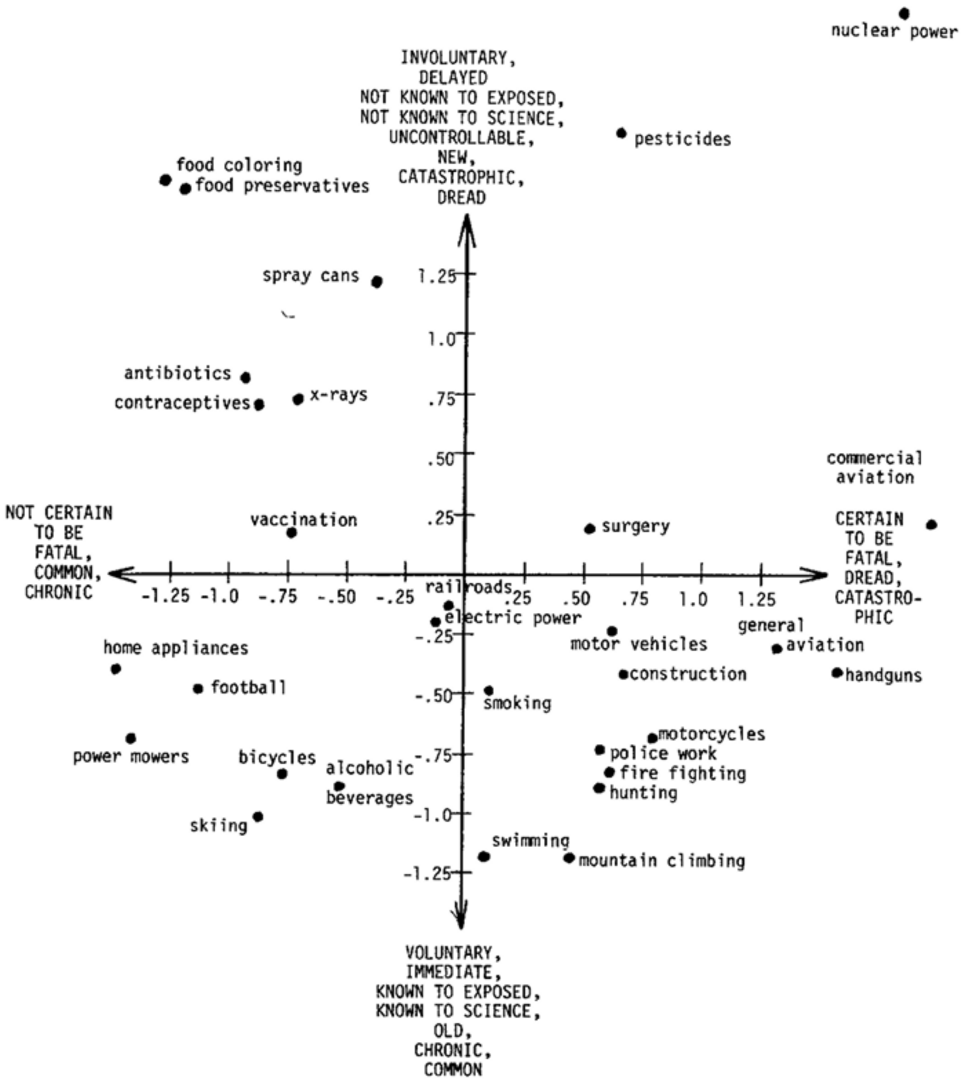

Figure 15 Location of risk items within the two-factor space (from Fischhoff et al. *(44)*)

Conclusion

Despite many potential merits of AVs, studies have found several barriers to AV adoption. The one obstacle that stood out the most during our literature review was the perception of safety. We were also interested in understanding challenges for the adoption of driverless ridehailing service. We hypothesized that individuals who are psychologically attached to car ownership are more likely to avoid such a service.

In this work, we quantified the impact of two latent constructs – the perceived safety of AVs and the importance of car ownership – on choosing two AV options: (1) privately owned self-driving car and (2) driverless ridehailing service. We used an integrated choice and latent variable model to model mode choice and incorporated the two latent variables through sets of structural and measurement equations.

We found that both safety perception and car ownership importance have a statistically significant effect on choosing AV modes. Our results show that car ownership importance has the most substantial impact on choosing privately owned cars, followed by driverless ridehailing and regular ridehailing. This finding confirms our initial hypothesis that the more psychologically attached individuals are to their vehicles, they are more likely to choose personal cars as their mode of transport. Interestingly, between the driverless ridehailing and regular ridehailing, individuals who are more car dependent prefer the former over the latter.

Another interesting finding of this analysis is the magnitude of safety perception effect on mode choice and how it compares with costs. We demonstrated what a one unit change in safety perception means in terms of equivalent monetary impact. However, one unit of safety perception improvement is not very intuitive. Therefore, we tested several scenarios to better grasp the effect of safety perception improvements. We determined a base scenario using API data collected for each individual's trip and base values for other attributes. Then, we discovered that shifting people's perceptions toward positive AV safety perception can drastically change AVs' market share. While keeping regular car monthly payments constant and reducing self-driving car payment, we observed that self-driving car market grew by 4.4%. However, when safety perception improved, its market share grew by about 35%, taking over 50% of the market. Based on our analysis, privately owned self-driving cars will dominate driverless ridehailing services and reducing fare can help expand their market share.

Under current conditions, we would not expect self-driving cars to take over the private car market. Even if prices were much cheaper, the market would only grow slightly. However, improving safety perception would have a big impact on demand for private AVs. In contrast, the mode share of driverless ridehailing would grow substantially if AVs permitted a 75% reduction in fares, even if safety perceptions did not change from today. And if safety perceptions did improve, the effect for driverless ridehailing could be negative, as more people would opt for personal AVs.

All in all, this study provides empirical evidence for the crucial role of psychological factors, specifically safety perception and car ownership importance, when analyzing AV modes adoption.

Limitations and future research

In this paper, we quantified the effect of safety perception on mode choices regarding self-driving vehicles and driverless ridehailing services, and illustrated the relationship between safety perception and market share of AV modes through scenario testing. The findings of this study do not tell us how to improve or change the public's safety perceptions; instead, they highlight and quantify the considerable role safety perception plays in the adoption of AV modes and its implications for mode share relative to other mode attributes. One of the avenues for future research, therefore, would be to study risk attributes relating to AVs and how perceptions of safety are formed. We further recommend exploring and quantifying the effect of various strategies on the evolution of the public's perceptions. These strategies might include exposure to the technology, policy instruments, educational and marketing campaigns. For example, Brell et al. (2019) studied the influence of experience on the perceived risk and safety of conventional and automated driving. They found that risk perceptions connected to the vehicle itself decrease as people are more experienced with high automation functions such as adaptive cruise control; however, the magnitude of this decrease is unknown. In addition, it is probable that different groups of users have different receptiveness to various strategies, and it is worthwhile to explore how individuals with diverse socio-demographics respond to them.

Chapter 4: Tour-based mode choice model

Introduction

In chapter two, we discussed the extensive survey we designed and implemented. In that survey, respondents participated in a choice experiment that included a travel day, and they needed to choose a mode for each trip of the presented travel day. The purpose of designing the experiment as described was to make it as realistic as possible. Even though trip-based mode choice models may be more appropriate for some cases, according to Ben-Akiva et al. (1998), they lack "behavioral realism," as one's mode choices for different trips in a tour are usually not independent. Additionally, historically, travel surveys are mainly focused on the primary mode of travel, and multimodal travel has been neglected (Clifton and Muhs, 2012) even though multimodal information is necessary to comprehend the market demand for modes beyond privately owned vehicles.

Ben-Akiva et al. (1998) explored the complexity of the work tours in Boston. They found that travel patterns vary dramatically across the population. They highlighted that simplistic models could not capture the heterogeneity of people and the variety of patterns in which travel occurs. They discussed policies that aim to achieve their objective by influencing individuals' behavior and capturing the complex ways that travelers adjust their behavior. Tour-based modeling matches the process of making travel decisions more closely compared to trip-based approaches. Tour-based mode choice models are often implemented as components of activity-based models when decisions such as car ownership, residential location choice, or destination choice are also included in the analysis. Previous studies have approached tour-based mode choice modeling using various methods, but many share some common traits such as (1) simplification in the definition and construction of tours and (2) assumption of a ''main'' mode (Miller et al., 2005).

Frank et al. (2008) used a tour-based modeling framework to explore how travel time, cost, and land-use patterns affect mode choice and trip chaining behavior. First, they identified the tour's primary mode based on which mode controls individuals' travel planning. Then, authors built a mode choice model for each type of tour (e.g., home-based work, home-based other, work other work) using revealed data from a household travel survey conducted in Puget Sound Region. They found that travel time was the strongest predictor of mode choice while urban form was the strongest predictor for the number of stops within a tour. Roorda et al. (2009) also used a tour-based model to incorporate minor modes (e.g., bicycling, drive/transit access commuter rail, drive access subway) of transportation into a simulation-based behaviorally realistic mode choice model. Authors reported limited success in modeling and correctly predicting some of the modes, such as drive access to subway, taxi, bicycle modes. Bastarianto et al. (2019) studied the relationship between tour type and mode choices using different logit models. However, their study did not explore multimodal tours, and it is focused on the effect of socioeconomic characteristics on mode choices for different types of tours. Ho and Mulley (2013) formulated a tour-based mode choice model contingent on the choice of joint tour patterns among household members. The authors adopted a nested logit framework for modeling and used the primary mode of travel for the mode choice level. Similar to our survey, they assumed that if car is used for the first trip of the tour, it should be used for the whole tour.

Miller et al. (2005) introduced a tour-based mode choice model framework that incorporates within-household, inter-personal interaction. The model allows variation in mode choices for different trips within a tour and assumes that respondents choose the "best" combination of modes available. Furthermore, the authors assumed the utility of choosing a combination of modes for the entire tour is equal to the sum of the utilities of the trips within the tour. We adopted part of their model structure for one of our models in this study.

In this chapter, we strived to adopt a tour-based approach to model mode choices and explore whether this approach improves the prior work in mode choice modeling. In particular, we aimed to create models with better behavioral realism. Behavioral realism is critical in the context of automated vehicles and future mobility services to understand how travelers incorporate these modes in their travel routines since having no experience planning their travels using these modes.

We used the dataset collected through the survey previously described in chapter two and hypothesized two possible approaches for their thinking process when deciding about trips within a tour. When making decisions, respondents may have considered each trip independently and maximized the utility of each trip independently of their prior mode choices, or they may have considered the previous mode when choosing the next mode. Based on these two thinking processes, we formulized and estimated two models. Later in the chapter, we discuss the results and findings from both models.

Data

Out of 1000 respondents who participated in our survey, 676 were eligible, and their corresponding data was used for analysis. Summary statistics of the data are described below.

From 676 respondents who were eligible for this analysis, 47% identified as female and 53% identified as male. Our sample represents more men than the U.S. population (51% females, 49% males) (U.S. Census Bureau, 2019b). The sample's household income distribution is shown in Figure 16. Both mean and median income falls into the $40,000-$59,999 category, which is close to the median household income for the United States in 2018, $61,937 (U.S. Census Bureau, 2019a). Figure 17 shows the sampled individuals' educational attainment, which is skewed toward higher education than the U.S. population (U.S. Census Bureau, 2019c). Figure 18 illustrates the age distribution of our sample. The mean and median age is 35 and 33 years old, respectively. The median age of individuals 18 years old and older in the U.S. is within the 45-49 years old range (U.S. Census Bureau, 2019d). Our sample is biased toward younger individuals compared to the national population.

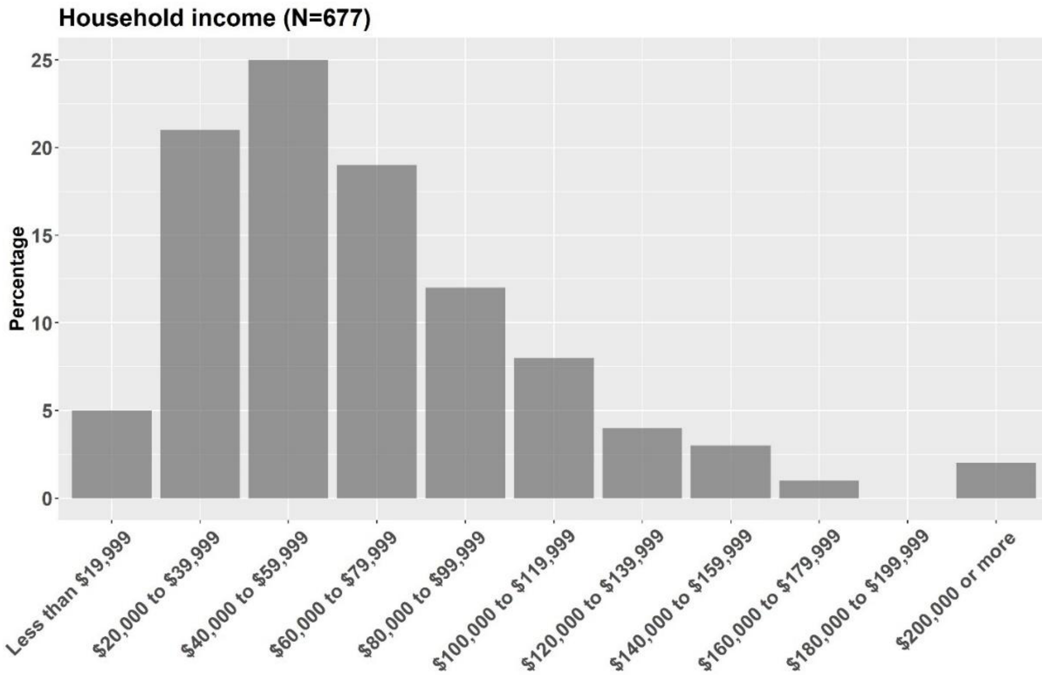

Figure 16 Sample's household income

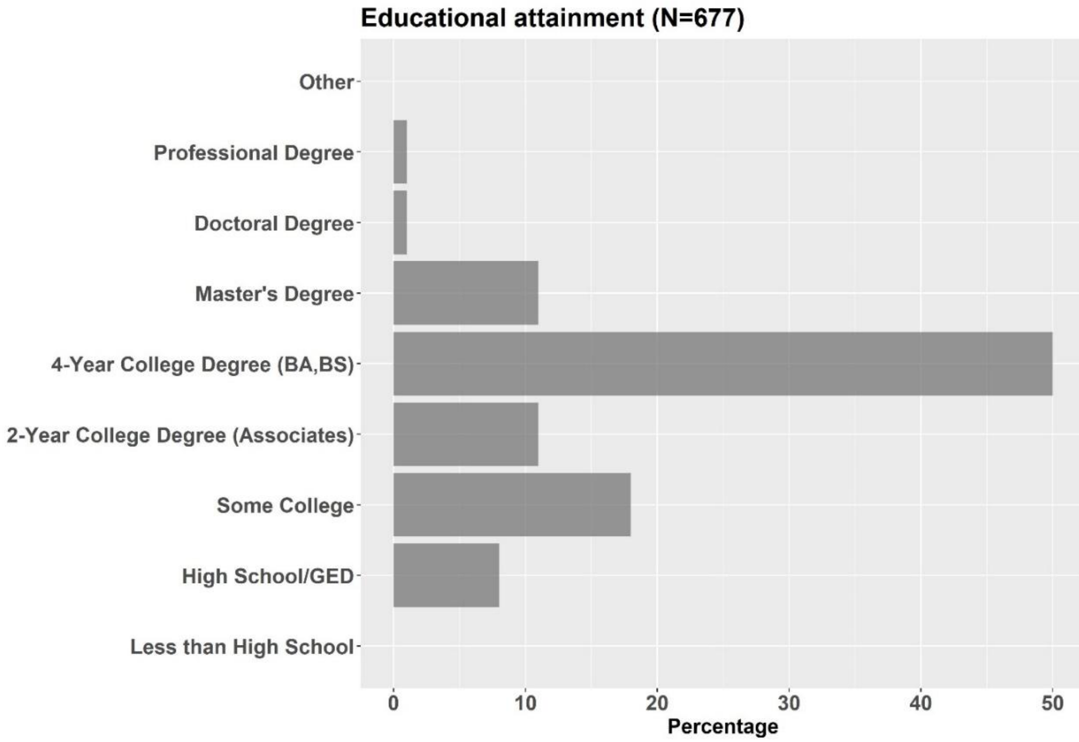

Figure 17 Sample's educational attainment

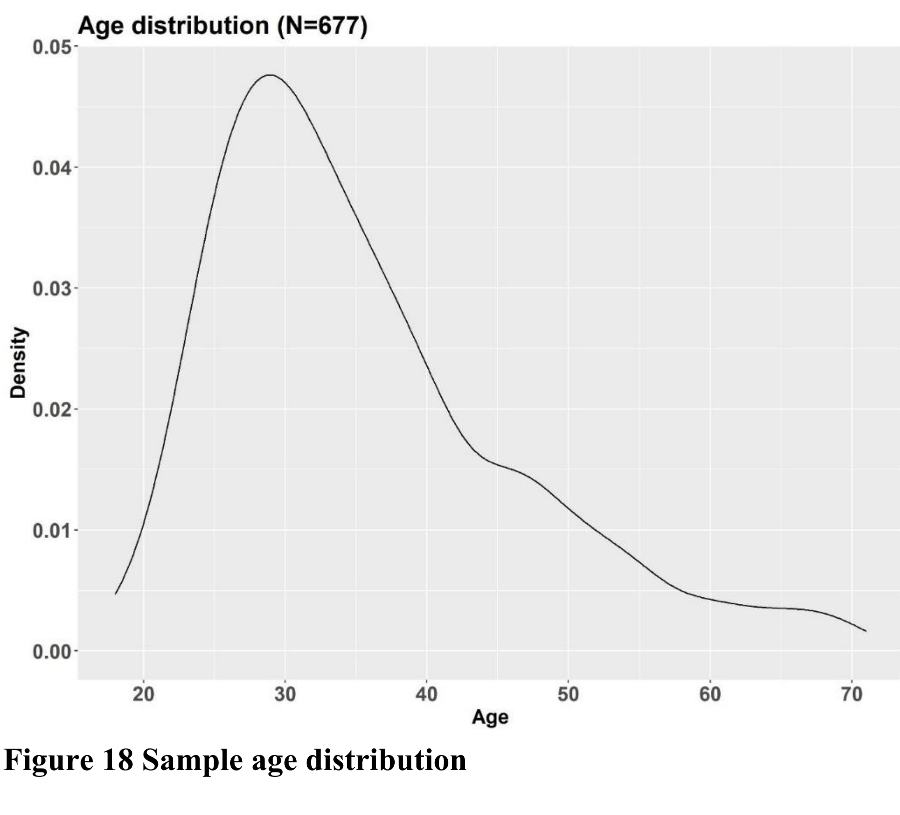

Figure 18 Sample age distribution

Methods

We created choice experiments based on users' typical workday and asked them to choose a mode for each trip within the tour, helping them imagine their day-to-day life with these new modes. However, it is not clear how respondents approached the experiment. For example, they may have considered each trip independently and tried to maximize their utility for each trip, or they may have considered previous options when choosing the next mode.

Respondents who chose car or self-driving car for their first trip had to stick with that mode for the rest of their trips on that travel day. However, if they chose any other mode, they could choose a different mode or the same mode for the next trip. Table 17 shows respondent counts for the number of trips per tour, and Figure 19 illustrates the combination of modes respondents chose in the choice experiment. The majority of people in our sample reported two trips per their travel day.

Table 17 number of respondents for per number of trips in a tour

Number of trips per tour	Number of observations
Two trips	584
Three trips	73
Four trips	20

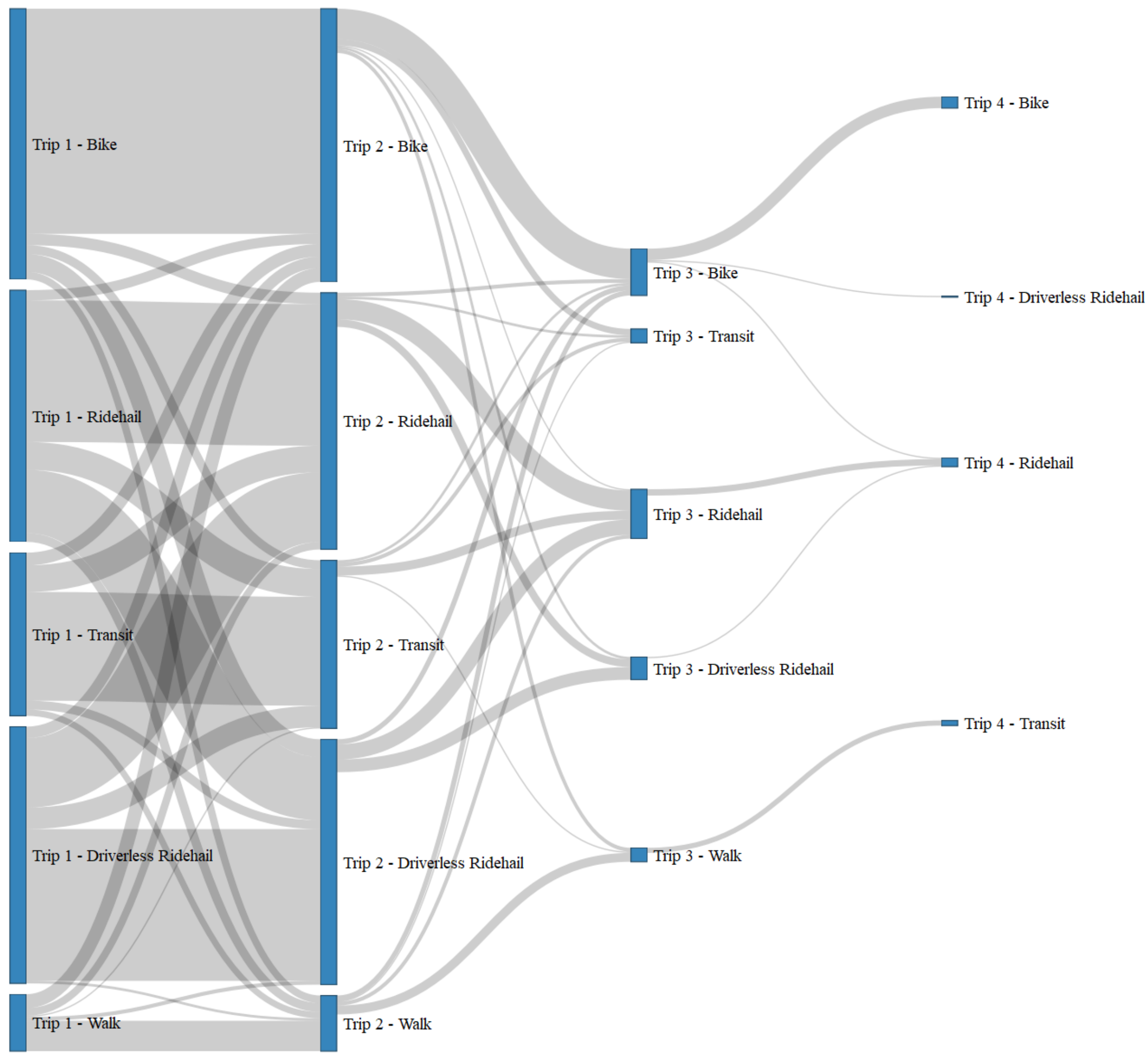

Figure 19 mode choices for tours (private cars and AVs are excluded from the diagram)

To estimate tour-based mode choice models, similar to chapter three, we used a random utility approach and integrated choice and latent variable (ICLV) framework. First, we assumed that respondents were maximizing their utility for each given trip. Therefore, they treat trips independently, and the total utility of the tour is the same as the sum of each trip's utility. We used two approaches to calculate the tour utility functions. For the first approach, we built a choice set of all the possible combinations of modes for tours and summed the utilities of each trip to calculate the mode choice utility for the tour. In the second approach, we used the expected utility of modes other than privately owned vehicles and then used the sum of the expected utilities to calculate utility for the whole tour. The second approach is considerably faster and computationally less intense than the first one. We used the second approach to build a third model that allows for interdependencies between the trips by including prior chosen mode as a predictive variable in the utility function of the current trip, similar to autoregressive models.

Below, we describe these models in more detail. The general utility function formula for the seven modes is described below:

$$U_{ijt} = V_{ijt} + \varepsilon'_{ijt} \quad (18)$$
$$V_{ijt} = \beta_{ij} x_{ijt} + \beta'_j x'_{ijt} + \Gamma_j x_i^* + ASC_j \quad (19)$$
$$\varepsilon'_{ijt} = \varphi_{ij} + \varepsilon_{ijt} \quad (20)$$

U_{ijt} is utility of mode j for individual i on trip t. V_{ijt} is the deterministic part of the utility. x_{ijt} indicates predictors such as travel time for which we defined alternative specific random coefficients, β_{ij}, to capture variation in taste or tolerance of decision maker. x'_{ijt}indicates predictors such as travel cost, monthly payment for privately owned cars, parking fee, and wait time that may have alternative specific or generic coefficients, β'_j. x_i^* is the vector of latent variables, and Γ corresponds to unknown model parameters for latent variables. φ_{ij} is the mode specific error component that captures individual *i*'s idiosyncratic taste variation for mode *j* which allows the variance of unobserved factors to differ over alternatives (Train, 2002) with the exception of driverless ridehailing. We assumed that driverless ridehailing is correlated both with regular ridehailing and self-driving car, and therefore, instead of using an alternative-specific error component in the utility function, we used sum of the error components for ridehailing and self-driving car. Additionally, alternative specific error components allow us to capture correlations between trips that has the same mode within the tour and individuals' preferences for mode *j*.

Full choice set approach

For this approach, we assumed respondents think about each trip independently and try to maximize their utility for each trip ($U_{i,t}$) and as a result the total utility for their tour ($U_{i,r}$) is equal to sum of the utilities of the trips within that tour. This approach is similar to model structure introduced by Miller et al., (2005). Following equation shows this relationship.

$$U_{ir} = \sum_t^T U_{it} \quad (21)$$

Utility of tour *r* for person *i*, $U_{i,r}$, is sum of trips' utilities, $U_{i,t}$, within the tour. Each person has *T* trips within the tour and *T* can range between 2 to 4 trips. Therefore, number of options in the choice set for each person dependents on the number of trips they had.

Tours start from home and there were seven modes in the choice set for each trip; car, self-driving car, walking, biking, transit, ridehailing, and driverless ridehailing. If respondents chose privately owned options such as car or self-driving car for their first trip, they had to stick with that choice for the whole tour. Even though they could see other modes attributes for all the trips, they could not choose them unless they changed their first trip chosen mode. If they chose any of the other five modes for the first trip, they could not choose the car and self-driving car option for the rest of trips.

If a respondent's tour had two trips, their choice set would include up to 27 options; car, self-driving car, walk-walk, walk-bike, walk-transit, walk-ridehailing, walk-driverless ridehailing, bike-walk, etc.; and if their tour has four trips, their choice set could include up to 627 options.

$$U_{ir} = \sum_t^T V_{it} + \sum_t^T \varepsilon'_{it} \quad (22)$$

Approximation approach

In this approach, instead of summing utilities of trips within a tour to get the total utility of the tour, we used expected utilities for modes except privately owned options (car, and self-driving car). As number of trips within the tour increases, it is more difficult to generate all the mode combinations possible and estimating the model becomes computationally more intense. Therefore, built models using expected utility for the purpose of alleviating model estimation complexity. As a result, we calculated the final probabilities in two steps. Except privately owned vehicles, the other five modes can be chosen in any trip conditional on that the first trip's mode is anything other than a regular or self-driving car. "Other" modes include biking, walking, ridehailing, driverless ridehailing, and transit. In the first step, we calculated expected utility of choosing "other" modes for each trip.

$$V_{i,t,other} = log \sum_j^J e^{V_{ijt}} \qquad j \in J = \{biking, walking, ridehailing, driverless\ ridehailing, transit\}$$

Then, we sum the expected utilities as the total utility of choosing "other" modes for the tour. Below, we formulate this approach. Utility functions for choosing a regular car, self-driving car, and other modes for tour *r* and person *i* are as below:

$$V_{i,r,car} = \sum_t^T V_{i,t,car} \quad (23)$$
$$V_{i,r,self-driving\ car} = \sum_t^T V_{i,t,self-driving\ car} \quad (24)$$
$$V_{i,r,other} = \sum_{t=1}^T V_{i,t,other} \quad (25)$$

The probability of choosing one of the of car, self-driving car and other options (from the set of {car, self-driving car, other}) is:

$$P_{j'} = \frac{e^{V_{j'}}}{\sum_{j'} e^{V_{j'}}} \ j' \in \{car, self - driving\ car, other\} (26)$$

Probability of choosing "other" mode for tour *r* by person *i* is:

$$P_{i,r,other} = \frac{e^{\sum_{t=1}^{T} log \sum_{j}^{J} e^{V_{ijt}}}}{e^{\sum_{t=1}^{T} log \sum_{j}^{J} e^{V_{ijt}}} + e^{V_{i,r,car}} + e^{V_{i,r,self-driving\ car}}} \quad (27)$$

Then, probability of choosing mode c from "other" modes set J is probability of choosing "other" conditional on probability of choosing mode combination c from all the available alternatives in the "other" category:

$$P_c = P(other)P(other) = \prod_t \frac{e^{Vict}}{\sum_j^J e^{V_{ijt}}} \times P_{i,r,other}$$

$$j \in J = \{biking, walking, ridehailing, driverless\ ridehailing, transit\} \quad (28)$$

Autoregressive models

In the choice experiment, participants could see the whole tour and mode options and their attributes all at once. There was no uncertainty about future modes and their attributes. As discussed earlier, one possible thought process could be maximizing the utility of each trip (which was captured through the previous two models) by making a decision solely based on the available options for each given trip. Another thought process could be considering their previous mode choices when choosing a mode for the current trip. In other words, they may demonstrate forward-looking behavior in the experiment setting. To capture this behavior, we added an autoregressive variable to the utility function of modes that are not privately owned vehicles. Equation 29 shows the utility function formula for this approach:

$$U_{ijt} = V_{ijt} + \rho y_{it-1} + \varepsilon'_{ijt} \quad (29)$$
$$U_{ijt} = V_{ijt} + \rho_j y_{it-1} + \varepsilon'_{ijt} \quad (30)$$

U_{ijt} is utility of mode *j* for individual *i* on trip t. V_{ijt} is the deterministic part of the utility. We assumed the current level of utility of mode *j* is partly dependent on the previously chosen mode. $\rho\ and\ \rho_j$ are weights that measure the effect of choosing mode *j* for trip *t-1* on choosing mode *j* for trip *t* and it is the same for each individual. ρ is a generic variable but ρ_j is an alternative specific variable. and y_{it-1} is a dummy variable with value one if mode *j* is chosen on trip *t-1*. The error term ε'_{ijt} captures unobserved factors. The assumption of independence of error terms $\varepsilon'_{ij(t-1)}$ and ε'_{ijt} is relaxed since we replace error term ε'_{ijt} by sum of two error terms as described previously. φ_{ij} captures preferences of individual *i* for mode *j*.

$$\varepsilon'_{ijt} = \varphi_{ij} + \varepsilon_{ijt} \quad (31)$$

Results

Table 18 shows the results of the three model and also the result from chapter three for the purpose of comparison. We cannot directly compare models from chapter three with the models in this chapter since sample size is quite different. The reason for this difference in sample sizes is that we had to remove some of the observations that had issues in the second to fourth trips of their tour.

Table 18 tour-based models result (numbers in parenthesis are standard error of estimations).

		Full choice set approach	Approximation approach		
	First trip only	Without autoregressive variables	Without autoregressive variables	One autoregressive variable	Alternative specific autoregressive variables
Variable	Estimate	Estimate			Estimate
Car					
Monthly Payment/Monthly Income	-3.08*** (0.41)	-3.06*** (0.41)	-3.07*** (0.41)	-3.60*** (0.44)	-3.63*** (0.44)
Parking fee/Daily Income	-6.60* (2.84)	-2.47 (2.51)	-2.94 (2.53)	-2.00 (2.71)	-2.24 (2.71)
Travel Time (hr) mean	-2.00*** (0.32)	-1.07*** (0.16)	-1.07*** (0.17)	-1.29*** (0.18)	-1.28*** (0.18)
Travel Time (hr) std. dev.	2.27*** (0.42)	0.09 (0.20)	0.21 (0.19)	0.47* (0.20)	0.47* (0.20)
Alternative-specific constant	0.98*** (0.27)	0.56* (0.23)	0.56* (0.24)	0.15 (-0.35)	0.26 (0.35)
Error component	-	0.20 (0.18)	0.17 (0.17)	0.18 (0.21)	0.16 (0.21)
Car Ownership Importance	1.22*** (0.14)	2.11*** (0.31)	2.07*** (0.30)	3.09*** (0.41)	3.09*** (0.41)
Self-driving car					
Monthly Payment/Monthly Income	-3.08*** (0.41)	-3.06*** (0.41)	-3.07*** (0.41)	-3.60*** (0.44)	-3.63*** (0.44)
Parking fee/Daily Income	-6.60* (2.84)	-2.47 (2.51)	-2.94 (2.53)	-2.00 (2.71)	-2.24 (2.71)
Travel Time (hr) mean	-2.35*** (0.43)	-1.18*** (0.18)	-1.19*** (0.18)	-1.46*** (0.20)	-1.45*** (0.20)
Travel Time (hr) std. dev.	3.21*** (0.52)	0.01 (0.22)	0.30 (0.20)	0.57* (0.22)	0.56* (0.22)
Alternative-specific constant	0.16 (0.28)	-0.19 (0.24)	-0.23 (0.25)	-0.58 (0.36)	-0.48 (0.35)
Error component	-	0.22 (0.17)	0.13 (0.15)	0.41 (0.21)	0.40 (0.21)
Safety of AVs	0.46*** (0.04)	0.16*** (0.04)	0.20*** (0.04)	0.18*** (0.05)	0.20*** (0.04)
Car Ownership Importance	1.22***	2.11***	2.07***	3.09***	3.09***

		(0.14)	(0.31)	(0.30)	(0.41)	(0.41)
Driverless Ride-hailing						
Cost/Daily Income		-5.21*** (0.69)	-0.69*** (0.19)	-0.73*** (0.19)	-0.73*** (0.18)	-0.73*** (0.18)
Wait Time (hr)		0.01 (0.02)	-0.31 (0.48)	-0.32 (0.47)	-0.24 (0.55)	-0.31 (0.54)
Travel Time (hr)	mean	-1.55*** (0.53)	-0.49* (0.24)	-0.48* (0.23)	-0.60* (28)	-0.59* (0.27)
	std. dev.	0.17 (0.53)	0.25 (0.29)	0.48 (0.27)	-0.19 (0.32)	0.19 (0.32)
Alternative-specific constant		-0.83*** (0.30)	-1.87*** (0.39)	-1.94*** (0.37)	-3.47*** (0.59)	-3.36*** (0.58)
Safety of AVs		0.46*** (0.04)	0.16*** (0.04)	0.20*** (0.04)	0.18*** (0.05)	0.18*** (0.05)
Car Ownership Importance		0.81*** (0.17)	2.53*** (0.66)	2.58*** (0.648)	4.84*** (1.00)	4.83*** (0.99)
Previous Mode: Driverless ride-hailing		-	-	-	3.50*** (0.09)	3.18*** (0.15)
Ride-hailing						
Cost/Daily Income		-5.21*** (0.69)	-0.69*** (0.19)	-0.73*** (0.19)	-0.73*** (0.18)	-0.73*** (0.18)
Wait Time (hr)		0.01 (0.02)	-0.31 (0.48)	-0.32 (0.47)	-0.24 (0.55)	-0.31 (0.54)
Travel Time (hr)	mean	-4.42*** (0.89)	-0.79** (0.25)	-0.78*** (0.25)	-0.83** (0.26)	-0.81** (0.25)
	std. dev.	2.44*** (0.68)	0.33 (0.24)	0.50 (0.23)	0.63* (0.29)	0.61* (0.29)
Alternative-specific constant		0.16 (0.28)	-1.1** (0.37)	-1.21*** (0.34)	-2.08*** (0.50)	-1.98*** (0.49)
Error Component		-	0.01 (011)	0.04 (0.10)	-0.13 (0.14)	0.13 (0.14)
Car Ownership Importance		0.57*** (0.17)	1.79** (0.58)	1.92*** (0.54)	3.20*** (0.78)	3.18*** (0.77)
Previous Mode: Ride-hailing		-	-	-	3.50*** (0.09)	3.19*** (0.16)
Transit						
Cost/Daily Income		-5.21*** (0.69)	-0.69*** (0.19)	-0.73*** (0.19)	-0.73*** (0.18)	-0.73*** (0.18)
Wait Time (hr)		0.03 (0.02)	-0.90 (1.01)	-1.20 (1.00)	-0.62 (1.19)	-0.57 (1.2)
Travel Time (hr)	mean	-2.97*** (0.55)	-0.27*** (0.07)	-0.28*** (0.07)	-0.34*** (0.07)	-0.34*** (0.07)
	std. dev.	1.92***	0.19**	0.20***	0.20***	0.20***

		(0.35)	(0.06)	(0.06)	(0.08)	(0.06)
Previous Mode: Transit		-	-	-	3.50*** (0.09)	3.75*** (0.21)
Bike						
Travel Time (hr)	mean	-10.80*** (1.28)	-1.55*** (0.15)	-1.74*** (0.16)	-2.04*** (0.21)	-2.04*** (0.22)
	std. dev.	6.50*** (0.74)	0.42 (0.26)	0.69*** (0.10)	1.12*** (0.13)	1.12*** (0.13)
Alternative-specific constant		2.63*** (0.29)	0.78*** (0.19)	0.82*** (0.19)	0.83*** (0.23)	0.77** (0.24)
Error Component		-	0.53** (0.16)	0.05*** (0.10)	0.63*** (0.11)	0.63*** (0.12)
Previous Mode: Bike		-	-	-	3.50*** (0.09)	4.25*** (0.20)
Walk						
Travel Time (hr)	mean	-55.80*** (13.10)	-2.06* (0.42)	-2.63*** (0.34)	-3.53*** (0.55)	-3.54*** (0.55)
	std. dev.	30.90*** (7.18)	0.96* (0.18)	1.14*** (0.14)	1.89*** (0.29)	1.91*** (0.29)
Alternative-specific constant		5.08*** (0.59)	0.17 (0.30)	0.47 (0.25)	0.87** (0.33)	0.95** (0.34)
Error Component		-	0.52** (0.17)	0.48*** (0.15)	1.34*** (0.18)	1.35*** (0.18)
Previous Mode: Walk		-	-	-	3.50*** (0.09)	3.17*** (0.35)
Null log likelihood		-18684.46	-22014.13	-22014.16	-22014.16	-22014.16
Final log likelihood		-13303.33	-13763.41	-13754.47	-12746.61	-12732.87
Adjusted Rho-square		0.285	0.372	0.373	0.418	0.419
Akaike Information Criterion		26708.66	27638.81	27620.95	25607.23	25587.73
Bayesian Information Criterion		26944.49	27891.72	27873.85	25864.65	25863.22
Number of draws		2000	1000	1000	10000	1000
Number of estimated parameters		51	56	56	57	61
Sample size		753	676	676	676	676

* *p*value ≤ 0.05, ** *p*value ≤ 0.01, *** *p*value ≤ 0.001

The full choice set approach and the approximation approach are different in their probability calculations. In the former, individuals could have up to 627 choice options in each choice situation depending on how many trips they have in their travel day. However, in the latter, instead of using one choice consisting of all the possible mode combinations, we summed the expected utility of trips to find the probability of each tour. The final log-likelihoods for models without autoregressive variables using these two approaches are somewhat close, but the approximation approach has a slightly higher log-likelihood. Estimated coefficients are also close in their magnitude comparing these two approaches. Table 19 shows the optimization time and other statistics for the two approaches. The approximation approach is considerably faster than the full choice set approach. We can conclude that the approximation approach is as good as the full choice set approach however it is more efficient and scalable. Number of choice options for the full choice set approach is k^n (n: number of trips, and k: number of modes available). Adding one more trip to the tour or one more mode to the mode set, would drastically changes number of utility functions that need to be calculated. Therefore, the approximation approach is a reasonable substitute for the full choice set approach.

Table 19 Full choice set approach vs. approximation approach

	Full choice set approach	Approximation approach
Number of draws	1000	1000
Number of estimated parameters	56	56
Sample size	676	676
Number of iterations	171	176
Number of function evaluations	506	501
Number of gradient evaluations	168	163
Optimization time	2.5 days	1 day

We conducted a likelihood ratio test to compare models without autoregressive variables and models with autoregressive variables. Results are show in Table 20. Model without autoregressive variable is rejected when compared to the model with one autoregressive variable, and model with one autoregressive variable is rejected compared to the model with alternative specific autoregressive variables.

Table 20 Likelihood ratio test results

	Model with one autoregressive variable vs. model without autoregressive variable	Model with alternative specific autoregressive variables vs. model with one autoregressive variable
Likelihood ratio test	2015.72 (>3.84)	28 (>9.48)

Estimated parameters for regular car and self-driving car are mainly consistent in all five models. One main difference is that parking fee is not a statistically significant variable in the tour-based models. This may be because parking fee is influential for a single trip, but it does not affect individuals' decision to take a personal car for a whole tour. On the other hand, car ownership importance is highly significant in all models. However, its effect has grown relative to the monthly payment in the tour-based models. This highlights the critical role attachment to cars plays when individuals plan for more than one trip.

Comparing the magnitude of coefficients for parameters of the other modes is rather difficult because not only the model specification has been modified in the tour-based models compared to the trip-based model, but also the number of observations for the models was different. In the trip-based model, we focused on the tour's first trip. Respondents may have chosen trips for the first trip because they optimized some of the tour-level variables. For example, they may aim not to exceed more than a certain number of minutes in time or dollars in costs for the whole tour. Therefore, respondents may consider those thresholds when making decisions for trips. In the trip-based model, we could not capture these interdependencies, which may be reflected in the estimated coefficients.

One point to highlight here is that unlike the model from chapter three, car ownership importance for different modes from the tour-based model cannot be compared since they are estimated differently. For example, in a tour with four trips, the tour utility functions for privately owned is equal to the sum of each mode's utilities (in all models), meaning that car ownership importance term is included in the tour utility four times. However, for the case of ridehailing modes, depending on how many times ridehailing modes are included in the mode combination, car ownership importance term could be included once or up to four times. Therefore, car ownership importance representation is not balanced between privately owned vehicles and ridehailing services and should not be compared.

The magnitude of autoregressive variables in both models with autoregressive variables indicates a "mode inertia" among our respondents. Individuals are inclined to use the same mode for consecutive trips in a travel day, and they gain higher utility from this repetition than using a new mode. The magnitude of these autoregressive variables is quite close and ranges from 3.15 to 4.26. This might mean that individuals prefer unimodal tours independent of the mode type.

To put this observation into context, we investigated a revealed dataset from NHTS to understand whether this preference for choosing repeating modes within tours is specific to our sample or also exists in the national household travel survey data. To achieve this, we first identified tours within NHTS data. We assumed that a tour includes at least two trips. When there were trips that started and ended at home, we assumed those trips, and all the trips in between were assumed to be within one tour. If the last trip of the day was not ending at home, we assumed that the tour ended with the last trip. Then, we looked at tours and the combination of modes used for them. We only considered tours that included at least one trip with a mode other than a car (since we used autoregressive variables only for non-car modes). We also removed tours that included one or multiple trips with an airplane as their nature is quite different from what we are interested in here.

We identified 41614 tours. 58% of the tours were unimodal, using walk, bike, public transportation, and taxi/ridehailing modes. 36% of these tours included at least one driving/ carpooling and one walk, bike, public transportation, and taxi/ridehailing modes. Only 6% of the tours were multimodal using a combination of walk, bike, public transportation, and taxi/ridehailing modes. In our choice experiment, out of 2562 choice situations, for 70% of them privately owned vehicles were chosen. Out of the remaining tours, 63% were unimodal.

Conclusions

In this chapter, we expanded the trip-based ICLV model from chapter three to tour-based models. We built three models using two approaches to formulate probability and two model specifications. The purpose of trying two different approaches for formulating probability was to determine whether there is a less computationally intense approach to estimating tour-based models with a higher number of trips within the tour. The purpose of using two model specifications was to explore whether the previous trip's mode impacts choosing a mode for the current trip.

We found that using expected utilities for "other" modes (e.g., walk, bike, transit, ridehailing, driverless ridehailing) and calculating utilities in two steps (model 2) performs slightly better compared to the model in which we used all the combinations of available modes as the choice set and summed utility of trips within the tour to calculate the utility of the tour (model 1).
When we added autoregressive variables to capture the effect of choosing the same mode as the prior trip for the next trip, we found that model improved in performance. Also, the likelihood ratio test rejects the null hypothesis that coefficients for autoregressive variables are zero. We discovered a considerably high "mode inertia" among our sample. Meaning that when choosing the same mode as the previous trip for the next trip, utility of that mode goes up considerably, and this finding is consistent for all the modes (not including personal vehicle options). This finding highlights that respondents in our sample are more likely to stick with unimodal tours than multimodal ones.

To understand whether this finding is unique to our sample of individuals or is consistent with other datasets, we looked at the 2017 National Household Travel Survey (NHTS). After processing the trips and identifying tours, we found a similar pattern in the NHTS data; most tours were unimodal. This is an important finding as decision makers, and experts have put a lot of effort into promoting multimodal travel as a vital component of sustainable urban mobility in the future (Kent, 2014). However, our findings show that despite providing a wide variety of mode options, including driverless ridehailing, and presenting full information about the available modes' attributes, there is a strong inclination toward unimodal travel.

Kent (2014) found that time competitiveness is not enough motivation for travelers to switch from personal vehicles to alternate modes. “Flexibility, freedom, and reliability, as well as the interminable pull of the sensory experience provided by the cocoon of the car,” are the main barriers for widespread use of alternate modes. Another study highlights that old age, employment, increase in the number of children, higher income, and higher car availability results in a lower probability of adoption multimodality while higher availability of biking and transit infrastructure increase the probability of multimodal travel (Klinger, 2017). Intuitively, factors identified by Klinger (2017) are predictors of how individuals prioritize between flexibility and freedom and mode attributes such as travel time and cost. For future research, it might be useful to explore how people with different sociodemographic perceive modes other than a personal vehicle in terms of reliability and flexibility.

Additionally, the data used in this study is based on individuals’ typical workday. However, evidence shows alternate modes are primarily used for specific purposes, whereas personal vehicles are used for all types of purposes (Kuhnimohf et al., 2006). Therefore, for future research, we recommend collecting and analyzing data for various purposes.

Chapter 5: Conclusions

In this dissertation, I have tackled three issues crucial to determining the impacts of AVs: (1) quantifying value of travel time as a determinant of induced demand; (2) trust in AV technology as a key determinant of adoption; (3) within tour inter-dependencies as determinant of multimodal travel and MaaS adoption. I achieved this by (1) developing a mode choice model of the current behavior of travelers using unique revealed data on carsharing and ridehailing and explore the implications of users time valuation differences for the adoption of future highly automated vehicles, (2) developing a survey including a stated preference choice experiment based on respondents travel day and actual data from APIs and attitudinal questionnaire to elicit choices, preferences, and attitudes regarding emerging transportation modes, (3) building an integrated choice and latent variable model to quantify the effect of individuals' perceptions of automated vehicle safety and the importance they place on car ownership on mode choices, (4) using tour-based mode choice model to improve the behavioral realism in modeling and explore preferences for multimodal travel.

Based on the revealed data analysis, in chapter one, I found a $23/hour reduction in the value of travel time (VoTT) when riding in a vehicle versus driving a vehicle due to being free from the burden of driving. Then I used NHTS data to understand the socioeconomic characteristics of the sample based on how frequently they use these services. I found that the $23/hour difference represents 38% of the mean hourly wage of frequent ridehailing users. This finding confirms a significant time savings benefit in eliminating the burden of driving for travelers.

Inferences regarding VoTT in AVs also depend on ridesharing's suitability as a proxy for automated vehicle travel. I found that, at least for a portion of society that our sample represents, the VoTT drop for riding rather than driving is considerable. This may be due to the ability to use in-vehicle travel time productively to work or participate in other activities (making a phone call, reading a book, listening to music/podcast, etc.), or due to reduced mental burden.

In chapter three, I explored two main obstacles to the adoption of AVs and driverless ridehailing services. (1) safety perceptions about AVs, and (2) importance of car ownership. I used these latent constructs in an integrated choice and latent variable model and found that both safety perception and car ownership importance have a statistically significant effect on choosing AV modes. Furthermore, my model shows that car ownership importance has the most substantial impact on choosing privately owned cars, followed by driverless ridehailing and regular ridehailing. This finding confirms that the more psychologically attached individuals are to their vehicles, they are more likely to choose their private car as their mode of transport. Interestingly, between driverless ridehailing and regular ridehailing, more car-dependent individuals prefer the former over the latter.

Another interesting finding of this analysis is the magnitude of safety perception effect on mode choice and how it compares with costs. I tested several scenarios to better grasp the effect of safety perception improvements. I discovered that shifting people's perceptions toward positive AV safety perception can drastically change AVs' market share. While keeping regular car monthly payments constant and reducing self-driving car monthly payments, I observed that self-driving car market grew by 4.4%. However, when safety perception improved to the point that most individuals were confident in the technology, its market share grew by about 35%, taking over 50% of the market. Based on our analysis, privately-owned self-driving cars will dominate driverless ridehailing services, and reducing fares can help expand their market share.

Under current conditions, self-driving cars are not expected to take over the private car market. Therefore, even if prices were much lower, the market would only grow slightly. However, improving safety perception would greatly impact the demand for private AVs. In contrast, the mode share of driverless ridehailing would grow substantially if AVs permitted a 75% reduction in fares compared to regular ridehailing, even if safety perceptions did not change from today. Moreover, if safety perceptions did improve, the effect for driverless ridehailing could be negative, as more people would opt for personal AVs.

In chapter four, I expanded the trip-based ICLV model from chapter three to tour-based models. I built three models using two approaches to formulate probability and two model specifications. I tried two different approaches for formulating probability to determine whether there is a less computationally intense approach to estimating tour-based models with a larger number of trips within the tour. Two model specifications were used to explore the effect of the previous trip's mode choices on choosing a mode for the current trip.

I found that using expected utilities for "other" modes (e.g., walk, bike, transit, ridehailing, driverless ridehailing) and calculating utilities in two steps performs slightly better compared to the model in which we used all the combinations of available modes as the choice set and summed utility of trips within the tour to calculate the total utility for the tour.

I also discovered that adding autoregressive variables to capture the effect of choosing the same mode as the previous trip for the following trip results in a better-performing model. The likelihood ratio test rejects the null hypothesis that coefficients for autoregressive variables are zero, confirming the model improvement. Furthermore, I observed a considerably high "mode inertia" among our sample of respondents, which means that choosing the same mode as the previous trip for the following trip increases utility considerably. This finding is consistent for all the modes (not including personal vehicle options). This finding highlights that the respondents in our sample are more likely to stick with unimodal tours than multimodal ones.

To understand whether this finding is unique to our sample of individuals or is consistent with other datasets, I looked at the 2017 National Household Travel Survey (NHTS). After processing the trips and identifying tours, I found similar patterns in the NHTS data, with most tours being unimodal. This is an important finding as decision-makers and experts have put much effort into promoting multimodal travel as a vital component of sustainable urban mobility in the future (Kent, 2014). However, my findings show that despite providing a wide variety of mode options, including driverless ridehailing, and presenting full information about the available modes' attributes, there is a strong inclination toward choosing the same mode for all the trips in a travel day.

The finding of this dissertation highlights the potential for increases in VMT and as a result increases in induced demand and GHG emissions, as it is expected that people's value of travel time considerably drops in AVs and market share of AVs grow substantially when users perceive them safe. Also, as highlighted in this dissertation, even with AVs and driverless ridehailing mode inertia is high among users, and solely introducing these new modes would not contribute to multimodal travels. This dissertation illustrates that the adoption of AVs cannot solve many of the pressing transportation issues if they are introduced to the current system without any changes to the system. There is a need for policies and plans in place to make sure the new technologies potential is directed toward a more sustainable future.

Limitations and Future Research

Revealed preference data used in chapter one of this dissertation helped overcome one of the main caveats of stated preference surveys: surveyed individuals have little to no experience with AVs, and their responses are affected by their expectations and perceptions of experiences in AVs. To the best of my knowledge, there is no other public dataset available that allows comparing mode preferences between ridehailing and carsharing services. However, our findings are based on a useful but limited-size dataset, and the sample is restricted to urban, mostly high-income travelers. Improving the dataset in terms of number of observations, diversity of sampled individuals, and variety of mode options can enhance our understanding of existing behaviors of the users.

Another caveat of this study is that the findings of this study do not tell us how to improve or change the public's safety perceptions; instead, they highlight and quantify the considerable role safety perception plays in the adoption of AV modes and its implications for mode share relative to other mode attributes. One of the avenues for future research, therefore, would be to study risk attributes relating to AVs and how perceptions of safety are formed.

Also, in the current study, safety perceptions regarding AVs are evaluated from AVs passengers. It is worthwhile to study and understand the perspective of users when they are sharing the road with AVs, for example when biking or walking. Understanding different users' perspective can help focusing efforts on improving public's perception of AVs.

Furthermore, the tour-based mode choice model can be improved by controlling for land use characteristics and latent variables relating to importance flexibility and reliability in mode choices. One of the limiting factors in tour-based mode choice modeling was computational power. Despite using high-performance computing systems, each model estimation took a considerably long time. Expectedly, more complex model specifications require higher computational power for estimation.

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