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16. Abstract

Emerging transportation services, whose development and adoption have been enabled by information and communication technology, are largely transforming people's travel and activity patterns. This study investigates the emerging transportation trends and how they transform travel-related decision-making in the population at large through the application of a unique longitudinal approach. As part of this project, a second wave of data collection in 2018 was built with a rotating panel structure as a continuation of the research efforts that started with the collection of the 2015 California Millennials Dataset. This report focuses on the analyses of the data collected in this project, in particular on the differences in attitudes towards transportation and the environment among different generational groups, the adoption and use of shared mobility services, and their relationship with vehicle ownership, the interest in the adoption of alternative fuel vehicles, and the interest in the future adoption of connected and automated vehicles. Due to the small number of respondents who participated in both surveys, for the purposes of the analyses contained in this report, we treated the data as repeated cross-sectional and analyzed the data from each survey separately. The study helps researchers evaluate the complex relationship between observed/latent characteristics and individual travel-related choices and decision-making. The study highlights attitudinal and mode-choice differences across generations. It explores the factors impacting current adoption of and future interest in new transportation technology including alternative fuel vehicles, automated vehicles and shared mobility. Divergent consumer segments are witnessed within each of these markets, with distinctive socio-demographics, latent attitudes, built environment, and level of familiarity with new technologies, which shape the uniqueness of their vehicle ownership, residential location, travel behavior, activity patterns, and lifestyle.

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Disclaimer

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Panel Study of Emerging Transportation Technologies and Trends in California: Phase 2 Findings

A National Center for Sustainable Transportation Research Report

November 2021

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Panel Study of Emerging Transportation Technologies and Trends in California: Phase 2 Findings

I EXECUTIVE SUMMARY

Changes in sociodemographics, individual lifestyles, the increased availability of modern communication devices (smartphones, in particular) and the adoption of emerging transportation technologies and shared-mobility services are quickly changing the way individuals travel. These changes are transforming travel-related decision-making in the population at large, and especially among specific groups such as young adults ("millennials") and the residents of urban areas.

The data collection was completed through a mixed sampling method: (1) A paper survey was mailed out to a stratified random sample of 30,000 California residents, by adjusting the sampling rates to obtain sizable numbers of respondents in all six geographic regions; (2) A sample of 2,000 Californians was recruited through an online opinion company using quota sampling based on six geographic regions, three neighborhood types (urban, suburban, and rural), and selected socio-demographics (age, gender, race, ethnicity, presence of children, household annual income, student status and employment status); and (3) All respondents from 2015, the first wave of data collection (N=1,975), were re-contacted through the same online opinion panel company. In the end, these three channels generated a total of 4,071 complete responses.

By integrating with the 2015 California Millennials Dataset, we built a rotating panel structure that allow analyzing multiple attitudinal and behavioral aspects of interest, using either longitudinal or repeated cross-sectional datasets. The data allows researchers to investigate the relationships among individual attitudes and lifestyles, residential location, vehicle ownership, travel behavior, the adoption of shared mobility, and the attitudes towards the adoption of other disruptive transportation technologies (e.g., autonomous vehicles). However, due to the low longitudinal response rates, the percentage of respondents who participated in both 2015 and 2018 survey, most of current analysis are based on the 2015 or 2018 cross-sectional dataset, but with a variety of research topics. As part of the project, both datasets have gone through comprehensive data cleaning, data weighting and geocoding process. The analyses presented in this project led to a large number of key findings, including:

- Millennials have different attitudinal and behavioral profiles from the members of Generation X. However, through the analysis of the existing generational gaps and associated factors, our study suggests that Millennials might be leaving part of their uniqueness behind and converging with those of Generation X as they enter later life stages. Nevertheless, Millennials adopt multimodality more often than Gen Xers. However, the analysis also points to substantial heterogeneity among Millennials and indicates that, perhaps contrary to expectations and the stereotype in the media, 84% of millennials are monomodal drivers. Perhaps, the concept of generations is just a way to arbitrarily slice up groups of travelers, while fails to capture their unique characteristics.

- By exploring factors impacting consumers' current vehicle fuel type choice and their future interest in purchasing or leasing an alternative fuel vehicle (AFV), our study suggests that people who are more pro-environment, tech-savvy and car-utilitarian are more likely to choose an AFV currently as well as in the future. Car-dependent people are also found to be more likely to adopt an AFV in the future than their counterparts. Also, an individual's current user experience in AFV has positive effect on their future interest in AFV. Thus, improving the EV awareness and increasing consumers' knowledge and experience on EV are critical strategies for EV market uptake.
- For the use of ridehailing services (Uber, Lyft) as well as adoption of shared (pooled) ridehailing (UberPOOL, Lyft Share), our study suggests that high-income, predominantly white individuals are more likely to be frequent users of regular ridehailing, while better-educated, younger individuals who currently work or work and study are more likely to use shared ridehailing services. Residents of urban neighborhoods with high employment entropy have higher likelihood of using both types of services. On the contrary, the increased travel time and lack of privacy decreases the likelihood of adopting shared services.
- In terms of ridehailing mode replacement, individuals living in vibrant and walkable neighborhoods tend to replace other travel modes, including active modes, with ridehailing. Pricing strategies should be employed to discourage short-distance ridehailing trips. Also, previous studies may have overestimated the complementary or supplementary relationships between public transit and ridehailing by ignoring confounding effects.
- By investigating the latent patterns in the modal impacts of ridehailing services, our study identified three classes of ridehailers: substituters who substitute transit modes and taxi cabs with ridehailing (30% of the total shared ridehailing adopters, and 50% of the frequent users in our sample), personal car augmenters who complement personal car with ridehailing (49% of the total adopters), and multimodal augmenters who use public transit and active modes and their usage are not impacted by ridehailing (21% of the total adopters).
- Our study reveals three clusters associated with ridehailing usage frequency. The "RH: Younger Eco-friendly" cluster (30% of the sample) is predominantly RH dependent, as a majority in it uses RH services on a regular basis, a characteristic in stark contrast with the "RH: Younger Non-eco-friendly" cluster (29% of the sample), where only 2% are among the regular users. The third "Older Car Enthusiast" cluster (40% of the sample) has a nearly zero share of regular RH users. Interestingly, those three clusters have in fact rather similar vehicle availability and age, and the one with higher ridehailing usage is less likely to expect an increase in household vehicle ownership within the next three years.

- Regarding AV adoption and use, our study reveals three main clusters. AV Early adopters" are the most interested in using and/or owning AVs. "AV Curious" individuals are interested in AVs but prefer to wait until the technology matures, and using them to supplement their current vehicle ownership rather than replace them with a shared-AV service. "AV Hesitant" individuals more often live in rural areas, are older and have lower income and are the most reluctant to consider AV use. Different level of external incentives and motivations can be applied to these segments to get them to adopt AVs.

Overall, this study helps assess the complex relationships behind the observed behaviors which support the development of better-informed transportation policies. The final data of this project is subject to the UC Davis Institutional Review Board (IRB) guidelines on the treatment of human subject data and is available upon request from the principal investigator.

II California Mobility Panel Study

Introduction

The rapid expansion of digital technology, the increased availability of locational data and smartphone apps, and the emergence of technology-enabled transportation and shared-mobility services are transforming transportation demand and supply. These disruptive trends might be confounded with other factors affecting travel patterns, behavioral differences across generations, changes in household compositions and lifestyles, and temporary changes that impact the way individuals interact, work, socialize, and travel. Despite the continued reliance on private cars, at least some segments of the population are apparently becoming more multimodal (Buehler and Hamre, 2016) and are more reliant on the use of information and communication technology (ICT) (Circella et al., 2016). Some of these changes might point towards positive impacts on the transportation sustainability. However, changes brought by new mobility options (e.g., ridehailing), or in the future driverless vehicles might increase the attractiveness of cars and reduce the use of other modes. Previous research has shown that the adoption of ridehailing might lead to a decline in the use of public transit (Circella et al., 2018; Circella et al., 2017; Clewlow and Mishra, 2017; Feigon and Murphy, 2018). The deployment of AVs will likely lead to even larger changes in travel demand, including a potential increase in the total vehicle miles traveled (VMT) (Harb et al., 2018), though these impacts will depend on the policies that are developed to regulate ownership and use (Circella, Ganson, and Rodier, 2017). These changes sum up to other factors that are already affecting passenger travel in the United States, and that have been attributed a role in explaining the changes in travel demand in recent years (Circella et al., 2016; Goodwin, 2012; Metz, 2012; Metz, 2013).

Despite of existing literatures, research on the relationships among the adoption of new transportation services, socio-demographics, lifestyles, vehicle ownership, mode choice, residential location choice and other components of travel behavior, as well as socio-demographics, attitudes and lifestyles, is still in preliminary stages, to date. More analyses based on robust data is required to better understand these trends and support policy making to increase transportation sustainability. This project will increase the understanding of the impacts of emerging transportation technologies and trends in California (Circella, Alemi, and Matson, 2018; Circella, Tiedeman, Handy, Alemi, and Mokhtarian, 2016; Circella, Alemi, Tiedeman, and Org, 2017).

This study capitalizes on the work developed in previous stages of this research project, which allowed us to collect a large longitudinal dataset through two detailed behavioral and attitudinal surveys in 2015 and 2018 with a rotating panel approach (Circella et al., 2016; Circella et al., 2018, 2016; Circella et al., 2017). However, due to small number of the respondents who participated in both waves of the data collection, for the purposes of the analyses contained in this report, we treated the data as repeated cross-sectional and analyzed the data from each survey wave separately. Throughout this research endeavor, we analyze this dataset and answer a number of research questions related to the impacts of emerging technologies and trends, the role of life stages in affecting changes in travel behavior, vehicle ownership and the adoption of technology, the use of various modes of transportation, and users' responsiveness to the introduction of new services (e.g., shared ridehailing services, such as UberPOOL and Lyft Line) and AVs. This project informs transportation agencies and the research community on the impacts of emerging technologies and trends on travel demand, helps enhance travel demand forecasting tools, and supports decision-making and investment decisions, to provide transportation services that best fulfill the mobility needs of Californians.

2018 California Mobility Survey

Data Collection Methodology

The 2018 mobility study builds on an existing research program which allowed the collection of the very rich 2015 California Millennials Dataset. As part of the previous Phase I of the research, our team designed a detailed online survey that was administered in 2015 resulting in a sample of 1,975 residents of California, including both millennials (young adults between 18 and 34, in 2015) and members of the preceding Generation X (middle-aged adults, 35 to 50 in 2015), who were recruited through an online opinion panel. The dataset includes many variables of interest and has allowed the development of several analyses of millennials and Gen Xers' attitudinal profiles, travel behavior, vehicle ownership, residential location, and adoption of shared mobility. For additional information on the Phase I of the research, which obtained large visibility in the scientific and planning community due to its ability to shed light into the factors affecting millennials' choices related to residential location, travel behavior and adoption of technology, see (Circella et al., 2016; Circella et al., 2017; Circella et al., 2018).

For the Phase II of the long-term research plan. we have built the longitudinal component of the research through a second wave of data collection. We employed a combination of sampling strategies to recruit respondents, including:

- **Paper and online survey for new recruitment:** we mailed out 30,000 paper surveys to randomly selected residential addresses in the state. To ensure representation from entire California, a stratified random sampling approach was used. California was divided into six regions (as Figure 1 depicts), and the sampling rates were adjusted according to the populations in these regions. The respondents had the option of mailing back the completed questionnaire or completing the survey through an online link. A total of 1,992 respondents (1,620 via mail and 372 online) completed the survey through this channel. In order to encourage more responses, respondents were entered into a drawing for the chance to win Amazon gift cards. Respondents who mailed back the survey (incomplete or complete) or those who provided contact details at the end of the online survey were eligible for the drawing.
- **New online opinion panel recruitment:** We also refreshed the panel by adding a group of participants in this wave of data collection, recruiting them through another online opinion panel company. The opinion panel company compensates survey respondents with points that can be converted into airline miles, gift cards etc., with the number of the accrued points commensurate to the length of the specific survey. We recruited these additional respondents to make up for the natural dropping out of respondents from the panel. We used quota sampling by California region and neighborhood type

(urban, rural, etc.) for this recruitment, and established socio-demographic targets for age, gender, children in the household, household income, race, ethnicity, work status and school status. The quotas and targets were set using the most recent 5-year estimates from the American Community Survey (ACS). A total of 1,833 respondents completed this survey through this channel.

- **Recontact of 2015 respondents:** We recalled all the respondents who completed the previous survey in 2015 using the same commercial online opinion panel from that data collection. Unfortunately, only 246 of the previous respondents completed the survey in 2018.

In the end, the sample is a combination of both longitudinal sample since 2015 and cross-sectional sample newly recruited in 2018. The socio-demographic distribution is in accordance with the 2018 American Community Survey statistics, with a slightly over-sampling of white people, people aged 55 or over, unemployed population and households without children. The full 2018 dataset consisted of 4,071 completed surveys, before data cleaning. For the purposes of this study, the state of California was divided in six main regions:

- San Francisco Bay Area corresponding to the boundaries of the Metropolitan Transportation Commission (MTC),
- Los Angeles/Southern California corresponding to the boundaries of the Southern California Council of Governments (SCAG),
- Sacramento region corresponding to the boundaries of the Sacramento Area Council of Governments (SACOG),
- San Diego corresponding to the boundaries of the San Diego Association of Governments (SANDAG),
- Central Valley corresponding to the eight counties in the central San Joaquin Valley,
- Northern California and Others which includes the rest of State not included in the previous regions)

Figure 1. The six regions of California included in this study

The panel dataset includes information on the personal attitudes and preferences, lifestyles, adoption of social media and ICT, e-shopping patterns, residential location, living arrangements, recent major life events, commuting and other travel-related patterns, auto ownership, awareness, adoption and frequency of use of shared mobility (carsharing, bikesharing, ridehailing services such as UberX or Lyft Classic, pooled ridehailing services such as UberPOOL or Lyft Line), propensity to purchase vehicle and/or modify vehicle ownership, perceptions and propensity to adopt driverless vehicles, interest in mobility-as-a-service (MAAS), propensity towards shared or personal ownership and use models of driverless vehicles, and sociodemographic traits.

Structure of the 2018 dataset

Figure 2 summarizes the sampling strategy for the first and second waves of this panel study.

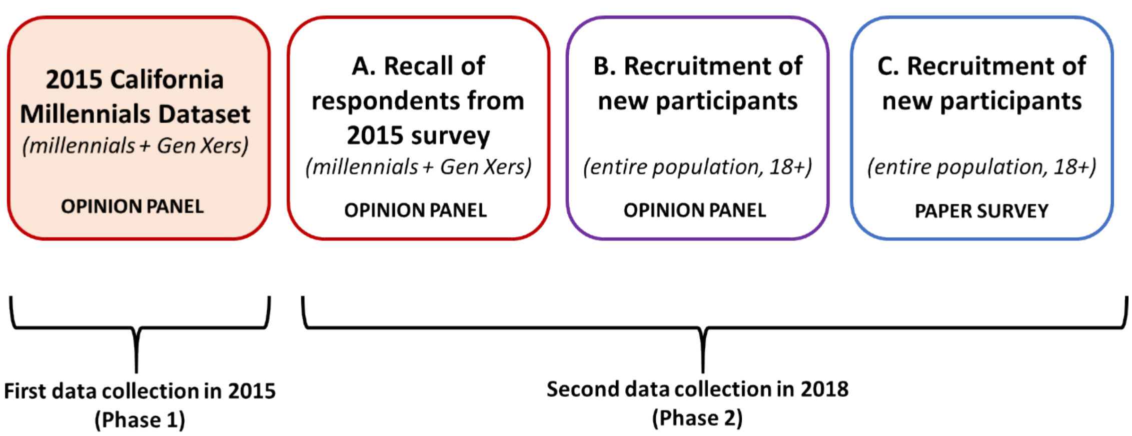

Figure 2. Structure of 2015-2018 California panel data

Although the panel provides a unique opportunity to study the impacts of emerging technologies and trends with longitudinal data and capture the causal relationships among the use of emerging transportation services, we do not present analyses based on the "longitudinal" component of the data in this report, due to low number of longitudinal observations that exist in both waves of the survey. Nevertheless, this project demonstrates how to design and administer a longitudinal panel study, and identifies what types of research questions that can be investigated with a longitudinal data.

During a further extension of this data collection to study the COVID-19 mobility project which was started in Spring 2020, some survey participants of this project were contact again to build a longitudinal panel that can be used to investigate the temporary and longer-term impacts of the COVID-19 pandemic, as well as in a number of other research questions in the future. As the Figure 3 shows, the research team is continuing to expand the panel study, with additional data collections carried out in Fall 2020 and Spring 2021. This unique dataset will allow researchers to investigate the complex relationships behind the formation of travel behavior over time (e.g., modifications in the use of shared mobility and their impacts on vehicle ownership due to the pandemic) among the various segments of the population.

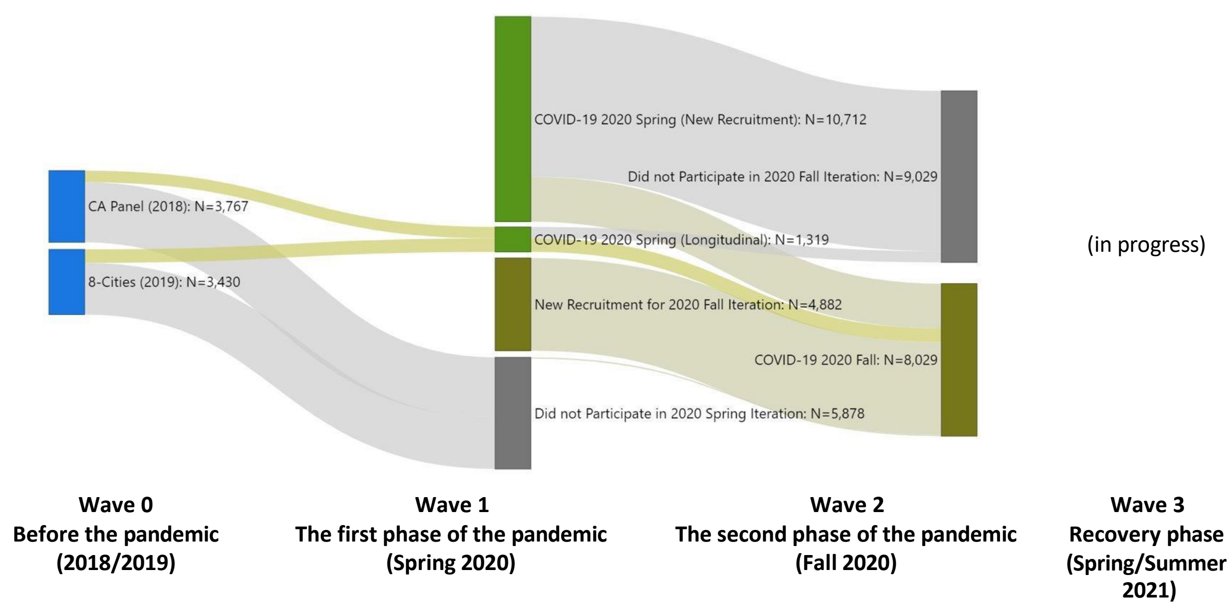

Figure 3. Recontact of respondents from 2018 dataset in a longitudinal study

Research Questions

Table 1. summarizes a list of research questions that we have investigated during the analysis of the data collected in this project by the time when this report is prepared. Most of the analysis have been presented in transportation-related conference or published in scientific journals. Detailed analysis and results of some research questions will be presented in the following chapter. Given such a rich dataset, more research may be carried out by the team in the future work.

Table 1. Research questions investigated f this project

Focus of Analysis	Research Questions
Impacts of stage in life on attitudes	• How different are Millennials' transportation-related attitudes from Generation X? • What are the effects of these attitudinal gaps? • How do millennials' attitudes change as they transition into later stages in life, start working, get married, have children and change residential location?
Impacts of stage in life on travel behavior	• Are there any forms of multimodality that can be observed in the population? • How do vehicle ownership, travel choices, propensity to use various transportation options change across age and generation? • How various demographic, built environment, and attitudinal attributes effect on the adoption of multimodality?
Adoption of alternative fuel vehicles	• What effects consumers' current vehicle fuel type choice and their future interest in purchasing or leasing an alternative fuel vehicle? • Does consumers' current experience with alternative fuel vehicles impact their future interest? • How do they vary within different population segments with various characteristics?
Use of shared mobility	• How does the adoption of shared mobility vary by geographic region of California, neighborhood type, and segment of the population? • What affect the use of services such as ridehailing (e.g., UberX, LyftClassic) and shared ridehailing (e.g., UberPOOL, Lyft Line) for different trip purposes in California? • How do they vary within different population segments with various characteristics?
Impacts of shared mobility on other modes	• How does ridehailing usage affect the use of other modes, including public transit, active travel and private vehicle? • How does ridehailing usage affect current household vehicle ownership and expectations to change? • What users are more willing to modify their vehicle ownership? How does that intention relate to the adoption of other travel modes and lifestyles? • How the adoption and use of shared ridehailing and its determinants are related to the different modal impact patterns of ridehailing? • How does it vary among various groups of users with various characteristics?
Adoption of AVs	• How does the willingness to use driverless vehicles vary across the population? • Who are the early adopters, i.e., willing to purchase an AV first? • What ownership (shared vs. personal) and use (shared vs. individual) models for AVs are more popular among various individuals?

Table 2. summarizes a list of research questions that could be investigated with the current data, and that will be the potential object of study for future extensions of this work.

Table 2. Potential research questions to be investigated in the future work

Focus of Analysis	Research Questions
The impact of ICT on travel behavior	• How does the adoption of technology vary among sociodemographic segments? • Is there a relationship between the adoption of smartphones, the use of social media, and the use of various travel modes (e.g., public transit)?
Adoption of e-shopping	• How is e-shopping affecting the physical amount of travel for shopping purposes? • What individuals adopt faster delivery-time services (e.g., Amazon Prime)? • How do purchasing behaviors (e.g., "searching in stores and buying online" or "searching online and buying in stores") vary by groups of users? • How does the return of items that are purchased online affect goods shipments?
Travelers' response to transportation policies	• Would Californians be responsive to policies designed to reduce vehicle ownership by adopting mobility-as-a-service transportation options? • What users might be interested in subscribing for flat-fee programs for ridehailing? • What users are more inclined to share rides with strangers? Under what circumstances would they share?

Geocoding

The respondents were asked to report their home and work addresses in the survey. We asked the respondents to either report their complete address or the nearest intersection of the two cross streets, along with the zip code. This information was then geocoded (converted into latitude and longitude) using Google API (Cooley, 2018). All cases were reviewed for accurate geocoding through a manual review process as the Google API can misinterpret the input provided by the respondents. The corresponding geocodes were then used to get measures of land use and built environment in the place which individuals live and work using external sources including the U.S. Environmental Protection Agency's Smart Location Dataset, and the *walkscore*, *bikescore* and *transitscore* from the commercial website walkscore.com.

Weighting

This section describes a two-stage weighting process (cell-weighting + iterative proportional fitting) for this dataset to compensate for the non-response bias present in the raw data.

Variable Selection for Weighting

Although a range of variables are possible for weighting, an inclusion of all is not ideal. If we have serious non-response by certain demographic groups in the data (e.g., low-income young male with Hispanic origin, studying and working, etc.), weighting is likely to produce extremely large weights for cases in such groups in order to be representative of the population. These large weights are problematic because by nature, cases with these weights are only a few in the sample, adding huge uncertainty to data analysis (i.e., large sampling errors). Thus, we narrowed down to two geographic attributes of participants' residence (i.e., region, neighborhood type) and six individual or household socioeconomic/demographic attributes (i.e., age, gender, race/ethnicity, household income, presence of children, employment/student status). We believe they are closely associated with non-response bias, and various measures of travel behaviors and mobility-related choices.

Data Handling

For carrying out the weighting process, the first step is to impute the missing values of the key variables for each case in the dataset. Then, recoding is needed for both the population targets and the raw data. Their variables were recoded to ensure their levels were consistent and at the same time avoid extremely large weights. For population target, we chose individual and household attributes from the 2014-2018 US Census American Community Survey 5-year estimates, the latest release at the time of weighting. For the raw sample data, two types of recoding were implemented. (1) There are cases where we recreate subgroups. The age variable was combined into three categories ("18-34", "35-54", "≥55"). For household income, less than $50,000 or larger than $100,000 are made as single group, respectively. (2) There were also two cases where we combined two variables into one to better represent certain characteristics. For employment and student status, we combined into three categories ("employee only", "student only", "employee and student"). For race and ethnicity, we combined into them five categories ("Asian/Hispanic", "Asian/non-Hispanic", "White or Other/Hispanic", "White/non-Hispanic", "Other/non-Hispanic"). In fact, those steps were iterative in that, if the first-round weights included extremely large values, we reduced the number of levels for certain variables and re-computed weights to avoid such large values in the second round, and so on. After making changes to a few variables and re-computing weights iteratively, we concluded that our chosen variables and levels were good enough for our sample.

Weighting Process

Cell Weighting

For the first stage, respondents' age, and the region and neighborhood type of their residential location are used in the cell weighting process. The cross-tabs of these three variables are calculated for both the raw survey data and population targets. The weights are calculated by dividing population proportions by sample proportions. In order to represent the non-respondents in that cell, weights for under-sampled respondents are increased by a multiplying factor that is greater than 1, and vice versa. In the end, weights ranging from 0.063 to 3.501 are derived and applied to the sample data.

Iterative-Iterative Proportional Fitting (IIPF)

The second stage of weight development involves a further adjustment to the derived weights to make the resultant weighted estimates from the sample conform to known population values for the six key variables identified. The sample joint distribution of certain variables is forced to match the known population joint distribution.

We employed the iterative proportional fitting (IPF) algorithm (i.e., raking) with the *mipfp* package in R (Barthélemy and Suesse, 2018). The iteration starts with the most unbalanced two variables, race and presence of children in our case, and ends when the differences between target marginal distribution of these two variables and the sample distribution is small than certain threshold (1e-9 in our case) and the IPF algorithm converges. With the new-derived weights, the IPF process iterates among the rest of variables until the change of weights is negligible. As such, the entire process is termed as Iterative IPF (IIPF). In our case, the process completes after the 9th iteration, which generate weights ranging from 0.025 to 8.627. Figure 4 shows the change of weights in each iteration, which becomes small and small as the number of iterations increase.

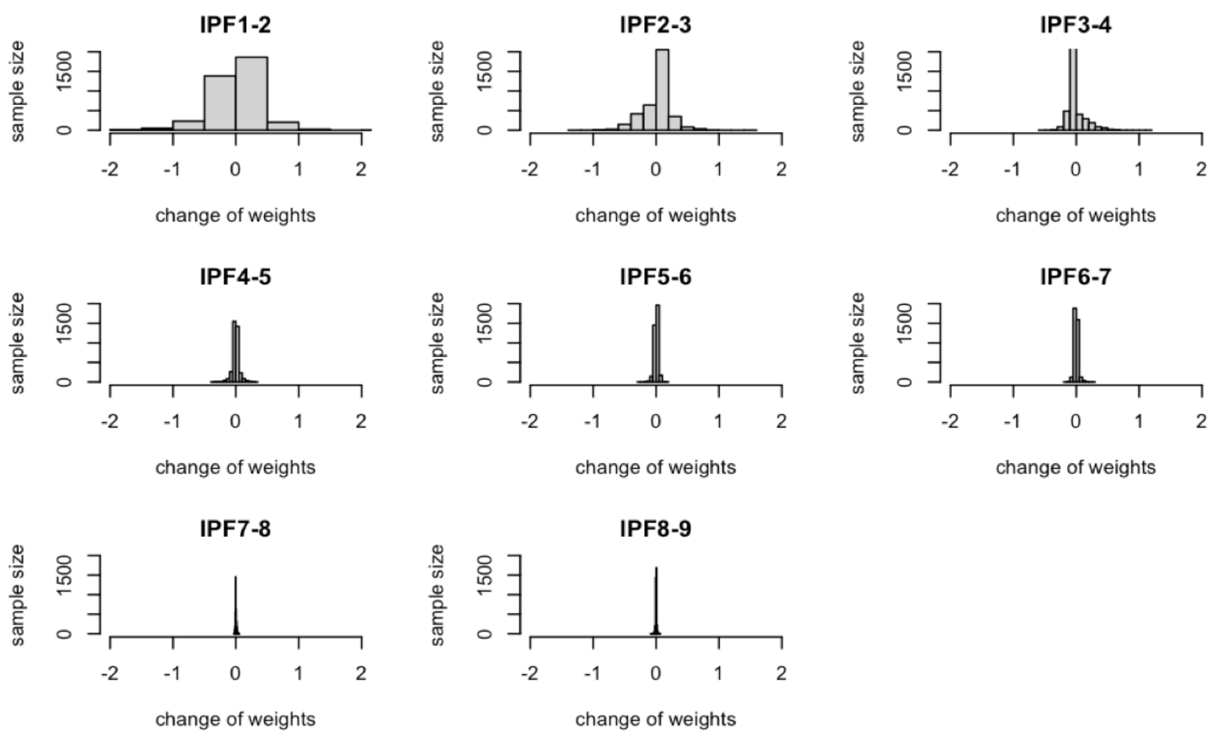

Figure 4. Change of weights in each IPF iteration

Weight Trimming

The final stage of the process is to moderate the extreme weights for the purposes of improving the mean square error (MSE) of estimates. In our case, the weights were trimmed to be between 0.025 and 3.678 (4 times of interquartile range).

Final Weights

As Table 3. suggests, the weighting process effectively reduces the gap between target marginal distributions (Column C) and those of the unweighted data (Column E), as the final gaps (Column J) are much smaller than original gaps (Column J).

Despite of this, small discrepancies still exist. As the color-coded Column J, red indicates under-representation of a given group in the weighted data, and green indicates over-representation of a given group in the weighted data. For instance, in the weighted data, urban residents are over-represented, while suburban and rural residents are under-represented. But overall, we believe the weighted data is a good representation of the population in California.

Table 3. Check for gaps between final weights and target distribution

A	B	C	D	E	F	G (=E-C)	H	I	J (=H-C)
		Population		Survey		Original Gaps	Final Weights		Final Gaps
		Perc	Freq	**Perc**	Freq	Perc	**Perc**	Freq	**Perc**
Region	Region_Central Valley	**10%**	375	**11%**	414	1%	**10%**	367	**-0.21%**
	Region_SFMTC	**20%**	758	**25%**	955	5%	**21%**	800	**1.10%**
	Region_NorCal and Others	**7%**	269	**13%**	483	6%	**7%**	245	**-0.63%**
	Region_SACOG	**6%**	236	**10%**	392	4%	**6%**	235	**-0.03%**
	Region_SANDAG	**9%**	322	**13%**	499	5%	**9%**	322	**0.01%**
	Region_SCAG	**48%**	1807	**27%**	1009	-21%	**48%**	1797	**-0.24%**
Neighborhood Type	NHTP_Urban	**24%**	889	**31%**	875	8%	**26%**	986	**2.56%**
	NHTP_Suburban	**47%**	1773	**45%**	1711	-2%	**47%**	1759	**-0.39%**
	NHTP_Rural	**29%**	1104	**23%**	1181	-6%	**27%**	1023	**-2.17%**
Age	>=55	**33%**	1249	**42%**	1596	9%	**34%**	1265	**0.42%**
	18-34	**32%**	1222	**22%**	813	-11%	**32%**	1203	**-0.52%**
	35-54	**34%**	1296	**36%**	1358	2%	**34%**	1300	**0.10%**
Gender	Male	**49%**	1849	**53%**	2006	4%	**49%**	1858	**0.23%**
	Female	**51%**	1905	**47%**	1753	-4%	**50%**	1897	**-0.21%**
	Other	**0%**	13	**0%**	8	0%	**0%**	12	**-0.02%**
Race-ethnicity	Asian_Hisp	**0%**	8	**0%**	16	0%	**0%**	8	**0.01%**
	Asian_NotHisp	**15%**	580	**11%**	420	-4%	**15%**	578	**-0.07%**
	Other_NotHisp	**9%**	324	**7%**	270	-1%	**9%**	324	**0.01%**
	White_NotHisp	**41%**	1547	**61%**	2290	20%	**42%**	1580	**0.88%**
	WhiteOther_Hisp	**35%**	1308	**20%**	771	-14%	**34%**	1277	**-0.83%**
Income	<50k	**31%**	1180	**32%**	1195	0%	**31%**	1180	**-0.02%**
	>100k	**40%**	1510	**36%**	1359	-4%	**40%**	1503	**-0.18%**
	50k-100k	**29%**	1077	**32%**	1213	4%	**29%**	1084	**0.21%**
Child	Child	**38%**	1445	**31%**	1183	-7%	**38%**	1424	**-0.56%**
	NoChild	**62%**	2322	**69%**	2584	7%	**62%**	2343	**0.56%**
	NA	**23%**	863	**34%**	1283	11%	**23%**	880	**0.44%**
Employment	Student_only	**3%**	120	**2%**	82	-1%	**3%**	119	**0.00%**
	Student_Work	**9%**	321	**8%**	317	0%	**9%**	323	**0.05%**
	Work_only	**65%**	2463	**55%**	2085	-10%	**65%**	2445	**-0.49%**

Factor Analysis

A number of studies have shown the importance of individual attitudes in predicting behavior (Ajzen, 1991; Paulssen, Temme, Vij, and Walker, 2014). In the first section of the survey, we show respondents 30 statements and ask them to indicate their level of agreement with each statement by selecting one of the five options in a Likert-type scale, from "Strongly Disagree" to "Strongly Agree". This battery of attitudinal statements was asked to measure the underlying latent constructs which can explain some of the observed behaviors of the respondents (in this case the use of ridehailing services). The statements were selected to understand respondents' attitudes towards the environment, land-use, modes of transportation etc. (see Table 4.). Previous research suggests that each construct must have three to five measurements statements; and directionality of the statements must be diversified to discourage respondents from falling into automatic response mode (Fabrigar, Wegener, MacCallum, and Strahan, 1999; Mokhtarian, Ory, and Cao, 2009). We followed this recommendation while designing the survey.

We had three main techniques at our disposal to estimate the latent constructs from the responses to these attitudinal statements—principal component analysis (PCA), exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). The primary goal of the current study is to use the latent constructs in the main choice models to explain the usage of ridehailing services. This rules out the applicability of PCA which is primarily a data reduction technique and does not attempt to model the structure of correlation among the measured variables (Fabrigar et al., 1999). PCA does not differentiate between common (latent variable) and unique (measurement error) variance of each attitudinal statement. Hence, it defeats our purpose of extracting behaviorally meaningful latent constructs. On the other hand, both CFA and EFA are based on common factor models. They attempt to preserve the correlation among measurement variables by extracting a small set of latent variables which can explain the common variances in the measurement variables.

CFA is a better approach when the goal is to test a specific theoretical hypothesis about the data. However, our goal is to extract the optimum latent variables for explaining the usage of ridehailing. Thus, we rely on EFA which is primarily a data driven approach. Unlike CFA, EFA does not make any prior assumption about the model. This is especially desirable in the current case where 30 attitudinal statements can lead to many plausible models making it impractical to test each one in the CFA framework. We conducted EFA using the 'Psych' package in R (Revelle, 2020).

While conducting an EFA, selecting the number of factors and the type of rotation are two most critical decisions which can influence the final outcome of the analysis. Fabrigar et al. (51) explain that oblique rotation is often superior to orthogonal rotation. The latter forces the factors to be uncorrelated with one another. This is an added restriction while performing EFA. On the other hand, oblique rotation relaxes this restriction. The optimal solution of an oblique rotation can have either correlated or uncorrelated factors. Allowing the factor scores to be slightly correlated also makes sense behaviorally. For instance, one can expect a slight correlation between a latent construct about the attitude towards owning a private car and the sensitivity towards environmental issues. Thus, we resort to oblique rotation while performing factor analysis. We tested solutions using 'Oblimin' and 'Promax' rotations (both are oblique). However, the solution from 'Promax' rotation was more interpretable.

Initial rounds of EFA with oblique rotation revealed that four out of the 30 attitudinal statements did not load well on any of the factors or led to solutions with very limited interpretability (which were most likely the results of other spurious correlations, rather than true common attitudinal components). Thus, we dropped these four statements and were left with 26 attitudinal statements. Next, to decide on the number of factors for the final solution we relied on the Kaiser criterion of computing eigenvalues for correlation matrix. The rule is to keep the factor scores which have eigen values greater than value 1 (Gorsuch, 1983). This criterion suggested seven factor scores for 26 statements. However, using seven factors scores in a Promax rotation led to a solution in which multiple seemingly unrelated statements were loading on the same factor. After multiple iterations we decided on a final solution with nine factors for 26 statements. The final solution was chosen for its trade-off between explanation of variance in the data (and the criterion based on the eigenvalues) and interpretability. Fabrigar et al. explain how having fewer factors (under-factoring) can potentially lead to more severe errors compared to over-factoring. The nine factors cumulatively explain 43% of variance of the 26 statements. We included individual attitudes using the Bartlett factor scores (which produce less biased estimates as compared to regression scores (DiStefano, Min, and Diana, 2009)) that were computed through a factor analysis (Promax rotation) of the original attitudinal variables included in the dataset. The details of these factors and the attitudinal statements loading from the pattern matrix are mentioned in Table 4.

Towards the end of the survey, we also asked respondents to evaluate a list of shared ridehailing attributes on a Likert-type scale from "Very limiting" to "Very encouraging", and report if they perceived those attributes as barriers or enablers to use of shared ridehailing services. This question was very specific about shared ridehailing and had a different scale of measurement from the previous batch of attitudinal statements. Fabrigar et al. (1999) say, "when EFA is conducted on measured variables with low communalities, substantial distortion in results can occur". Thus, we performed a separate EFA for these limitations using 'Promax' rotation and two factor scores. The two factor scores cumulatively explain 67% variance of the six measurement variables. The results are shown in Table 4. as well. We used a cutoff value of 0.3 for the factor loadings to retain statements for each factor. The only exception is the first statement in Table 4. which loads in "Pro-Environmental Regulation" with a factor loading of 0.29. We still included it since it is fairly close to the cutoff value and it contributes to the interpretation of that factor.

This two-step approach of first estimating the latent variables and then using the factor scores in a choice model introduces a measurement error in the choice model. This is because the attitudinal statements, are not the perfect measurements of the latent constructs, but are merely indicators of the latter. Researchers sometimes jointly estimate the measurement variables and choice outcomes using the Integrated Choice and Latent Variable (ICLV) approach. However, Vij and Walker (Vij and Walker, 2016) found that in many cases ICLV models do not fit the data any better than equivalent choice model. The analysis with EFA holds insights about how attitudes influence the decision to use ridehailing services and will guide our work in defining the configuration of latent variables with the corresponding measurement variables. Two studies using the ICLV approach to jointly model the measurement and choice variables will be discussed in the next section.

Table 4. Factor Scores for attitudinal statements

Factor Scores for Personal Attitudes	Factor Loadings
Pro-Environmental Regulation	
The government should put restrictions on car travel in order to reduce congestion.	0.29
We should raise the price of gasoline to reduce the negative impacts on the environment.	0.99
We should raise the price of gasoline to provide funding for better public transportation.	0.82
Pro-Urban	
I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.	0.79
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	0.46
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.	-0.81
Tech-savvy	
I like to be among the first people to have the latest technology.	0.59
Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.	0.49
I like trying things that are new and different.	0.42
Learning how to use new technologies is often frustrating for me.	-0.61
Car Lover	
I definitely want to own a car.	0.90
I prefer to be a driver rather than a passenger.	0.41
I am fine with not owning a car, as long as I can use/rent one any time I need it.	-0.46
Pro-Environment	
I am willing to pay a little more to purchase a hybrid or other clean-fuel vehicle.	0.56
I am committed to an environmentally friendly lifestyle.	0.76
I prefer to minimize the material goods I possess.	0.39
Car Dependent	
Most of the time, I have no reasonable alternative to driving.	0.43
I am too busy to do many things I'd like to do.	0.37
My schedule makes it hard or impossible for me to use public transportation.	0.83
Car Utilitarian	
The functionality of a car is more important to me than its brand.	0.68
To me, a car is just a way to get from place to place.	0.62
Pro-Multitasking	
I try to make good use of the time I spend commuting.	0.46
My commute is a useful transition between home and work (or school).	0.54
I like to juggle two or more activities at the same time.	0.38

Factor Scores for Personal Attitudes	Factor Loadings
Pro-Luxury	
I am uncomfortable being around people I do not know.	0.32
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.	0.46
I would/do enjoy having a lot of luxury things.	0.51

Factor Scores for Attitudes Specific to Shared Ridehailing	
Longer Travel Time	
Longer travel time	0.80
Longer waiting time	0.95
Unreliable travel time	0.84
Deviation from main route	0.62
Safety/Privacy	
Interacting with other passengers	0.68
Sitting next to a stranger	0.92

III Data Analysis

Decomposing Generational Differences in Transportation-Related Attitudes

Considerable recent work suggests that Millennials' behaviors may be converging with those of Generation X as they enter later life stages, but few have investigated whether attitudes, which are often strong predictors of behavior, are undergoing the same convergence. In this study, we analyze the existing generational gap in four transportation-related attitudes (*currently* pro-urban, *long-term* pro-urban, pro-car ownership, and pro-environment), and examine the differential effects of other characteristics, including life-stage variables, on these attitudinal gaps. We apply the threefold Blinder-Oaxaca decomposition method to a statewide (weighted) sample of 1029 Millennials and 946 Generation Xers from California to unravel these effects. The method distinguishes among: (1) effects due to the cohorts having different *characteristics* (*endowments*); (2) effects due to those characteristics having different *influences* on attitudes (*coefficients*); and (3) the *interaction* of those two effects. We observe that Millennials' attitudes: (1) differ from those of Generation X only by small, albeit statistically significant, amounts on average; and (2) *are* closer to those of Generation X as they gain on a host of life-stage variables such as marital status, income, and education. For example, if Millennials were married, employed, and earning higher incomes at the same *rates* as Generation X (but retaining their own model *coefficients*), the generational gap in the currently pro-urban attitude would be reduced by 25%. This study brings an econometric approach to the study of generational divides in transportation-related attitudes, with findings suggesting that Millennials might be leaving part of their uniqueness behind as they enter later life stages.

The following is a short version from a paper that was peer-reviewed and published in the journal Transportation (Etezady et al., 2021). The application of the Blinder-Oaxaca decomposition method to our context was inspired by an unpublished presentation by Dr. Noreen McDonald. An earlier version of this paper was presented at the 98th Annual Meeting of the Transportation Research Board, and the present version has been improved by comments from four anonymous reviewers of the earlier one. Please use the following citation to cite the full paper:

> *Etezady, A., Shaw, F. A., Mokhtarian, P. L., and Circella, G. (2021). What drives the gap? Applying the Blinder–Oaxaca decomposition method to examine generational differences in transportation-related attitudes. Transportation. doi:10.1007/s11116-020-10080-5*

Introduction

Although in modern times all generations have engendered a certain amount of media attention, the Millennials cohort has disproportionately enjoyed a spotlight so intense that, for many, the word “Millennials” now evokes something of an ad nauseum catchphrase. Examining the deluge of popular news, opinion, and academic pieces on Millennials makes it clear that this fascination can be traced to several attributes, the most notable of which is that (based on national and global projections) Millennials will soon become the largest living adult cohort (having been the largest living cohort among all age groups since the 1990s), a prediction with reverberating implications across all domains. Compounding this demographic dominance is the fact that members of this cohort have long been making choices that fly in the face of trends observed in prior generations, with increased preferences for spending their money on experiences as opposed to products (Barton et al., 2013; Benckendorff, 2010; Bilgihan, 2016; Rita et al., 2018), achieving work-life balance in the form of a satisfying life outside of work (Ng et al., 2010; Straub, Zhang, and Kusyk, 2007), living in urban centers (Delbosc and Nakanishi, 2017; Okulicz-Kozaryn and Valente, 2018), accompanied by reduced rates of licensure (Delbosc and Currie, 2013; Sivak and Schoettle, 2011, 2012), vehicle ownership, and vehicle miles traveled (VMT) (Hopkins, 2016; Kuhnimhof et al., 2012; Polzin, Chu, and Godfrey, 2014), leading to them being dubbed the “go-nowhere” generation (Buchholz and Buchholz, 2012; McDonald, 2015), although several studies have suggested that some of these contrasting behaviors may be converging with those of prior generations as Millennials enter later life stages. Identified behavioral differences between Millennials (defined here as those born in the 1980s and 1990s; also known as Generation/Gen Y) and the preceding Generation X (born between 1965 and 1980; also referred to as Gen X) have been attributed to a range of personal (ex. attitudinal differences, technological exposure), environmental (ex. built environment policies intended to encourage denser living), and economic (ex. effects of recession) factors (Blumenberg et al., 2012; Delbosc et al., 2018; Kuhnimhof et al., 2012; Thigpen and Handy, 2018).

Within transportation, there is substantial evidence that attitudes play a role in influencing behavioral choices (Domarchi, Tudela, and Gonz?lez, 2008; Kitamura, Mokhtarian, and Laidet, 1997; Kuppam, Pendyala, and Rahman, 1999; Mokhtarian and Salomon, 1997). However, due largely to a lack of attitudinal data, the majority of comparative studies on generational differences have relied primarily on behavioral indicators, although there *are* segments of the literature that have examined market-oriented attitudes such as brand loyalty, or work/life-oriented attitudes such as satisfaction. We assert that continued examination of attitudinal differences between Millennials and Gen Xers is critical to placing into context behavioral differences, with particular importance in the transport sector where infrastructure planning revolves around forecasting travel behaviors, of which attitudes play an important explanatory role. To our knowledge, this analysis is the first, in the dense collection of Millennials literature, to apply a decomposition approach, specifically the Blinder-Oaxaca (BO) method, to extricate *group (endowment)* and *effect (coefficient)* differences influencing transport-related attitudinal gaps between Millennials and Gen Xers. As such, while this study contributes specifically to the Millennials literature, it may also inform future work on other generational and demographic divides of interest within transport contexts.

Overview of The Dataset

Data used in the analysis for this chapter comes from the first wave (2015) of survey data. Table 5. provides an overview of the descriptive statistics for the sample. Additional details regarding study implementation, survey variables, and sociodemographic distributions are presented in Circella et al. (2016, 2017b).

Table 5. Selected sociodemographic characteristics of the sample (N = 1975)

Variables	Characteristics	Frequency [a]							
		Unweighted				Weighted			
		Gen Y		Gen X		Gen Y		Gen X	
		N	%	N	%	N	%	N	%
Gender	Female	629	58.3	525	58.6	518	50.4	481	50.8
Race	White	405	37.5	600	33.0	527	51.2	525	44.5
	Asian	188	17.4	136	15.2	177	17.2	175	18.6
	Hispanic	271	25.1	150	16.7	445	43.2	266	28.1
	African-American	50	4.6	47	5.2	36	3.5	43	4.5
	Native American	39	3.6	28	3.1	40	3.8	25	2.6
Age [b]	18-24 years	335	31.0	-	-	400	38.9	-	-
	25-34 years	744	69.1	-	-	679	61.2	-	-
	35-44 years	-	-	584	65.2	-	-	629	66.5
	45-51 years	-	-	312	34.8	-	-	317	33.5
Annual household income	<US $40K	351	32.5	207	23.1	329	33.0	183	19.4
	US $40K-$100K	472	43.8	414	46.2	385	37.3	342	36.2
	> US $100K	176	16.3	220	24.6	237	23.0	366	38.7
Education	High school diploma or less	193	17.9	102	11.4	184	17.8	81	8.5
	Some college or technical school	452	41.9	341	38.1	425	41.2	329	34.8
	College degree	332	30.8	306	34.2	308	29.9	345	36.5
	Graduate degree and higher	98	9.1	143	16.0	107	10.3	189	20.0
Employment	Employed	689	63.9	612	68.3	796	77.4	796	84.2
Occupation	Full-time student	166	15.4	24	2.7	178	17.3	30	3.2
	Manager	97	9.0	129	14.4	121	11.7	183	19.4
	Professional/ technical	148	13.7	193	21.5	174	16.9	259	27.4
	Clerical/ administrative	106	9.8	78	8.7	109	10.0	87	9.2
	Other [c]	338	49.0	212	23.7	392	49.2	267	28.2

Variables	Characteristics	Frequency [a]							
		Unweighted				Weighted			
		Gen Y		Gen X		Gen Y		Gen X	
		N	%	N	%	N	%	N	%
HH size	Single-person HH	170	15.8	131	14.6	158	15.4	120	12.7
	Two-person HH	267	24.7	203	22.7	244	23.7	212	22.4
	Three-person HH	248	23.0	211	23.5	243	23.6	227	24.0
	Four-person or larger HH	394	36.5	351	39.2	384	37.4	387	40.9
Marital status	Married	412	38.2	557	62.2	370	36.0	606	64.1
Built environment	Urban dweller	209	19.3	173	19.3	289	28.1	240	25.4
Political affiliation	Republican	183	17.0	196	21.9	153	14.8	180	19.0
	Democrat	433	40.1	322	35.9	428	41.6	370	39.1

[a] Frequencies do not add up to 100% or the total N because of rounding errors, non-responses, or "other" categories.
[b] Average age (weighted sample): 33.8 years (median: 33.0 years); lowest age: 18 years; highest age: 51 years.
[c] Includes education/training, service and repair, sales or marketing, production or construction, and other.

Attitudinal constructs

Data used in the analysis for this chapter comes from the first wave (2015) of survey data with a focus on Millennials and Generation X. The survey used in this study measured individual attitudes through 66 variables that collected information on a variety of topics including adoption of technology, residential preferences, vehicle ownership, travel behavior, etc. using a 5-point Likert-type scale ranging from "Strongly disagree" to "Strongly agree". Exploratory factor analysis (specifically, principal axis factoring with maximum likelihood estimation and oblique rotation) was first executed across the full set of statements (Circella et al., 2017b), after which confirmatory factor analysis (CFA) was applied across 14 of the initial 66 statements to extract four transportation-related constructs for further study. The selected attitudinal constructs represent desires for an *urban lifestyle*, separately in both present and future time frames, *feelings toward owning a private vehicle,* and *attitudes toward environmentally conscious living*. These constructs are selected due to their conceptual and/or empirical relationships with transport-related behaviors, and because they are also stereotypically expected to differ between Millennials and older cohorts (Delbosc and Nakanishi, 2017; Forward et al., 2010; Hopkins, 2016; Malokin et al., 2017; Shaw et al., 2018).

A visual representation of the constructs is shown in Figure 5, which follows latent variable diagram convention with single-headed arrows representing the effects of constructs on observed indicators, and double-headed arrows representing correlations between variables (Loehlin, 2004). Significant correlations between constructs are retained; item error correlations were also tested for significance, but most were ultimately restricted to zero (consistent with the assumption that the latent variable accounts for most of the correlation between items), with the exception of one significant error correlation shown in the diagram which both increases the fit of the model and is conceptually interpretable (i.e., having shared sources of unexplained variation between the respective statements is logical). The overall CFA model has acceptable fit with an RMSEA of 0.061 and a CFI of 0.902. The chi-squared test of discrepancy between the sample and model-implied covariance matrices is significant (χ^2 = 578.667, df = 70, $p < 0.001$, $\alpha = 0.05$), but this may be attributable to the large sample size and is therefore a minor concern. Factor scores (continuous variables indicating respondents' relative measurements on each latent construct or factor) for the derived attitudinal constructs are computed using linear regression with the mean vector and covariance matrices from the fitted model (StataCorp, 2017), and standardized across the sample.

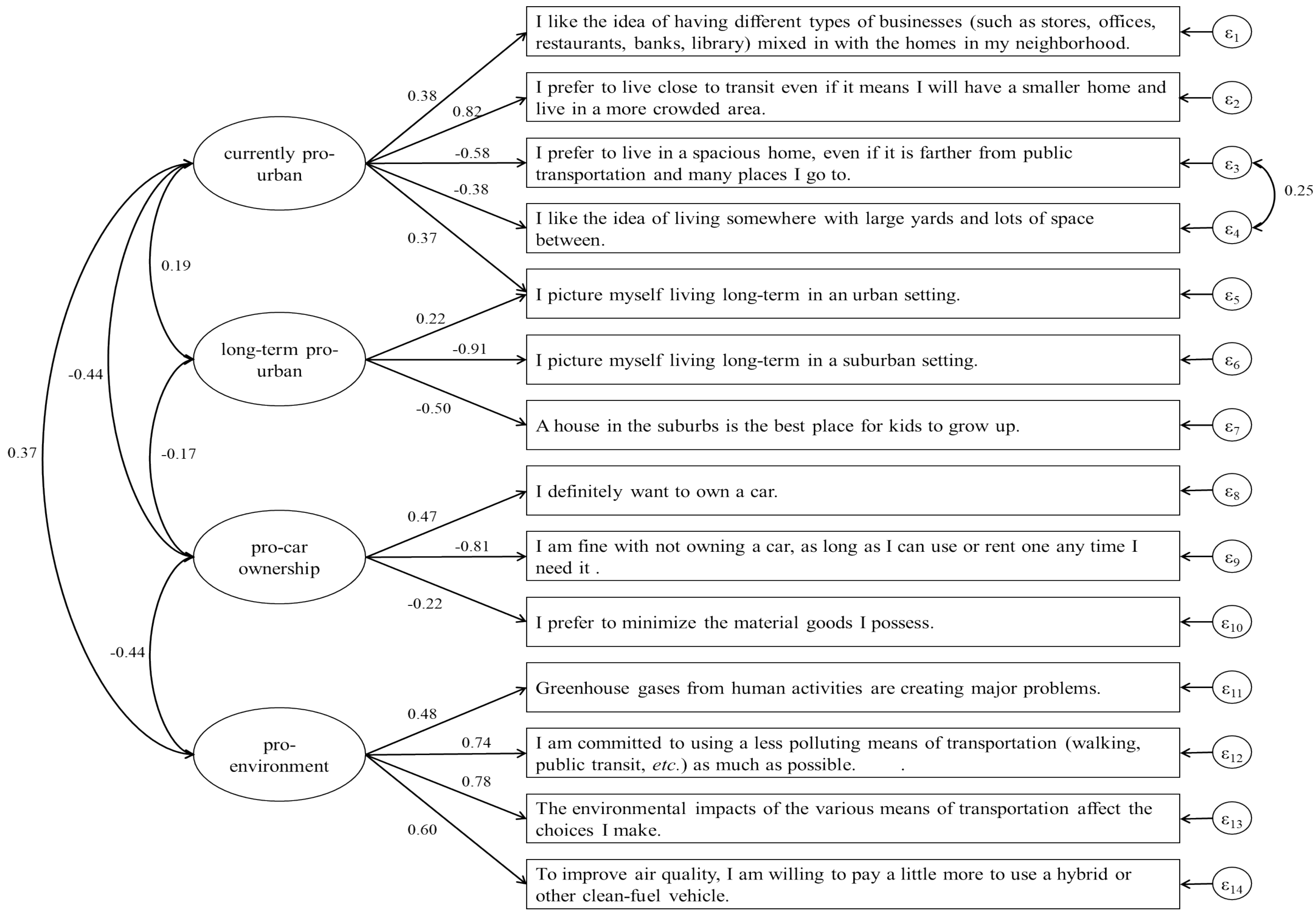

Figure 5. Confirmatory factor analysis of transportation-related attitudinal constructs (N = 1975)

Currently pro-urban

Numerous findings concur that Millennials have increased tendencies to prefer urban environments with denser land use (Delbosc and Nakanishi, 2017; Okulicz-Kozaryn and Valente, 2018), while their parents (i.e., Generation X) epitomize the suburban lifestyle, with their minivans and long commutes. This construct allows us to test that expectation with the current sample, as it reflects the mindset of respondents toward living in urban rather than suburban or rural areas—residential location choices that are critically tied to travel behavior (Ewing and Cervero, 2010; Handy, Cao, and Mokhtarian, 2005; Lavieri et al., 2017). A higher score on this construct tends to signify a preference for living in mixed-use developments with high transit accessibility, even if it means sacrificing larger home and/or yard sizes. As alluded to earlier, the statements measuring attitudes toward large homes and yards were allowed to have correlated error terms, since it is conceptually plausible that common unobserved variables help explain the variance in both of these items. The inclusion of the error term correlation produces an increase in fit for the overall model.

Long-term pro-urban (i.e., long-term urbanite)

While the prior construct captures primarily *current* land-use preferences, this factor measures *long-term* preferences toward one's residential environment. As the statements indicate, a respondent with a higher score on this construct tends to see herself as living in an urban setting in the long term and tends not to consider a suburban setting as necessarily the best environment in which to settle down and raise children. This construct is informed by a statement shared with the prior factor (i.e., a double-loaded statement), regarding urban living in the current time frame. As before, the inclusion of the double-loaded statement produces a substantial increase in fit, further improving the validity of the overall model. As expected, the pro-urban constructs in the current and long-term time frames are positively correlated, although the magnitude of this correlation is fairly low (0.19).

Pro-car ownership

As discussed, a substantial body of work indicates that Millennials have been bucking the upward trend on car ownership and VMT (Buchholz and Buchholz, 2012; Delbosc and Currie, 2013; Kuhnimhof et al., 2012; McDonald, 2015; Polzin et al., 2014; Sivak and Schoettle, 2011, 2012), with recent concern in the literature about the stability of this deviation (Blumenberg et al., 2012; Delbosc and Nakanishi, 2017; Garikapati et al., 2016; Lavieri et al., 2017; Newbold and Scott, 2017). In this study, this construct measures attitudes toward car ownership, with one indicator related to general attitudes toward owning material goods. A respondent with a high score on this factor tends to prefer *owning* a car, tends not to be satisfied with just having access to a vehicle when needed, and tends not to feel the need to minimize material possessions. It is pertinent to note here that we also developed and investigated a materialism construct for further analysis in this chapter (following its previous appearance in the exploratory factor analysis of the same data mentioned earlier; Circella et al., 2017b), and did find significant differences between Millennials and Gen Xers on this construct (with Millennials exhibiting greater materialism than Gen Xers, on average, consistent with their consumerist orientation). However, we chose not to focus on this attitudinal construct, as its causal relationship to travel behavior has not been clearly shown. Nevertheless, an indicator of the materialism construct (i.e., the general attitude toward material possessions) is retained as part of the pro-car ownership latent construct. Overall, we see that positive attitudes toward car ownership are negatively correlated with the pro-urban and pro-environmental attitudes being studied, which is conceptually reasonable as the latter constructs are associated with favorable views toward sustainable modes of transport and denser residential locations that facilitate car-free or "car-lite" lifestyles.

Pro-environment

Previous studies have found that Millennials tend to be more environmentally conscious than prior generations—for example, they are more likely to support environmentally-focused policies such as alternative energy (Rainie and Funk, 2015). We note that such positions are somewhat at odds with other attitudes and behavior associated with Millennials, such as materialism and the proclivity for air travel to distant experiences. Perhaps for this reason, the literature reports mixed results with respect to the influence of environmental consciousness on mobility decisions: while some find significant effects (Forward et al., 2010; Hopkins, 2016), with more lasting implications compared to financial or situational effects (Hopkins, 2016), others report little to no relationship between environmental attitudes and travel behavior (Anable, 2005; Delbosc and Currie, 2012). These differential conclusions may also be due to differences in sample constitution, experimental design, environmental attitude measurement, and choice of travel behavior studied. Nevertheless, in view of the clear conceptual relationships between environmental awareness and travel behavior, as well as the intriguing clash of stereotypes, we investigate differences in environmental attitudes between Millennials and Gen Xers.

As such, this construct measures a pro-environment mindset, with an emphasis on how this mindset affects transportation-related choices and behaviors. Three of the four statements measured by this construct are related to attitudes toward transportation mode and vehicle choice, while the fourth measures a general belief that greenhouse gases from human activities are creating problems. As such, a respondent with a high score on this construct tends to believe that there are environmental problems present, and tends to report being willing to alter his/her lifestyle and pay more to lead a more environmentally friendly life. We also see that this construct is positively correlated with positive views toward urban living in the present timeframe, but in line with findings from the literature, is negatively correlated with positive views toward car ownership.

Where is the gap?

Having introduced the attitudinal constructs that are examined in this chapter, we now analyze how each generation scores on these constructs and how large a gap, if any, exists between Millennials and Generation X in their attitudes. To this purpose, Table 6. summarizes the descriptive statistics and t-test results for differences in mean attitudinal factor scores for the generations being studied. One observation is that gaps in the mean scores for all four attitudinal constructs are not large, suggesting that generational differences in these attitudes may not be as pronounced as popular opinion has tended to portray. Nevertheless, the differences are statistically meaningful, even if modest. Figure 6 provides a more fine-grained look at the differences, by splitting the Millennials cohort into younger and older segments. For three of the four attitudes studied, a clear progression in attitudes from younger to older respondents can be seen.

Table 6. Descriptive statistics and t-tests of differences in weighted means

Attitudinal construct	Generation	N (weighted)	Mean	S.E.	Difference in Means	t-statistic[1] *(p-value)*
Currently pro-urban	Generation X	946	-0.010	0.046	-0.161	2.58 *(0.010)*
	Millennials	1029	0.151	0.042		
Long-term pro-urban	Older Millennials[2] and Generation X	1490	-0.093	0.035	-0.149	2.17 *(0.003)*
	Younger Millennials[2]	485	0.056	0.059		
Pro-car ownership	Generation X	946	0.037	0.047	0.195	3.160 *(0.002)*
	Millennials	1029	-0.158	0.039		
Pro-environment	Generation X	946	0.043	0.047	-0.149	2.39 *(0.017)*
	Millennials	1029	0.192	0.040		

[1] t-test statistic corresponding to differences in means between generations.
[2] Younger Millennials represent those aged 18-25, while older Millennials represent those aged 26-34 years, all numbers relative to 2015 when the survey data was collected. As further discussed in the text, the generational divides reported in this table are those that are significant, and which will, accordingly, be decomposed in the next section.

As Table 6. illustrates, consistent with stereotype, Millennials on average have more favorable views toward currently living in urban locations, while Generation X has less favorable views. The t-test on the difference in means between generations shows the gap to be statistically significant, implying that the -0.161 gap between the mean factor scores can be validly decomposed. Further dissection of the Millennials cohort on this construct, as demonstrated in Figure 6, shows that “younger” Millennials (18-25 years old) have a larger mean factor score (0.215) compared to the “older” Millennials (26-34 years old), whose factor score averages at 0.093 (thus putting older Millennials between younger Millennials and Gen X on the attitudinal “continuum”).

Long-term attitudes toward one’s living environment did not prove to be significantly different between Millennials and Generation X, but when we separated the younger Millennials (as previously demarcated) from the others, there was a more defined change. Younger Millennials, per Table 6. and Figure 6, have a positive mean factor score, while older Millennials aggregated with members of Gen X have an almost equal negative mean factor score. The similarity between older Millennials (-0.100) and Gen X (-0.091) in this construct (both having negative mean scores) resembles the findings for the currently pro-urban construct previously discussed, in that it suggests a state of attitudinal transition. Based on the relationships shown in the figure, to investigate the drivers of this gap, for this variable we combine older Millennials with Gen Xers, and decompose the statistically significant -0.149 difference in the mean values of the long-term urbanite attitude for that group versus the younger Millennials.

Attitudes regarding the desire to own a car are significantly different between the two generations (mean gap of -0.195), with Millennials indicating that on average they are more averse to owning a personal vehicle, despite their tendencies to be actually more materialistic in general (Circella et al., 2017b). For this construct, as Figure 6 shows, the mean factor score for younger Millennials (-0.224) is more negative (*farther* from the Gen X mean of 0.037) than that of older Millennials (-0.099). Regarding environmental views between the two generations per se, we again see a statistically significant difference in attitudes (-0.149), with Millennials being more environmentally conscious on average. For this variable, the difference between younger and older Millennials is relatively small, and not statistically significant.

Based on the findings discussed here, attitudinal gaps between Millennials and Generation X are further analyzed for residential location choice attitudes in the present time frame, as well as for attitudes toward car ownership and the environment. However, for the long-term urban residential choice construct, we decompose the gap between younger Millennials and the aggregate group of older Millennials and Generation X instead, for reasons explained above. As mentioned earlier, the statistics discussed here illustrate a general trend across constructs whereby older Millennials tend to have mean factor scores that are between those of younger Millennials and Generation X, reinforcing expectations that many transport-related attitudes (and thus, observed behaviors) may exist along an age and/or life stage-related continuum.

With that in mind, it is reasonable to ask, why not simply incorporate age as a continuous explanatory variable in a regression model for each attitude, interacted with at least some of the other variables in the model? Why artificially dichotomize a continuous variable, thereby throwing away considerable information about its effects? We readily acknowledge the advantage of this alternative approach, and do not assert that our approach is unequivocally superior. Rather, we suggest that it has advantages of its own. First, for better or worse, it is common to analyze generations as discretely-defined cohorts rather than as falling along an age-based continuum, and so this study provides insight that is directly useful to this popular paradigm. Second, the gap decomposition approach clarifies and quantifies the sources of attitudinal differences more readily than would a regression model with continuously varying age and age interaction terms. Third, the present context offers a convenient and topical platform from which to highlight a methodology that, although little-used in transportation to date, has numerous potential applications in our field.

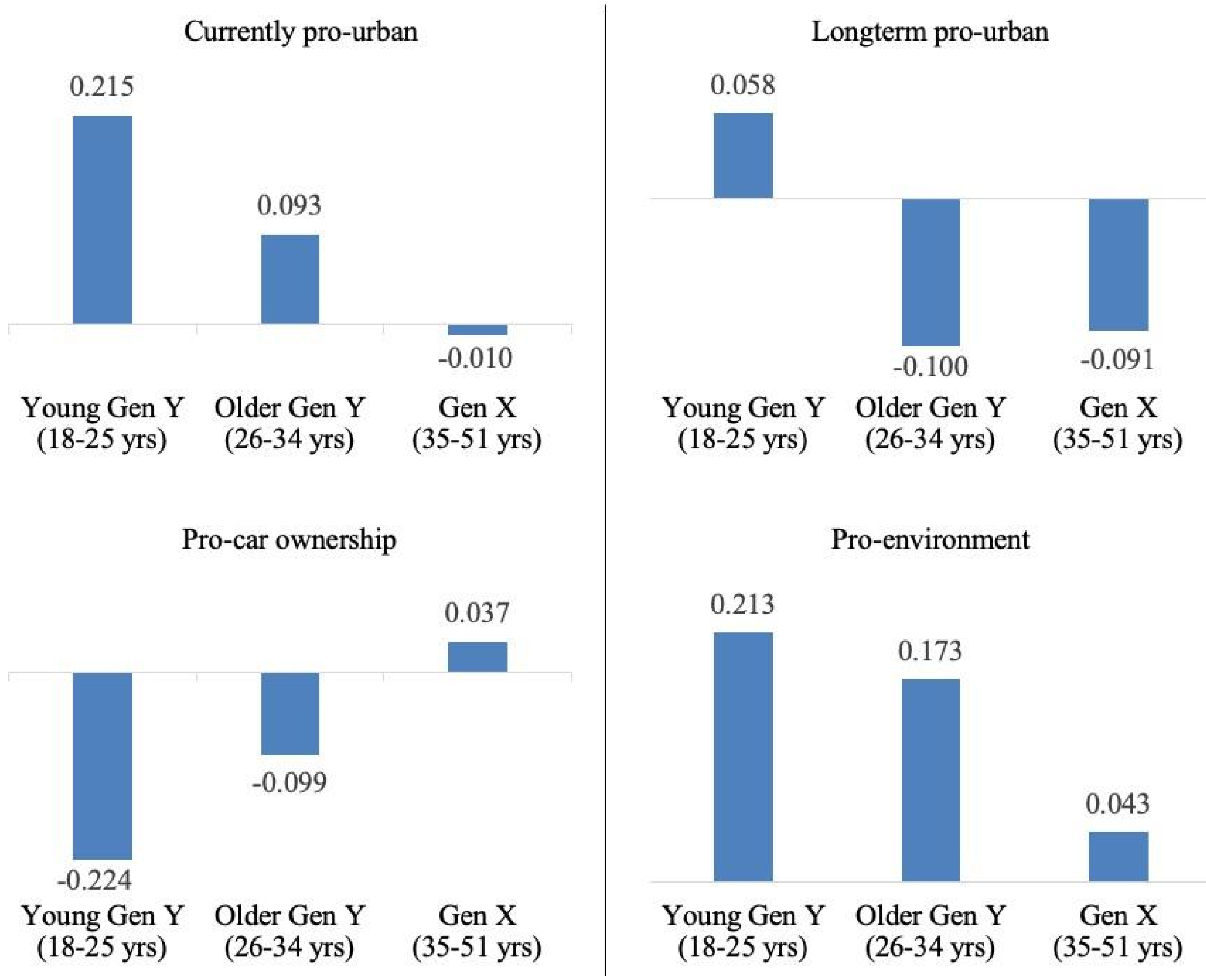

Figure 6. Detailed comparison of mean attitudinal values among generations

Decomposing the gap

We are often interested not only in finding differences (i.e., "gaps") in observations over time or across groups, but also in finding the drivers (i.e., significant explanatory variables) of these differences. Going a step further requires us to ask, what are the *differential effects* of these explanatory variables on groups between which gaps have been identified? Ensuing from the seminal works of Oaxaca and Blinder (Blinder, 1973; Oaxaca, 1973), the Blinder-Oaxaca (BO) decomposition methods have been most widely applied in economics to study discriminatory behaviors of employers resulting in gender wage gaps. The gender wage gap disparity is a favored application because it is clear that while there is a plethora of *explanatory variables* (such as differing levels of education) contributing to wage differences between genders, it is also true that the *return* for men with the *same* level of a variable like education is often greater, due to discriminatory practices against women. Because the BO method has not been widely used in transportation, we next provide a detailed overview of the method.

Results and discussion

In this study, we apply the threefold BO decomposition to investigate generational differences in attitudes, which presents a more fine-grained decomposition by separating the interaction term from the other two terms, thus allowing for a more consistent and "cleaner" interpretation. We select Millennials as the reference group, and thus, the results should be interpreted as representing how Millennials' mean attitudes would change if they only had Generation X characteristics (endowments) or if Millennials' own characteristics were only influenced to the same extent that Gen Xers' characteristics were (coefficients), or if both effects occurred at once (interaction). In principle, this allows us to separate the portion of the gap that is attributable to Millennials currently just being at a different life stage (part of their endowment), from that which is due to more fundamental shifts in effects (coefficients) that may persist even after (if) their endowments converge to those of Gen Xers. In reality, however the constant term of each model captures the average impact of all relevant *unobserved* variables on the associated attitude, and as such, the composite contributions of those variables to the gap are accounted for as a difference in the constant term between cohorts. Although this is technically a difference in coefficient, in actuality the constant term will include (average) unobserved *endowments*, together with their coefficients. If the Millennials' constant term were to approach that of Gen Xers' over time, it would be unknown whether this were due to both *unobserved endowments* and the *coefficients of those endowments* converging, or whether changes in one of those things narrowed the gap while changes in the other widened it (but with the first effect predominating).

The segmented linear regression models are estimated using sociodemographic and (when appropriate) built environment characteristics, as these variables facilitate clearer interpretation of life-stage effects and are less likely than behavioral or other attitudinal variables to be endogenous. We first estimate segmented models (for Millennials and Generation X) for each construct, and identify significant explanatory variables across the two regression models. We then test all identified significant variables in the decomposition model. To better focus on the decomposition results, we present the fully estimated models and more detailed discussion on the impact of the significant variables in the Appendix, and bring only an overview of the models into the following sections. As a general observation, it should be noted that the R^2 goodness-of-fit measures for the models—i.e., the proportions of variance in attitudes that are explained by observed variables—are fairly modest (ranging from 0.058 to 0.143), albeit consistent with typical values for disaggregate travel behavior-related models. Nevertheless, as just indicated, the composite contributions of the remaining, *unobserved* variables to the gap are accounted for as a difference in the constant term between cohorts.

Table 7. provides a summary of the decompositions for the four attitudes studied in this chapter. In the following sections we discuss these results in greater detail.

Table 7. Summary of decomposition of attitudinal gap results

Attitudinal construct	Generation	Mean	Gap	Endowment	Coefficient	Interaction
Currently pro-urban	Generation X Millennials	-0.010 0.151	-0.161 100%	-0.052 32%	-0.048 30%	-0.061 38%
Long-term pro-urban	Older Millennials and Generation X Younger Millennials	-0.093 0.056	-0.149 100%	-0.265 178%	-0.019 13%	0.135 -91%
Pro-car ownership	Generation X Millennials	0.037 -0.158	0.195 100%	0.082 42%	-0.032 -16%	0.145 74%
Pro-environment	Generation X Millennials	0.043 0.192	-0.149 100%	-0.047 32%	-0.052 35%	-0.050 33%

Currently pro-urban attitude

The segmented regression results for the currently pro-urban attitude associate life-stage variables such as being married and having higher income with a lower pro-urban tendency, while employment status shows a positive association. In addition, female Millennials tend to be significantly less pro-urban than their male counterparts, a trend that is not present (or significant) for Gen Xers. Moreover, Millennials who have a parent (or parents) with graduate-level education tend to be more pro-urban, while this influence is the opposite (though not significant) with Gen Xers, potentially pointing to a critical generational difference in how those raised in well-educated (higher-earning) households view the desirability of living in urban areas. With regard to race, Native Americans tend to be less pro-urban, while Asians tend to be more pro-urban, relative to other races.

Based on these regression results, Table 8. shows the threefold decomposition of the gap between the mean currently pro-urban attitudes of Millennials and Gen Xers. The total gap for this attitude is -0.161 (standard deviations), with the three decomposition portions explaining approximately equal shares of this gap (i.e., ~ -0.05 each). The endowment term, itself only marginally significant at a 10% level, includes several significant (at the 10% level) life-stage and political affiliation variables, while gender, race, and childhood residential location appear to explain little of the overall endowment portion of this decomposition. Similarly, the coefficient term, while itself not statistically significant, contains significant contributions associated with variables such as gender, marital status, parental education, and political affiliation. To provide a more intuitive basis for interpretation, Figure 7 and Figure 8 show the detailed contributions of each variable to the endowment and coefficient portions of the currently pro-urban attitudinal gap, respectively; each bar shows the contribution (in standard deviation units) associated with each variable, in addition to its 95% confidence interval.

Table 8. Detailed threefold decomposition for the currently pro-urban attitude

	Endowment		Coefficient		Interaction		Total
	Coef. (Std. Err.)	p-value	Coef. (Std. Err.)	p-value	Coef. (Std. Err.)	p-value	Coef.
Raised in Hawaii	-0.003 (0.006)	0.622	-0.010 (0.006)	0.108	0.003 (0.006)	0.621	-0.010
Raised in Northeast	0.001 (0.002)	0.766	0.013 (0.008)	0.114	0.004 (0.005)	0.447	0.018
Native American	0.005 (0.005)	0.356	-0.0003 (0.011)	0.975	0.0001 (0.003)	0.975	0.005
Asian	-0.003 (0.005)	0.579	0.019 (0.025)	0.453	0.001 (0.003)	0.649	0.017
Female	-0.001 (0.006)	0.882	0.109 (0.062)	0.079	0.001 (0.007)	0.882	0.109
Married	-0.019 (0.024)	0.440	-0.097 (0.048)	0.044	-0.076 (0.038)	0.047	-0.192
High household income (> $100K)	-0.032 (0.018)	0.067	0.012 (0.041)	0.765	0.007 (0.024)	0.765	-0.013
Parent w/ graduate education	0.004 (0.006)	0.556	-0.074 (0.032)	0.019	-0.006 (0.010)	0.555	-0.076
Employed	0.011 (0.006)	0.081	-0.059 (0.097)	0.543	-0.005 (0.009)	0.549	-0.053
Democrat	-0.001 (0.003)	0.748	0.083 (0.056)	0.137	-0.005 (0.007)	0.464	0.077
Republican	-0.020 (0.011)	0.074	0.050 (0.024)	0.040	0.014 (0.010)	0.156	0.044
Constant	-	-	-0.093 (0.157)	0.552	-	-	-0.093
Total	-0.052 (0.031)	0.100	-0.048 (0.067)	0.473	-0.061 (0.042)	0.148	-0.161

Endowment

As shown in Figure 7, disparities in generational shares of high-income groups, political affiliation, employment status, and marital status contribute the most to the overall endowment portion of the gap, although the contribution of disparity in marital status shares is not statistically significant, despite its magnitude. Those in higher-income households tend to have less favorable currently pro-urban attitudes; therefore, with Millennials currently lagging in earnings compared to Gen X, we may expect their favorability toward currently pro-urban living to drop by as much as 0.032 (standard deviation units) if (all else equal) the Millennials' share of high income (>$100K) households matched Gen Xers' current share. In other words, the younger generation's attitude toward currently pro-urban living could close the gap (through becoming less pro-urban) by as much as 20% (-0.032 / -0.161 = 0.20) given these conditions. On the other hand, being employed has a positive effect on this attitudinal construct (see regression results in the Appendix), suggesting that if the employment rate among Millennials were to match that of their older peers (as they graduate and enter the workforce), they may on average (holding all else constant) become slightly more pro-urban (+0.011 s.d. units), thereby *widening* the gap by 7%. With regard to marriage rates, we see that if Millennials were to have the same shares of marriage as Gen Xers, their favorability toward currently pro-urban living (all else equal again) would decrease by 0.019 s.d. units (narrowing the gap by 12%).

Considering the overall impact of the life-stage variables discussed, the model suggests that there may be an overall 0.039 s.d. (roughly 25%) decrease in the gap (due to Millennials becoming less pro-urban) as more Millennials enter the workforce, marry, and ultimately earn higher incomes. Such predictions, needless to say, assume the temporal invariance of the Millennials' model coefficients. In other words, it assumes that as Millennials continue to age, their currently pro-urban attitudes will be *influenced* by these life-stage variables in a similar way as they are now, even though the *measured values* of these variables are changing. Testing the validity of these assumptions requires longitudinal data, and as with many other models in practice and literature, such insights into the future based on cross-sectional data should be interpreted with due caution.

Finally, we see (that those who identify as Republican have lower tendencies to be pro-urban and this party also has lower shares in the Millennials generation, a disparity that accounts for approximately 38% (-0.020/-0.052) of the endowment gap and 12% of the total gap.

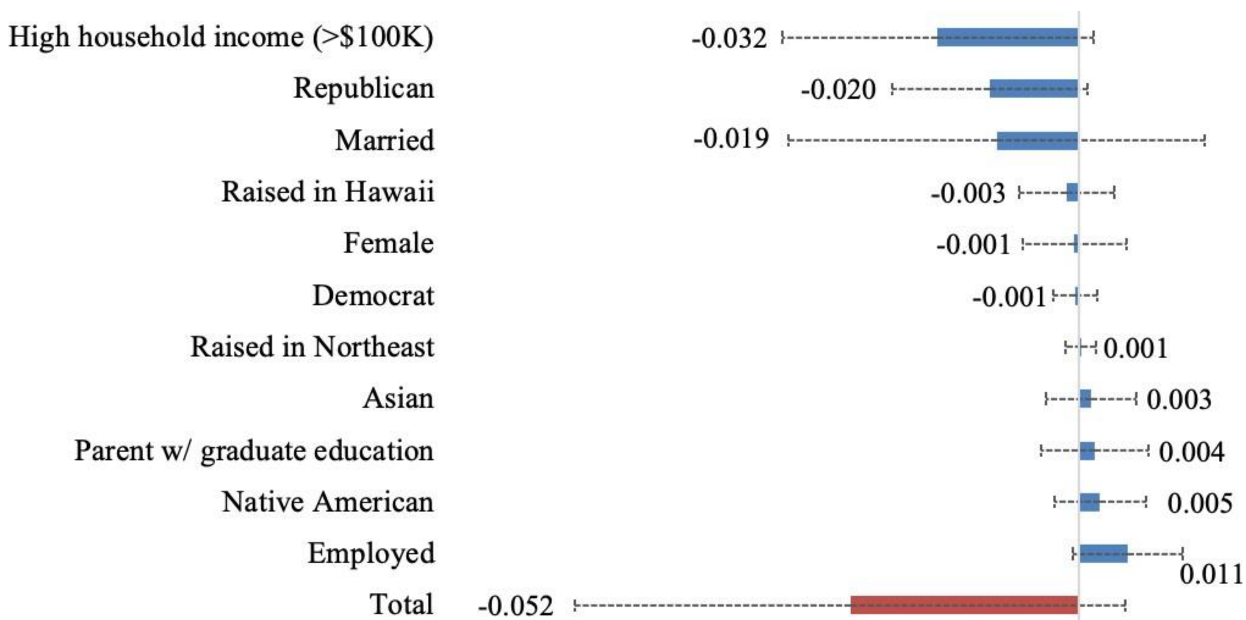

Figure 7. Contributions to the endowment portion of the difference in mean "currently pro-urban" attitude (Horizontal dashed lines portray the 95% confidence interval)

Coefficient

Figure 8 details the coefficient portion of the gap, with effect disparities of marital status, parental education level, political affiliation, and gender having relatively large and significant contributions to the overall coefficient portion. Although both generations tend to be less pro-urban when married, this effect is stronger among Gen Xers, hence the decrease (all else equal) in Millennial's average "currently pro-urban" attitude if marriage were to influence *their* attitude similarly to the way it influences Gen Xers'. Meanwhile, Millennials having a parent with graduate-level education tend to be more "currently pro-urban", while Gen Xers with the same characteristics show the opposite effect, and so if Millennials had the coefficients of Gen X on these attributes, there would again be decreases in their overall attitude toward urban living. Finally, we see that right-leaning political affiliations and gender (being female) both have a stronger negative effect on the pro-urban attitude among Millennials, hence, in this case if Millennials had the coefficients of Gen X on these attributes, there would be *increases* in their overall affinity for urban living. Thus, as illustrated in this discussion, the BO method facilitates an examination of not only the *variables* that are affecting pro-urban attitudes, but also the role of differential *effects* of the explanatory variables on the identified attitudinal differences between generations.

We further discuss the aggregated effect (by life-stage variables and other characteristics) of the three terms, pointing out that, although the total coefficient effects are generally smaller than the endowment effects, the *life-stage* coefficient effects per se tend to be much larger than their endowment counterparts. This aggregated decomposition brings additional insight into how different groups of variables impact the gap differently.

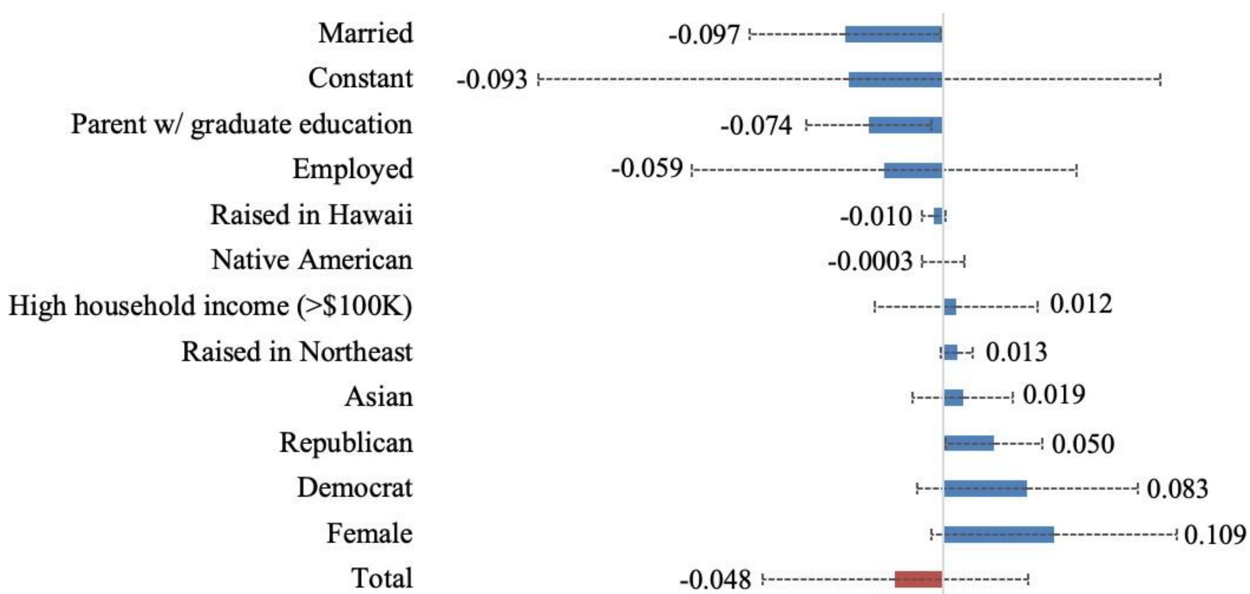

Figure 8. Contributions to the coefficient portion of the difference in mean "currently pro-urban" attitude (Horizontal dashed lines portray the 95% confidence interval)

Interaction

With respect to the interaction term of -0.061, following the earlier discussion, we can say that (as already seen from Table 8., Figure 7 and Figure 8): the baseline endowment effect for Millennials is -0.052 (holding their coefficients constant but changing their endowments to those of the Gen Xers); and the baseline coefficients effect for Millennials is -0.048 (holding their endowments constant but changing their coefficients to those of the Gen Xers); but an *additional* effect of -0.061 is accrued if *both* their endowments and their coefficients were to change to those of the Gen Xers at the same time. The relative magnitude of this interaction effect (it is the largest component of the gap, accounting for 38% of it) demonstrates its importance.

We can also interpret the specific contribution of the most important variable in the interaction effect, namely marital status. As previously discussed, if Millennials were to achieve the *same marriage rate* as Gen Xers while keeping all coefficients constant (the *endowment* effect), the mean contribution to the total gap of -0.161 would be -0.019, closing it by 12%. If marital status were to have the same *effect* on the currently pro-urban attitude for Millennials as for Gen Xers while not changing their actual marriage rates (the *coefficient* effect), the mean contribution to the gap would be -0.097, closing it by 60%. But if *both* the marriage *rate* and the *effect of marital status* for Millennials converged to those of Gen Xers, the *additional* contribution to the gap would be -0.076, closing it by a further 47% (the fact that the sum of these contributions exceeds 100% merely indicates that other explanatory variables contribute to *widening* the gap, as we saw with the endowment effect for employment status).

Long-term pro-urban attitude

As discussed, the long-term pro-urban attitude is segmented based on the younger Millennials cohort (< 26 years old) relative to an aggregate group of older Millennials and Generation X. For this attitude, we see that attributes related to childhood residential location, current residential location, race, income level, education level, political affiliation, and the interaction between marital status and children are statistically significant predictors of the long-term pro-urban attitudinal construct. Notably, among younger Millennials, those who currently live in urban areas tend to have significantly more favorable attitudes toward long-term urban living than non-urban dwellers, an effect that is consistent but not significant for their older peers. In addition, those who identify as White in both cohorts being studied tend to have significantly more favorable attitudes toward long-term urban living relative to other races.

With regard to life stage variables, we see that the interaction of being married and number of children (in the household) is significant for both cohorts, indicating that those who are married and with more children in the household tend to have less favorable attitudes toward long-term urban living. Additionally, we see that those with lower levels of education and income show a more favorable opinion toward living long-term in urban environments.

Based on these regression results, Table 9. presents the decomposition of the difference in means for the long-term urbanite attitude (-0.149). We see that the endowment portion of the gap is the largest, with the interaction portion cancelling out roughly half of its negative value.

The magnitude of the interaction term here is mostly due to the "married ´ number of children" term, with the other interaction effects significantly smaller. This illustrates that the simultaneous change in the share and effect of this variable plays a large role in defining the gap in this attitude, as will be discussed further below. The overall coefficient portion is significantly smaller than the endowment and interaction portions, with none of its terms having large magnitudes or showing statistical significance. As before, Figure 9 and Figure 10 visually illustrate the endowment and coefficient portions of the long-term urban living gap to allow for a more intuitive interpretation of Table 9..

Table 9. Detailed threefold decomposition for the long-term pro-urban attitude

	Endowment		Coefficient		Interaction		Total
	Coef. (Std. Err.)	P-value	Coef. (Std. Err.)	P-value	Coef. (Std. Err.)	P-value	Coef.
Raised in the Southeast	0.015 (0.012)	0.223	-0.021 (0.013)	0.100	-0.022 (0.015)	0.139	-0.028
Raised in Hawaii	-0.002 (0.005)	0.661	-0.006 (0.006)	0.296	0.002 (0.005)	0.661	-0.006
Raised in Alaska	-0.009 (0.010)	0.352	-0.010 (0.01)	0.303	0.008 (0.009)	0.380	-0.011
White	0.013 (0.011)	0.250	-0.047 (0.068)	0.491	-0.005 (0.007)	0.541	-0.039
Number of children	0.023 (0.041)	0.571	-0.013 (0.064)	0.841	-0.010 (0.052)	0.841	0.000
Employed	-0.280 (0.107)	0.009	0.038 (0.027)	0.157	0.177 (0.119)	0.138	-0.065
Married	0.051 (0.090)	0.569	-0.0001 (0.035)	0.998	0.003 (0.031)	0.934	0.054
Low household income	-0.045 (0.028)	0.103	-0.006 (0.067)	0.934	-0.0003 (0.099)	0.998	-0.051
High school education only	-0.019 (0.020)	0.328	0.023 (0.044)	0.610	-0.013 (0.025)	0.612	-0.009
Urban dweller	-0.0001 (0.001)	0.908	0.053 (0.048)	0.269	-0.001 (0.007)	0.865	0.052
Republican	-0.012 (0.010)	0.211	-0.004 (0.017)	0.798	-0.003 (0.012)	0.798	-0.019
Constant	-	-	-0.026 (0.145)	0.855	-	-	-0.026
Total	-0.265 (0.086)	0.002	-0.019 (0.075)	0.796	0.135 (0.092)	0.143	-0.149

Endowment

With respect to the baseline endowment effect, Figure 9 shows that by far the strongest influence belongs to the interaction of marital status with number of children in the household, but this term should be interpreted in conjunction with its constituents, the marital status and number of children variables. The interpretation is that if younger Millennials were to have the same share of married people, the same average number of children, and the same average number of children per married person as the older group does (holding all else constant), they would have a significantly less favorable attitude toward living long-term in urban environments. With respect to other life-stage variables, we see that the contributions of having a lower income (relatively large, although not statistically significant) and only a high school level education suggest that younger Millennials' views of long-term urban living will become less favorable as they graduate from college and increase their earnings.

The combined contributions of these life-stage disparities add to -0.270 overall, accounting for 181% of the total gap of -0.149. This implies that if younger Millennials took on the same life-stage endowments as their older peers but kept their own coefficients (and all else constant), they could end up even less favorable toward long-term living in urban areas than the older group is now. However, note from the coefficient and interaction effects of these variables that if the younger Millennials' *coefficients* also changed to those of the older group, the net effect of the four life-stage variables (low income, high school education, married, and number of children, plus the interaction of the last two) on attitudes would be -0.072, closing just 48% of the gap rather than "overshooting" it.

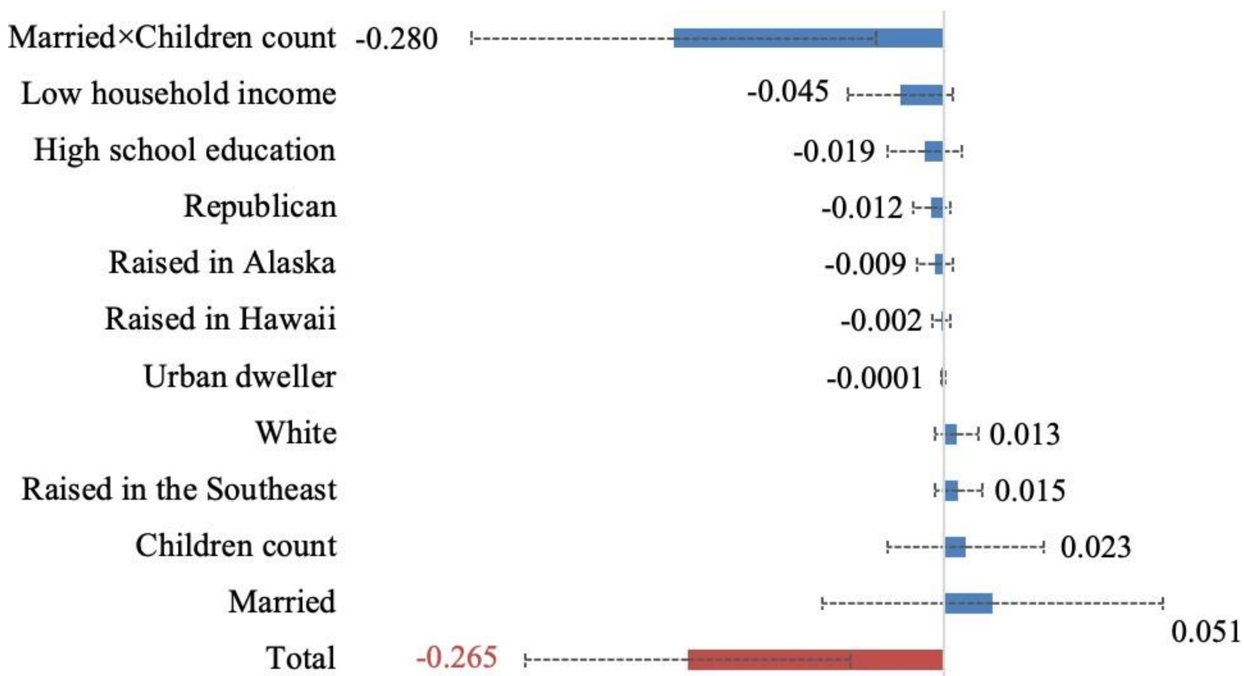

Figure 9. Contributions to the endowment portion of the difference in mean "long-term pro-urban" attitude (Horizontal dotted lines refer to the 95% confidence interval)

Coefficient

Figure 10 portrays the coefficient portion of the gap; however, none of the effect disparities are statistically significant nor practically large, and we therefore do not discuss the results of this portion further.

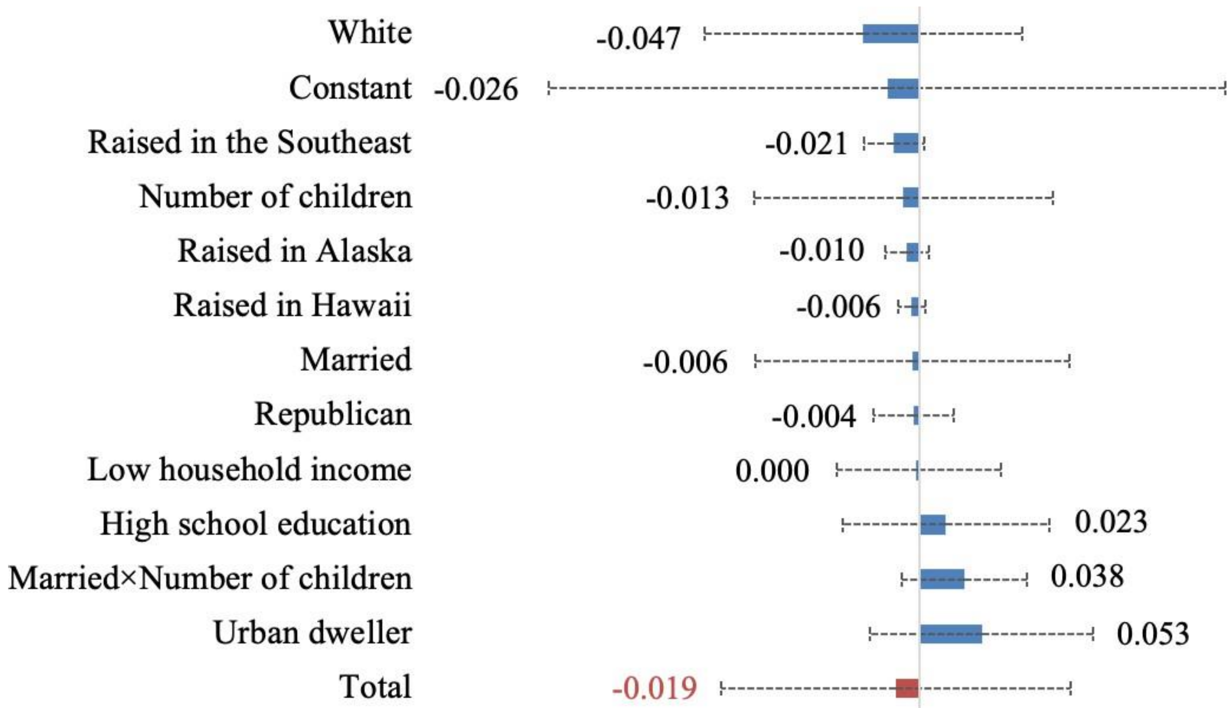

Figure 10. Contributions to the coefficient portion of the difference in mean "long-term pro-urban" attitude (Horizontal dashed lines refer to the 95% confidence interval)

Interaction

The interaction term here has a relatively large contribution, and as discussed, indicates an incremental effect of 0.135 s.d. units that substantially counteracts the baseline endowment and coefficient effects when *both* endowments and coefficients of younger Millennials change to those of their older peers at the same time. The large magnitude of this term can mostly be attributed to the "married ⍰ number of children" variable. Considering this variable together with its main-effects constituents, we see that if *both* the *means* and the *effects* of these variables (married, number of children, and their interaction) for younger Millennials converged to those of the older group, the *incremental* contribution (on top of endowment and coefficient effects) to the gap would be 0.170. However, it is best to consider the interaction effect *together* with the endowment and coefficient effects: the total effect of these three variables is a scant -0.011, indicating that the net impact on the gap of this bundle of variables, if both endowments and coefficients of the younger Millennials achieved those of the older group, would be negligible (closing only 7% of the -0.149 gap). Viewed this way, the other two life-stage variables, low income and high school education, are more powerful: the total combined effects of these two variables is -0.0603, which would close 40% of the overall gap if the younger Millennials replicated the income and education endowments and coefficients of their older counterparts.

Pro-car ownership attitude

The significant variables in the regression models for the pro-car ownership attitude include attributes related to childhood and current residential locations, gender, race, education level, marital status, occupation, student status, and political affiliation. We see that urban dwellers tend to be less pro-car, although this effect is attenuated among Millennials. Regarding race, Whites and African Americans tend to have more favourable views toward car ownership, while Asians have less favourable views, relative to the base group which represents all other races (Native Americans, mixed race, and others). Gender is also a significant predictor, with women tending to have more favourable car ownership attitudes than men. With respect to education, those with a high school education, and those who are college students, are less insistent on owning a car, potentially because of lower income levels and overall needs relative to those with higher education levels. Those who identify as Republican tend to have more favourable views toward owning a car, and in conjunction with previously reported results, we see that Republicans in the sample tend to be less pro-urban, less pro-environment, and more pro-car ownership than those of other political affiliations.

We now turn to the BO decomposition for the pro-car ownership construct (Table 10.). The endowment portion of the gap significantly explains 42% of the total gap, while the coefficient portion is much smaller and contributes in the opposing direction. The interaction portion in this decomposition is the largest, explaining about 74% of the gap. In the endowment portion of the decomposition, education level and student status have the largest contributions, while in the coefficient portion of the model, race, marital status, and built environment have the largest contributions. Figure 11 and Figure 12 illustrate the contributions of the explanatory variables to the endowment and coefficient portions of the gap.

Table 10. Detailed threefold decomposition for pro-car ownership attitude

	Endowment		Coefficient		Interaction		Total
	Coef. (Std. Err.)	P-value	Coef. (Std. Err.)	P-value	Coef. (Std. Err.)	P-value	Coef.
Raised in Hawaii	0.002 (0.003)	0.620	0.007 (0.005)	0.112	-0.002 (0.005)	0.622	0.009
Raised in Southeast	-0.006 (0.006)	0.315	-0.015 (0.009)	0.104	0.005 (0.005)	0.358	-0.016
Native American	0.008 (0.006)	0.161	-0.003 (0.005)	0.507	-0.002 (0.003)	0.541	0.003
White	0.001 (0.004)	0.809	0.165 (0.073)	0.024	0.014 (0.012)	0.237	0.180
African-American	0.004 (0.004)	0.379	0.007 (0.009)	0.392	0.002 (0.004)	0.521	0.013
Asian	-0.004 (0.008)	0.573	0.050 (0.030)	0.098	0.004 (0.007)	0.588	0.050
Female	0.001 (0.007)	0.882	-0.106 (0.059)	0.073	-0.001 (0.007)	0.882	-0.106
High school education only	0.026 (0.011)	0.016	0.019 (0.030)	0.528	-0.010 (0.016)	0.531	0.035
Urban dweller	-0.0001 (0.002)	0.955	-0.111 (0.041)	0.006	0.011 (0.012)	0.373	-0.100
Student	0.052 (0.020)	0.010	-0.031 (0.059)	0.598	0.023 (0.044)	0.598	0.044
Married	-0.016 (0.024)	0.494	0.119 (0.046)	0.009	0.092 (0.037)	0.011	0.195
Republican	0.014 (0.009)	0.108	0.017 (0.024)	0.492	0.005 (0.007)	0.517	0.036
Employed in service	0.001 (0.002)	0.679	0.009 (0.006)	0.169	0.003 (0.004)	0.430	0.013
Constant	-	-	-0.158 (0.169)	0.348	-	-	-0.158
Total	0.082 (0.034)	0.016	-0.032 (0.075)	0.671	0.145 (0.058)	0.013	0.195

Endowment

As shown in Figure 11, education-related variables contribute the most to the overall endowment gap, with disparities in shares of students and those with only a high school education between the two generations explaining a significant portion of the endowment gap. As before, these terms indicate that if the shares of Millennial students and those with only a high school education diminish to the Gen Xers' levels, the mean pro-car attitude among Millennials could increase by 0.052 and 0.026 s.d. units, respectively. Additionally, the disparity in marriage rates demonstrates a relatively large (although not statistically significant) contribution, albeit in the negative direction. Overall, assuming that Millennials were to end up having the same shares for these life-stage variables (and holding all else equal), we may see an increase of as much as 0.062 s.d. units (i.e., a 32% decrease in the gap) in the mean pro-car attitude of Millennials as they graduate with a college degree and begin to get married. In addition to the life-stage variables, the difference in shares of political affiliation also results in a relatively large contribution. Millennials, with a lower share of Republicans in our weighted dataset, would have a stronger pro-car attitude if they had as many Republicans as the Gen X generation does.

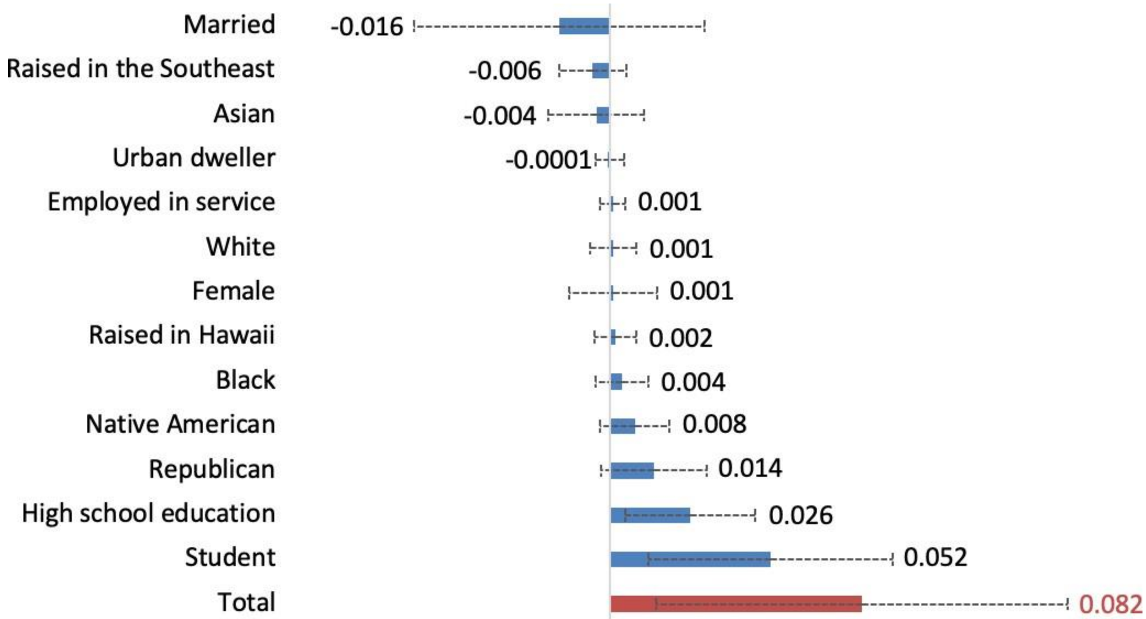

Figure 11. Contributions to the endowment portion of the difference in mean "pro-car ownership" attitude (Horizontal dashed lines refer to the 95% confidence interval)

Coefficient

The overall contribution of the coefficient portion (Figure 12) is relatively small and insignificant, although this insignificance and low magnitude is due largely to sizable contributions in opposite directions. The constant term, which indicates the difference in the effect of unobserved variables between the two groups, has the largest, yet not statistically significant, contribution. The effect disparity of the built environment is also significant, with Gen Xers living in urban areas interestingly having a *lower* tendency to be pro-car than their Millennial neighbors do (perhaps suggesting that living in an urban area signifies more of a lifestyle commitment for Gen Xers, who may be married and with families, than for the more transient Millennials, who may yet move to the suburbs when *they* marry and have children). The effect disparity for marital status also explains a relatively large portion of the gap, showing that if being married were to have the same impact on the pro-car attitude of Millennials as it does for Gen Xers, Millennials' attitudes would become more favorable on average. Finally, race plays a significant role, specifically the differential impact on pro-car attitudes of being Asian or White that is exhibited by Millennials relative to their Generation X peers.

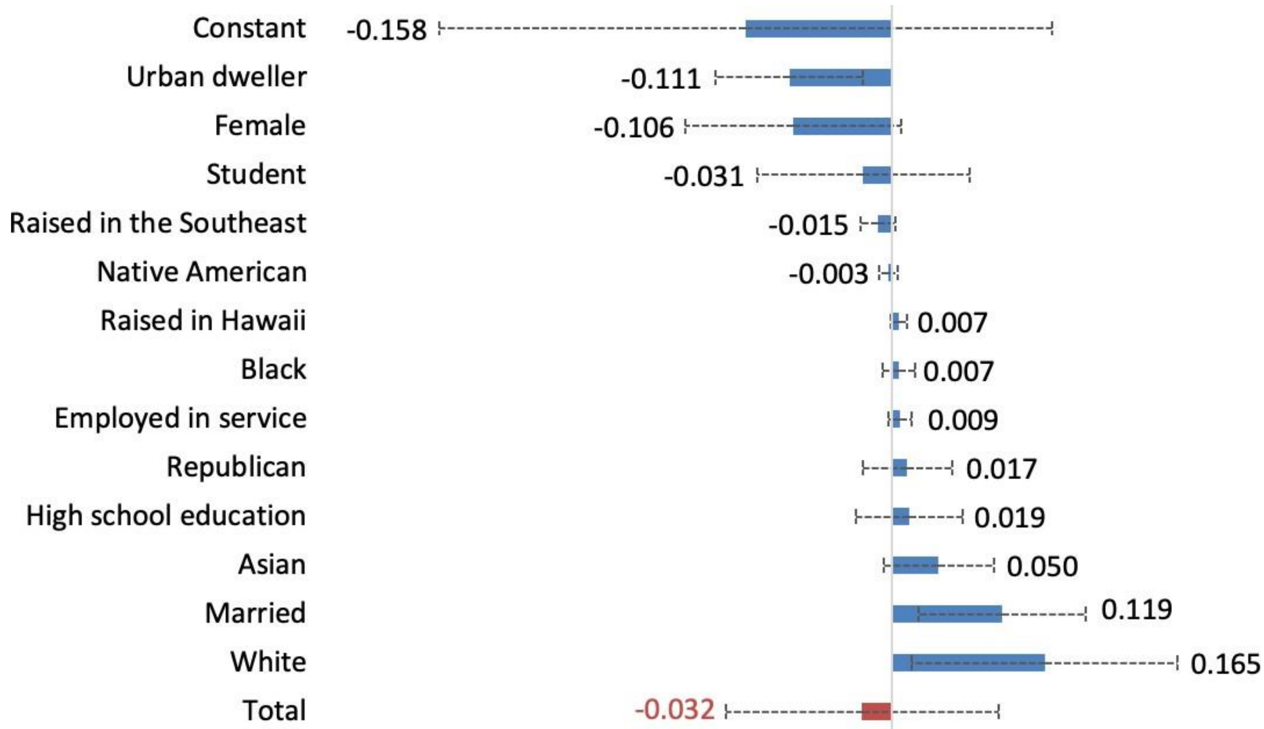

Figure 12. Contributions to the coefficient portion of the difference in mean "pro-car ownership" attitude (Horizontal dotted lines refer to the 95% confidence interval)

Interaction

The interaction term has a relatively large value here (0.145), stemming largely from marital status (the only significant interaction effect). We see that the incremental effect (on top of the all-else equal terms) of the simultaneous change of endowments and coefficients for the married variable would result in a more favourable pro-car ownership attitude for the Millennials. This incremental effect is in the opposite direction to the endowment effect, but in line with the coefficient effect. The total of all three effects for the married variable essentially accounts for the entire attitude gap of 0.195 s.d. units; the effects of all other variables almost exactly cancel each other out.

Pro-environment attitude

The regression models for the pro-environment attitude, show that childhood residential location, current residential location, race, income level, education level, employment status, student status, and political affiliation are all statistically significant predictors of attitudes toward environmentally-conscious living. Living in an urban area tends to indicate more favorable pro-environment attitudes for both cohorts. In addition, we see that being a member of either Hispanic or Asian racial/ethnic groups is a significant predictor of environmental attitudes for both cohorts, with members of these groups tending to be more pro-environment than those from other races. Furthermore, among Millennials, those who are students, employed, or have high individual income levels (>$100K) tend to be more pro-environment than their counterparts, while for the same groups of Gen Xers, although the average effects are also positive, they are smaller and not statistically significant. This observation suggests a generational divide in which employed Millennials with or without well-paying jobs report a greater care for the environment than the preceding generation.

Table 11. summarizes the detailed threefold decomposition of the generational difference in the mean pro-environment attitude. The total difference in mean attitude between Millennials and Generation X (Table 6.) is -0.149 s.d. units. This difference is approximately equally explained by the three components of the decomposition, although the statistical significance of each term is poor. Upon closer investigation, however, we can see that these lower significance levels are largely due to statistically significant contributions of several influential variables in opposite directions that end up cancelling each other out, resulting in a smaller total contribution for each portion with consequently a lower significance level. Figure 13 and Figure 14 show the detailed contribution of each variable to the endowment and coefficient portions of the overall difference, respectively. Given that none of the effects for the interaction term are significant or relatively large, we do not discuss those in detail here.

Table 11. Detailed threefold decomposition for pro-environment attitude

	Endowment		Coefficient		Interaction		Total
	Coef. (Std. Err.)	p-value	Coef. (Std. Err.)	p-value	Coef. (Std. Err.)	p-value	Coef.
Raised in the Pacific region	0.001 (0.002)	0.560	0.008 (0.005)	0.086	-0.002 (0.003)	0.562	0.007
Raised in Alaska	0.002 (0.002)	0.350	-0.004 (0.004)	0.298	0.003 (0.004)	0.398	0.001
Asian	0.002 (0.004)	0.587	0.053 (0.022)	0.019	0.004 (0.007)	0.578	0.059
Hispanic	-0.031 (0.014)	0.027	0.031 (0.061)	0.610	-0.011 (0.021)	0.612	-0.011
Urban dweller	-0.005 (0.006)	0.390	0.032 (0.043)	0.457	-0.003 (0.005)	0.559	0.024
High individual income (> $100K)	0.071 (0.030)	0.018	-0.027 (0.016)	0.085	-0.062 (0.036)	0.083	-0.018
Student	-0.084 (0.021)	<0.001	-0.050 (0.066)	0.446	0.038 (0.050)	0.446	-0.096
Employed	0.021 (0.008)	0.009	-0.197 (0.089)	0.027	-0.017 (0.009)	0.063	-0.193
Republican	-0.021 (0.012)	0.077	0.012 (0.028)	0.670	0.003 (0.008)	0.677	-0.006
Democrat	-0.004 (0.005)	0.440	0.044 (0.052)	0.394	-0.003 (0.005)	0.549	0.037
Constant	-	-	0.047 (0.132)	0.719	-	-	0.047
Total	-0.047 (0.041)	0.254	-0.052 (0.075)	0.486	-0.050 (0.061)	0.417	-0.149

Endowment

As Figure 13 demonstrates, significant contributors to the endowment portion of the mean attitudinal difference, i.e., contributions arising from differences in the levels of explanatory variables, are student status, employment status, high individual income levels, Hispanic ethnicity, and Republican affiliation. Focusing on non-life-stage variables first, we see that differences in shares of Republicans and Hispanics between Millennials and Gen Xers in the weighted dataset explain part of the difference between the pro-environment attitude means. There are more Hispanic Millennials in the weighted dataset relative to Hispanic Gen Xers, and considering that the models indicate Hispanics as being more pro-environment, a lower share of this ethnicity in Gen Xers is contributing negatively to the overall difference. Similarly, Republicans, who are less inclined toward a pro-environment attitude, constitute a higher share among Gen Xers, therefore contributing negatively to the overall difference.

Now turning our attention to the contribution of life-stage variables, i.e., being a student, being employed, and having high individual income, we see that these variables contribute the most to the overall gap, although their opposing directions cancel out the overall effect. In other words, if Millennials were to “grow” into the shares of Gen Xers for these variables, their attitudes toward environmentally conscious living would roughly stay the same. We again caution that such predictions assume the temporal invariance of model coefficients.

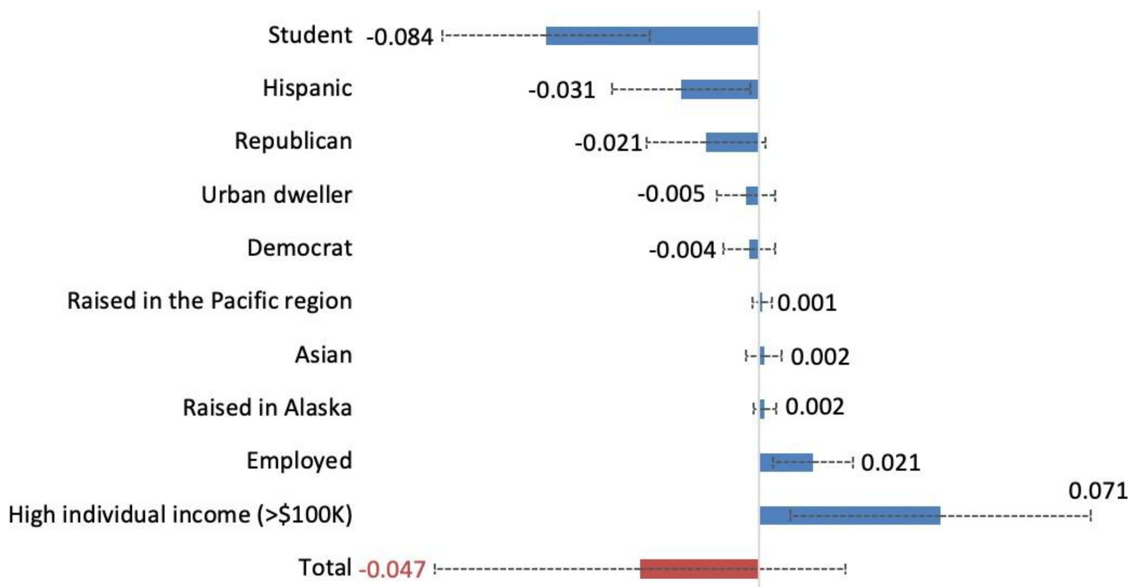

Figure 13. Contributions to the endowment portion of the difference in mean “pro-environment” attitude (Horizontal dashed lines refer to the 95% confidence interval)

Coefficient

The portion of the gap due to the difference in coefficients between the two generations is illustrated in Figure 14. Employment status and high individual income levels influence the two generations differently, with Millennials who are employed or have high incomes showing a more environmentally friendly attitude relative to Gen Xers with the same characteristics.

These differences, in other words, indicate that were the Millennials to have the same model coefficients as Gen Xers on these two variables, their average score on the pro-environment attitude would decrease by 0.224 (excluding the impact of other coefficient differences). Other non-life-stage variables whose (statistically meaningful) coefficient effects on the pro-environment construct differ between generations include belonging to the Asian race, and having a childhood residential location in the Pacific region. Gen Xers with these two characteristics tend to be more pro-environment than Millennials with the same characteristics, hence the positive change shown in Figure 14.

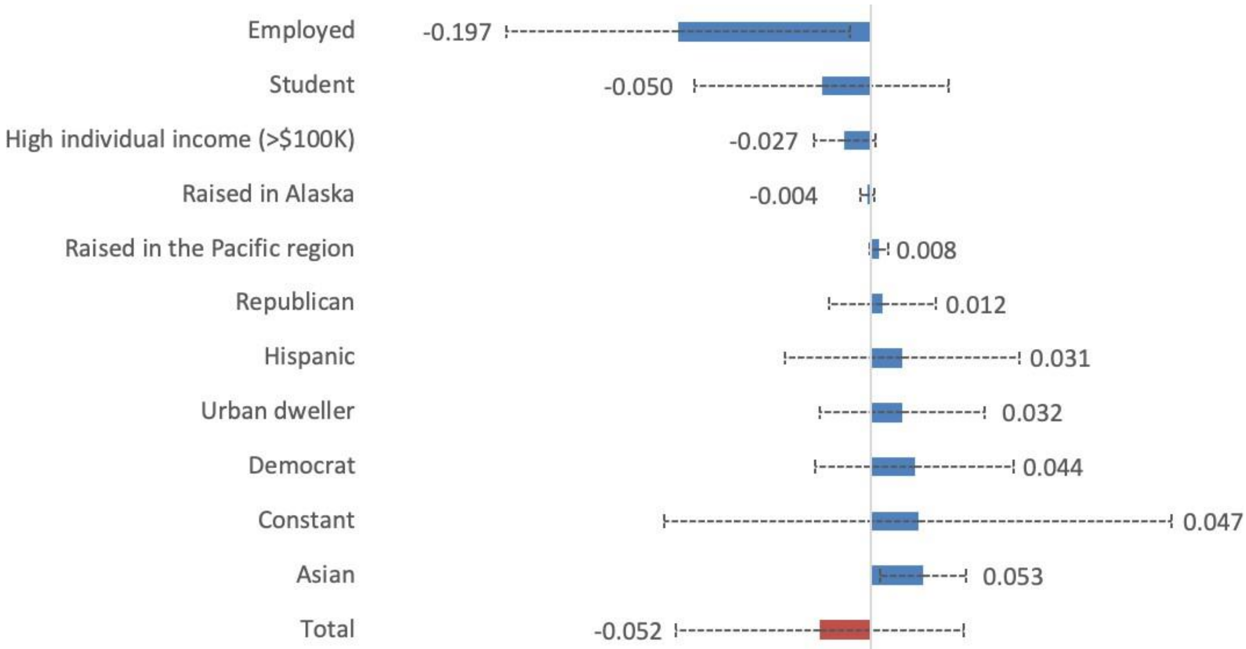

Figure 14. Contributions to the coefficient portion of the difference in mean "pro-environment" attitude (Horizontal dashed lines refer to the 95% confidence interval)

Interaction

With respect to the interaction term, the life-stage variables have the largest contributions (although at lower significance levels). Based on Table 11., the incremental effects (on top of the all-else equal terms) of the simultaneous change of endowments/ coefficients for having a high individual income and being employed are -0.062 and -0.017, respectively. These two amplify the corresponding coefficient effects, and partly counteract the corresponding endowment effects. The total contributions of employment status considering all its components amounts to -0.193 s.d., the largest contribution of all variables, while the total contribution of high-income status here equals a relatively low -0.018 s.d., largely due to the opposite sign contribution of its interaction term compared to its endowment. With respect to the other life-stage variable, student, the interaction term contributes in the opposite direction to its endowment and coefficient terms, resulting in an overall contribution of -0.096 s.d. to the gap (second largest after employment status).

Conclusions and future work

This analysis utilized data from a research survey executed in California to investigate generational differences in transportation-related attitudes, namely toward *urban living* (distinguishing between currently and long term), *car ownership*, and *environmentally-conscious lifestyles*. One simple but important result is that on average, those differences are small (0.15–0.20 standard deviation units)—albeit statistically significant—suggesting that generational distinctions are not as dramatic as they have been portrayed to be by popular media. Nevertheless, it is of interest to explore the sources of the differences that do appear—and, separately from the substantive content of the results in this study, to demonstrate a flexible methodology for comparing two groups that has numerous potential applications in transportation beyond the present one.

We linearly decomposed the differences in mean attitudes between Millennials and Generation X, and examined the decomposition terms which may be more likely to change as Millennials move into later life stages. The analysis shows that life-stage-related *endowment* disparities, such as in employment status, student status, income level, and marital status, explain significant portions of the overall attitudinal gaps. Our analysis also shows differential generational influences (*coefficients*) of these life-stage variables on attitudinal differences. We discussed interaction effects in greater depth and demonstrated the importance of considering such effects, highlighting the roles of the endowment and coefficient effects in concert with interactions.

In general, we can expect that the share of Millennials with life-stage characteristics such as being married will increase over time, i.e., that their *endowment* will approach that of Gen Xers (although, importantly, it may never *reach* Gen Xers', which has profound implications in a number of ways). It is much less clear how much the *effect* of such life-stage variables on an attitude will come to resemble that of Gen Xers' as Millennials continue to age. Effect magnitudes (*coefficients*), after all, are often functions of attitudes, lifestyles, and values—and so we can imagine an infinite regress, in which we need to know how much certain attitudes will change in order to fully understand how much others will change.

With respect to the pro-environment attitudinal construct, we see that Millennials tend to be more environmentally conscious, and it is unlikely that convergence of their life-stage variable shares to those of the Gen Xers will significantly impact this tendency—although convergence of the *coefficients* of those variables *would*. On the other hand, changes in life-stage variables may decrease the stronger tendencies of the younger generation toward urban living in the present time frame. With respect to long-term pro-urban tendencies, the generational differences appear less clear. Although there is not a statistically meaningful difference between Millennials and Gen Xers in long-term pro-urban attitudes, the difference becomes meaningful when we compare younger Millennials (< 26 years old) to older Millennials combined with Gen Xers. The greater tendency of younger Millennials toward long-term urban living may be reversed as they get married and start to have children. Similarly, the pro-car ownership attitude among Millennials, currently lower than for Gen Xers, would diminish the gap by 32% if the younger generation were married and had college degrees to the same extent as their older counterparts.

This study represents one of the first examinations of the influence of life stage variables on Millennials' transportation-related *attitudes*, and complements existing literature findings that Millennials' *behaviors* may be converging to those of Generation X as they enter later life stages. A limitation of this work revolves around the cross-sectional design of the survey, which precludes deductions about whether the coefficient portion of the gap is likely to diminish over time. The authors intend to extend the application of this approach to longitudinal data in the future. A further useful extension (particularly in a new dataset with broader reach) would be to decompose differences between *geographically* distinct groups. Additionally, as a number of studies (e.g., Myers, 2016) indicate, the real-world impact of these attitudes and preferences would be determined by contextual factors, therefore future work that builds upon findings in this chapter will seek to investigate how much of the reduction in attitudinal gaps translates into behavioral choices. This intended extension would have direct policy implications, since policy-makers are often more interested in revealed behavioral choices.

As such, the results of the current study pave the way toward better understanding if, why, and how travel-related behaviors or choices differ between generations. Such studies have important implications for transportation planning and forecasting, and further examination of differences in behaviors and attitudes across generational divides using longitudinally-designed studies should be a priority for transportation researchers moving forward.

Are Millennials More Multimodal?

Millennials tend to use a variety of travel modes more often than older birth cohorts. Two potential explanations for this phenomenon prevail in the literature. According to the first explanation, millennials often choose travel multimodality at least in part because of the effects of the economic crisis, which affected young adults more severely than their older counterparts. Another explanation points to the fact that millennials may have fundamentally different preferences from those of older birth cohorts. This chapter presents an examination of millennials' travel behavior as compared to the preceding Generation X, based on a survey of 1,069 California commuters. It shows that millennials adopt multimodality more often than Gen Xers, on average. However, the analysis also points to substantial heterogeneity among millennials and indicates that, perhaps contrary to expectations and the stereotype in the media, the majority of millennials are monomodal drivers. The chapter contributes to the literature on millennials' mobility in several ways. First, it rigorously classifies various forms of travel multimodality (on a monthly basis and distinctively taking trip purpose into account) through the analysis of a rich dataset that includes individual attitudes and preferences; second, it explores gradual changes of multimodality across age and generation; and third, it analyzes the effects of various demographic, built environment, and attitudinal attributes on the adoption of multimodality.

The following is a short version from a paper that was peer-reviewed and published in the journal Transportation (Lee et.al, 2019). Please use the following citation to cite the full paper:

> *Lee, Y., Circella, G., Mokhtarian, P. L., and Guhathakurta, S. (2020). Are millennials more multimodal? A latent-class cluster analysis with attitudes and preferences among millennial and Generation X commuters in California. Transportation, 47, 2505-2528.*

Introduction

The millennial generation, which includes those who were born from the early 1980s to the late 1990s (Dimock, 2019), has travel patterns that differ from those of preceding generations when they were at the same age. Millennials wait longer to obtain a driver's license, own fewer cars, drive less, and make more trips by alternative or emerging modes such as car sharing and on-demand ride services (Delbosc and Currie, 2013; Kuhnimhof et al., 2012; Kuhnimhof, Zumkeller, and Chlond, 2013a, 2013b; Millard-Ball et al., 2005; Circella et al., 2018). Scholars have speculated about the possible causes for their unique travel patterns and coalesced around three dominant hypotheses. First, researchers point to the effects of economic hardship on today's young adults and the fact that life course events such as independent living from parents, marriage, and childbearing are delayed compared to previous years, while pursuing higher education has increased. According to this theory, lack of economic resources (especially in the past few years) has prevented millennials from owning and driving personal vehicles and moving onto the next stage in the lifecycle (e.g., starting their own household and having children), at which people usually make more trips (Blumenberg, Ralph, Smart, and Taylor, 2016; Delbosc and Currie, 2013; Klein and Smart, 2017; McDonald, 2015). Instead, millennials choose cities where they can find affordable rental units and travel without cars.

Second, researchers also assert that the increasing share of college graduates among young adults and their delay in experiencing life course events are manifestations of long-term social trends. One factor behind these trends is the transition towards knowledge-based economies that demand highly educated labor and agglomeration economies (Millsap, 2018). As an effect of such trends, millennials are the most educated generation in US history, while on average the amount of their debt from student loans is higher than that of previous generations (Fry, Parker, and Rohal, 2014; Taylor, Fry, and Oates, 2014). Together with delaying marriage and childbearing, millennials neither can afford to buy nor need their own home until later in their lives (Census, 2011), or simply prefer smaller housing units, so they tend to choose urban neighborhoods and travel more with non-car travel modes (Scheiner, Chatterjee, and Heinen, 2016). Moreover, scholars point out that work arrangements and commute trips are changing as part of the transformations in the economy, including an increase in zero-hour contracts and home-based workers (Chatterjee et al. 2018; Marsden, Dales, Jones, Seagriff, and Spurling, 2018; Mateyka, Rapino, and Landivar, 2012). These changes bear implications for travel behavior in general and mode choice in particular, and they do so more for young adults, who are starting to build their careers in the evolving job market of the moment.

Third, scholars, according to reports in the academic journals and popular media, note that changes in attitudes and preferences and the adoption of information and communication technologies (ICT) may play a key role in affecting millennials' choices. They observe that millennials have pragmatic attitudes towards car ownership, are more conscious of the negative externalities of driving, are more informed about environmental and public health issues, prefer closer access to vibrant parts of cities, and are more willing to substitute virtual contacts for physical trips (Couture and Handbury, 2017; Delbosc and Currie, 2014; Hopkins, 2016; Puhe and Schippl, 2014; Raymond, Dill, and Lee, 2018; Smith and Page, 2016; Taylor, Doherty, Parker, and Krishnamurthy, 2014; Vij, Carrel, and Walker, 2013). Since these explanations have different implications for planning and policy, it is important to assess the contribution of various factors to current travel patterns of millennials and understand what these mean for possible changes to their travel in the near future (Delbosc and Ralph, 2017; Polzin, Chu, and Godfrey, 2014).

One less studied aspect of millennials' travel behavior is their use of multiple travel modes in a given period, or multimodality (Kuhnimhof, Chlond, and von der Ruhren, 2006; Nobis, 2007). By multimodality, scholars imply travel patterns that present some balance among various modes (e.g., half of trips made by driving and the other half by non-motorized modes), instead of relying on a single mode. While previous studies focused on various dimensions of millennial travel separately, the lens of multimodality helps researchers understand the unique patterns of millennial travel in more comprehensive ways (Ralph, 2017). In addition, understanding trends in multimodality could reveal how millennials might respond to policy interventions. Multimodal travelers are found to be better informed about and more sensitive to level-of-service attributes of various modes than habitual users of certain modes (Heinen and Ogilvie, 2016; Van Exel and Rietveld, 2009). These characteristics of multimodality may lead them to choose the mode that best matches their needs, which may differ by circumstance. Certainly, understanding how many millennials are multimodal travelers is of importance in that it informs the development of travel demand management (TDM) strategies for this birth cohort.

A few studies have analyzed millennials' multimodality. According to these studies, millennials represent several distinctive traveler groups based on daily travel patterns and longer-term mobility choices. By analyzing the 2009 National Household Travel Survey (NHTS), Ralph (2017) suggested that four groups of travelers could be identified: *drivers*, *long-distance trekkers*, *multimodals*, and *carless.* Among these groups, multimodals made more than half of their trips by walking, biking, and public transit; were less likely to have a driver's license and access to household vehicles; but traveled more frequently than the first two groups who traveled almost exclusively in automobiles. Unlike the popular depiction in the mass media, only 3.6% of those aged between 16 and 36 fit into this category in the 2009 NHTS. With a simpler measure of travel multimodality, Buehler and Hamre (2014) found that younger people tended to travel more by walking, biking, and using public transit than their older counterparts. The authors also showed that the longer the measurement period, the higher the proportion of users that would be categorized as multimodal travelers in the population. For example, while only 22.1% of respondents in the 2009 NHTS data used more than one mode on the surveyed day, the share of "multimodal travelers" increased to 72% if its definition includes users that adopted different modes on different days of the same week. Thus, identifying multimodal travelers based only on daily travel patterns may omit a substantial portion of the population, who may be (nearly) as responsive to policies and interventions as daily multimodals (Buehler and Hamre, 2014; Molin, Mokhtarian, and Kroesen, 2016; Van Exel and Rietveld, 2009; Schlich and Axhausen, 2003). While the aforementioned studies analyzed one or more cross-sectional datasets separately, Vij and his colleagues (Vij, Gorripaty, and Walker, 2017) estimated *pooled* models using two repeated cross-sectional datasets to see if (in the aggregate) young and older adults prefer multimodality more over time. Using two regional travel survey datasets in the San Francisco Bay Area in 2000 and 2012, they reported that "Car Preferring Multimodals" increased their shares in the population while "Complete Car Dependents" decreased in the 2000s. Interestingly, in their study, the trend of increasing multimodals was not limited to young adults, but present in all age groups. In contrast, Heinen and Mattioli (in press) documented (at the aggregate level) decreasing trends in multimodality in England from 1995 to 2015 by analyzing the Great Britain National Travel Survey, a nationally representative cross-sectional dataset that is collected annually. The study found that those who were between 16 and 30 (in all years) always tended to exhibit more multimodal travel behavior than those who were older than 30. However, on average, the level of multimodality of the young adults decreased in these two decades (while those of the older groups had remained stable at their *lower* levels).

Researchers have developed a variety of multimodality definitions and indices, most of which have not been applied to studies with a focus on millennials. Buehler and Hamre (2014) classified all individuals into three traveler groups: (a) those who use only automobiles, (b) those who use both automobiles and several alternatives (walking, biking, and public transit), and (c) those who use only these non-automobile modes. Although intuitive and convenient, this approach fails to capture the continuous degree of mono/multimodality that each traveler might have and its multidimensionality. Heinen and her colleagues (Heinen, 2018; Heinen and Chatterjee, 2015; Heinen and Mattiolo, 2017; Scheiner, Chatterjee, and Heinen , 2016) tested several continuous measures, each of which focused on specific aspects of multimodality. For example, the share of trips made with the most frequently used mode captures individuals' degree of concentration on a single mode, but does not take into account the distribution of use across other modes. In contrast, the *Herfindahl-Hirschman Index (HHI)* and *Shannon's Entropy* index measure how concentrated or dispersed individuals' use patterns are across multiple modes, but do not consider what their primary mode is.

Other researchers have attempted to measure the multidimensional nature of multimodality. Diana and Mokhtarian (2009) classified survey respondents from France and the US into four traveler types, using a k-means cluster analysis on objective, subjective, and desired levels of travel by various modes. Ralph (2017) employed a latent profile analysis in which she included seven indicators of mobility choices for various time horizons, from daily travel patterns to medium-term commitments such as driver's license, car ownership, and annual miles driven. Molin et al. (2016) avoided arbitrarily weighting indicators of various time horizons by employing monthly frequencies of various modes in their latent-class cluster analysis. Vij et al. (2017) employed a latent-class choice model to estimate unobserved modal preferences of individuals, which they define as "behavioral predisposition towards a certain travel mode or set of travel modes that an individual habitually uses" (p. 242). In brief, although a wide range of measurement techniques is available in the literature, researchers of millennials' travel behavior have not employed many of them yet. In particular, more complex approaches that capture the multidimensional nature of travel modality have been rarely used.

The objectives of this chapter are two-fold. First, we examine various types of multimodality and their relative shares in a sample of millennials and members of Generation X by employing a rich set of variables, including individual attitudes and the use of shared mobility services—

these variables are rarely available in conventional travel-diary data. Second, we analyze the effects of various individual attributes, such as socioeconomics and demographics, attitudes and preferences, and residential location, on the likelihood of belonging to certain traveler groups.

Data and variables

In this chapter, we analyze the California Millennials Dataset collected by 2015. To capture various patterns of travel multimodality, we employed a subsample of 1,069 cases who regularly commute either to work or school, and constructed several indicator variables from their frequency of using various transportation modes for *commute* and *leisure/shopping/social* (henceforth, "non-commute") trips. For commute trips, we asked the frequency of using various modes for one-way trips. Unlike previous studies, we analyze multimodality in a way that takes into account trip purposes, because reports and statistics suggest that millennials' mode choice may differ from that of older birth cohorts only for trips with certain purposes, e.g., non-commute (Jaffe, 2013, 2014). Note that this study examines the travel patterns of a sample of commuters, whose mode choice behaviors may differ from those of non-commuters. After all, commute trips usually take place in similar circumstances, so commuters may well develop habits of choosing a certain (set of) mode(s). Their habits may also affect their mode choices for non-commute trips and their overall multimodality.

The original raw data include frequencies of using 13 travel modes reported on a 7-point ordinal scale, separately for the two categories of trip purposes. For each of the 26 mode/purpose combinations, individuals marked a choice that ranges from "Not available" to "5 or more times a week." Since the survey asked individuals to report retrospectively how often they "typically" use various travel modes, they may have inaccurately reported their frequencies (Stopher, FitzGerald, and Xu, 2007). For analysis, we grouped the 26 variables into nine indicators based on similarity and uniqueness of modes and purposes, developing "monthly" frequencies for four groups of modes for commute trips and five groups of modes for non-commutes. The four groups of modes common to both commute and non-commute trips are: *car as a driver*, *car as a passenger* (including taxi and ridehailing services for commute trips, which are classified separately for non-commute trips), *public transit* (including both bus and rail options), and *active modes* (including walking, biking and skateboarding). An additional group of modes was included for non-commutes, measuring the use of *emerging transportation modes* (ride-hailing services such as Uber/Lyft and carsharing services such as Zipcar/Car2Go).To obtain the monthly frequencies for these nine groups, we summed proxy values that capture the monthly frequencies of the raw modes that belong to each group (refer to Appendix 2). Given that many studies analyzed the NHTS datasets, which lack information on use of various modes for more than a day (Buehler and Hamre, 2014; Ralph, 2017), our indicators capturing monthly use of various travel modes are expected to reveal unexplored patterns of multimodality, which may substantially differ from those measured only on one day.

We used three groups of explanatory variables in the model: sociodemographic traits and economic characteristics, attitudes and preferences, and built environment attributes. For attitudes and preferences, the dataset contains individuals' level of agreement with 66 statements on a 5-point Likert-type scale from "Strongly disagree" to "Strongly agree". We conducted a factor analysis and identified 17 factors as the best solution, leaving 14 stand-alone statements that were not included in the final factor solution (but were retained for further analysis), based on multiple criteria including interpretability (Circella et al., 2017b; refer to Appendix 3). For built environment attributes, the California Millennials Dataset contains individuals' home addresses, which we geocoded using the Google Maps Application Programming Interface (API). Using these geocoded locations, we extracted information on land use and transportation systems from external sources. The Smart Location Database of the US Environmental Protection Agency provides a wide range of land use variables, which we factor analyzed to obtain composite indexes capturing activity intensity and land-use balance. For the level of service by public transit, we collected the transit connectivity index, i.e., a composite index that takes into account bus routes and train stations within walking distance for each census block group, from alltransit.cnt.org (CNT, 2016). In addition, we used the five neighborhood types that Salon (2015) developed based on the land use characteristics of individual census tracts throughout California. While her typology included central city, urban, suburban, rural in urban, and rural, we rename the fourth type exurban based on the census tracts' geographical locations and land-use patterns.

Methods

In this chapter, we employ latent profile analysis to *probabilistically* assign individuals to traveler groups, each of which is characterized by relatively similar mode use patterns, while maximizing the heterogeneity of these patterns across groups. This analytical approach has several advantages over simpler methods for identifying multimodal travel behaviors. First, we attempt to measure multimodality in its entirety, instead of developing a *single* (composite) index. We believe that travel multimodality cannot be easily reduced to a mono-dimensional measure such as HHI or Shannon's Entropy. The same values for these indexes may refer to travel behaviors which are very different from each other, and each of which could be the target of unique sets of policies and interventions. Instead, we classify individuals into *latent classes* based on multiple indicators, all of which depict the unique mode use patterns of each class.

Second, unlike deterministic classification schemes (Buehler and Hamre, 2014; Diana and Mokhtarian, 2009; Kuhnimhof et al., 2006; Nobis, 2007), latent profile analysis estimates individuals' probabilities of belonging to various latent classes. Each of these classes shows its own profile consisting of average frequencies of use of various modes. Specifically, they are the group-specific probability-weighted averages of indicator variables (the nine mode use frequencies) across the sample. In brief, the latent profile analysis better captures the heterogeneity of multimodal travel behaviors by creating an unobservable construct consisting of multiple modality styles, each of which characterizes a given individual to varying degrees (i.e., with varying probabilities). Third, as for the effects of various factors (i.e., active covariates) on the individuals' probabilities of belonging to various latent classes, the latent profile analysis simultaneously estimates these effects while classifying individuals into various classes. Several researchers, to date, have deterministically identified traveler groups and then assigned individuals to these groups in a separate stage (Buehler and Hamre, 2014; Nobis, 2007; Ralph, 2017). However, their methods (1) do not use information available in the active covariates to help estimate the probability of belonging to a given group, and (2) do not guarantee to maximize the heterogeneity between groups. Figure 15 presents the relationships among the latent construct of mobility styles, the indicators, and the active and inactive covariates.

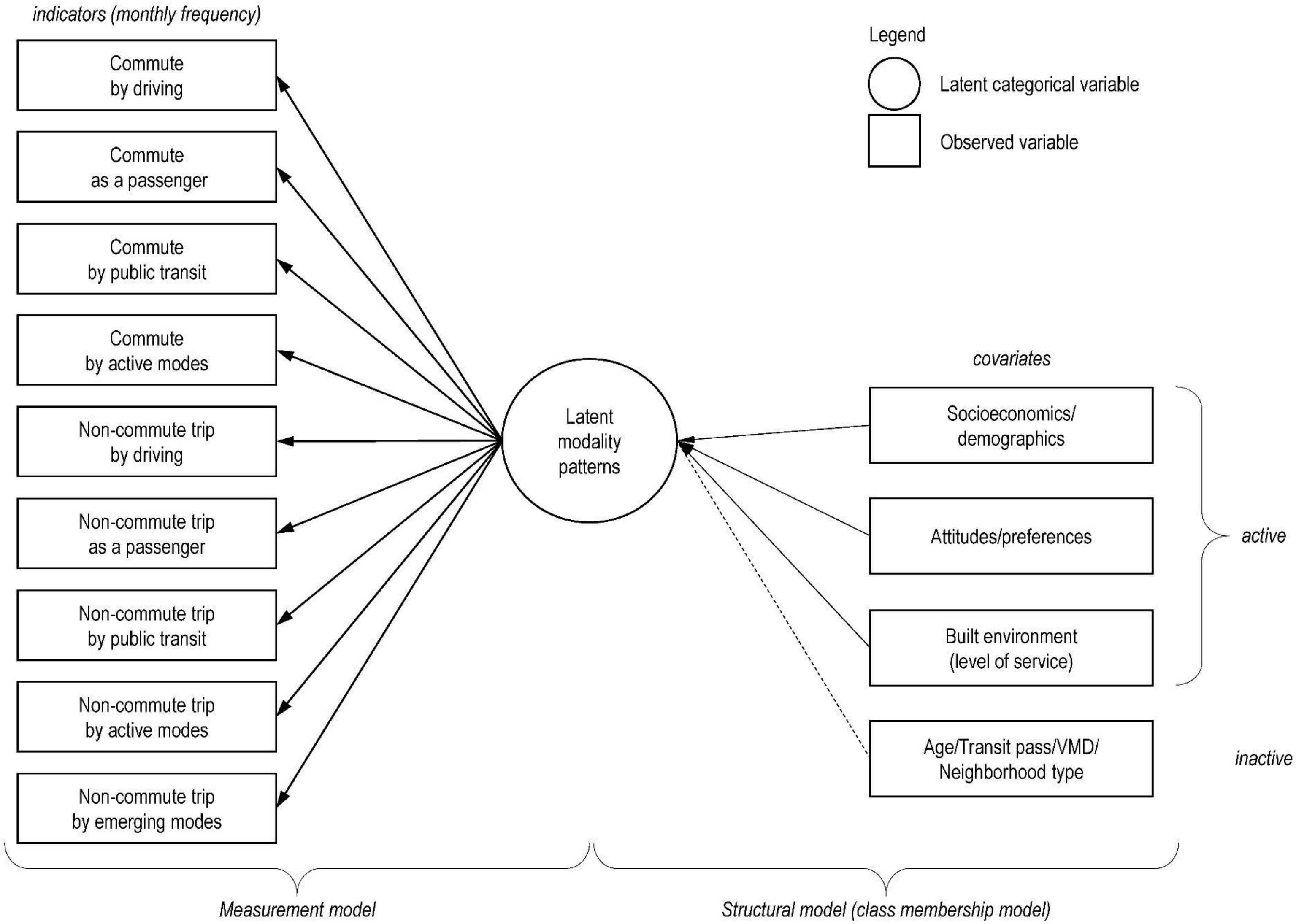

Figure 15. Graphical representation of the latent profile analysis with covariates (Source: modified from Fig.1 in a previous study (Molin et al., 2016))

Results

After testing several alternatives, we chose the four-class solution as best, based on several goodness of fit measures and interpretability. Information criteria help determine the best among models with varying specifications (e.g., differing numbers of latent classes). Mplus reports several such criteria, including the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and sample-size adjusted BIC (for formulas, see Akaike, 1987; Schwartz, 1978; Sclove, 1987). Low values for these criteria are associated with better model fit. However, because the values of these criteria kept decreasing as the number of latent classes increased, we considered the tradeoffs between model if and interpretability of the model results to determine the number of latent classes in the final model. Additional consideration was given to discarding model solutions that included very small classes (containing only a few cases in the sample).

Four Traveler Groups

We identified four traveler groups, having different frequencies of use of various travel modes for two trip purposes. Figure 16 displays the frequency profiles for the use of various modes by the four traveler groups: monomodal drivers (including 84.2% of cases in the weighted sample), carpoolers (4.9%), active travelers (7.7%), and transit riders (3.1%). In this section, we briefly introduce the multimodal travel patterns and socioeconomic attributes of these classes. To understand the distinctive traits of each traveler group, we use both active and inactive covariates. Note that class-specific (probability-weighted) summary statistics in need to be understood in the context of the small sample size in this study (N=1,069), which is subject to large sampling errors, compared to large-sized samples.

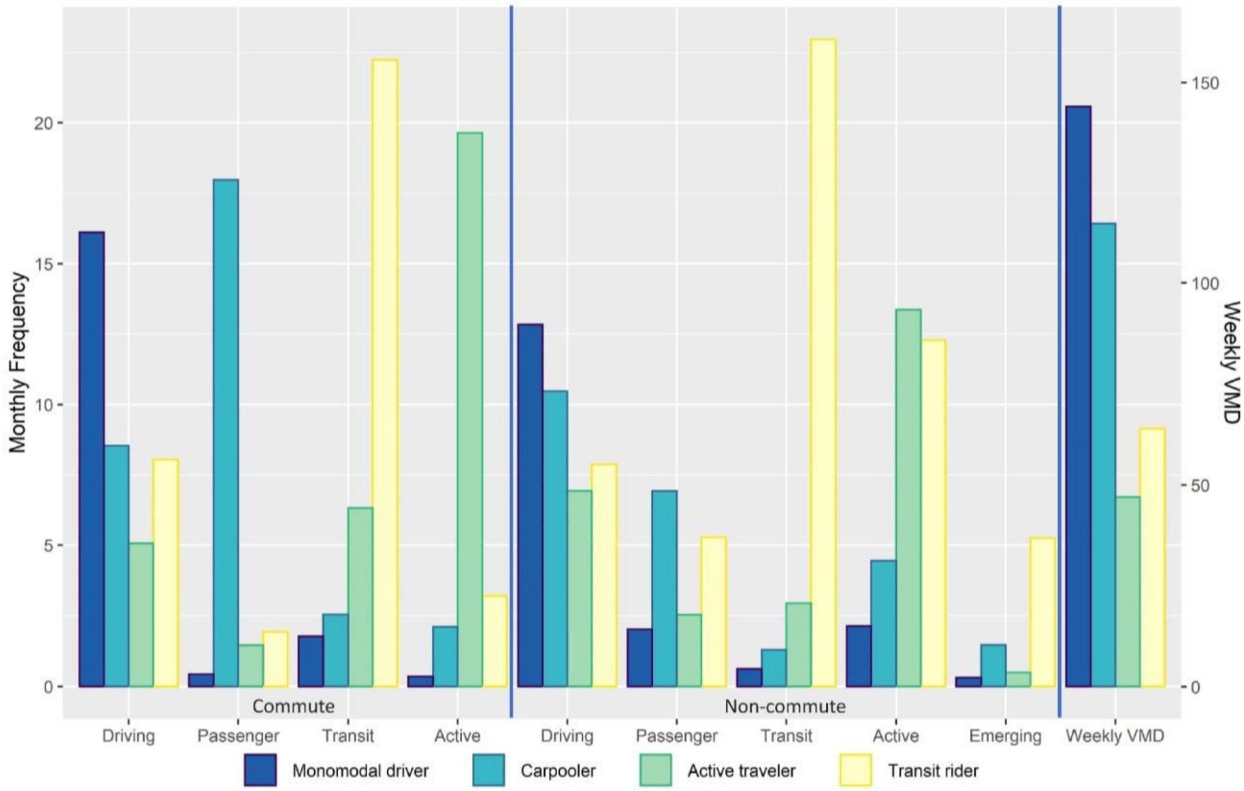

Figure 16. Monthly frequencies of use of travel modes and weekly vehicle miles driven by class. (Note: The right y-axis applies only the last set of bars)

Containing the vast majority of cases, ***monomodal drivers*** drive for most of their commute (16.1 times per month) and non-commute (12.8 times per month) trips. Monomodal drivers own the most vehicles and have the greatest access to their household's vehicles (available 92.7% of the time). The majority of monomodal drivers are full-time workers (73.1%), usually with either an associate's or bachelor's degree (37.8% and 36.3%, respectively), and their commute distance is the second longest (8.99 miles), following carpoolers (9.39 miles). Many monomodal drivers tend to live with their partners and children, and have average household incomes between $60,000 and $120,000. The members of this group are older on average, are likely to perceive that a car is more than a tool, and more often reside in suburban or exurban neighborhoods. As expected, they drive the most (144 miles per week), which is three times the average driving distance for transit riders.

Carpoolers drive occasionally; however, they commute more often as a passenger in a car driven by someone else, either via carpool, a taxi, or on-demand ride services (17.98 times per month, or more than four times a week). For non-commute trips, they tend to drive instead of having others drive for them (10.47 versus 6.92 times per month). Carpoolers have the longest commutes among all groups (9.39 miles one-way), and they likely work full time. Many carpoolers earn household incomes more than $120,000 a year, and they live in a large household with many working adults. While a majority of carpoolers have a driver's license (80.7%) and a car available most (71.6%) of the time on average, these values are lower than those of monomodal drivers (at 95.7% and 92.7%, respectively). Carpoolers feel more constrained to travel by car, for reasons such as their inflexible schedules or destinations not served by public transit. Not surprisingly, most carpoolers rate cars either "good" or "very good" as their means of transportation, but overall, they are less averse to alternative travel modes, public transit and active modes, than monomodal drivers. Carpoolers' household composition, somewhat limited car availability, and attitudes appear to explain their weekly vehicle-miles driven (VMD), which are 20 percent fewer than those of monomodal drivers.

Active travelers travel most frequently by walking, biking or skateboarding for both commute (19.64 times per month) and non-commute (13.37 times per month) purposes. Many active travelers do not hold a driver's license (i.e., only 71.4% of them are licensed), they own few household vehicles (0.59 per adult), and report lower car availability (50.7%) than the two car-oriented groups. Active travelers reveal the most pragmatic attitudes towards cars; they do not feel they are constrained in terms of scheduling trips or choosing travel modes; and they view active modes more positively than those in the other classes. Three of every four members of this group are millennials (74.0%), and their share of urban residents is the highest (43.1%) among the four groups (followed by the transit riders group, at 36.7%).

As the smallest among the four traveler groups (including only 3.1% of the 1,069 cases, or 33 travelers in the weighted sample), ***transit riders*** use public transit almost every day for commute (22.24 times per month) and non-commute (22.96 times per month) trips. For non-commute trips, they often travel by active modes, possibly as an access or egress mode for public transit, because they lack access to a car (e.g., only 56.4% of the members of this class hold a driver's license, and their household vehicles are available only 41.8% of the time on average). Not surprisingly, this group has the largest share of transit pass holders (73.6%). Moreover, the transit rider class has adopted emerging transportation services (e.g., carsharing or ridehailing) more than the other classes, using these services more than once a week. Their total numbers of commute and non-commute trips are the highest among all classes, implying that either their trip rates are the highest or (more likely) they tend to use multiple modes for a single tour.

Transit riders contain the largest share of college graduates and current students (27.7% of this group being either part-time or full-time students). While college/graduate students in certain areas (e.g., college towns) or other countries (e.g., European countries, as discussed in Buehler, Pucher, Merom, and Bauman (2011)) may choose walking more than other modes to reach their place of study, many students in our sample, which covers the entire state of California, appear to live in locations that are not within a walkable distance from their school. On average, they have the lowest annual household income (55.4% of this group earns $60,000 or less). Also, this group shows the strongest support for environmental policies that would regulate driving. Counterintuitively, transit riders are not particularly pro-exercise, suggesting that their choice of public transit is not to increase their level of daily physical activity but to meet their travel needs. Members of this class accept public transit as either a "good" or "very good" means of travel, and on average they live in neighborhoods with high development density, mixed land use, and decent transit levels-of-service. Many transit riders reside in neighborhoods located either in or close to the central core of cities (e.g., downtown Los Angeles and San Francisco). As a result, they drive fewer miles (64 miles per week, on average) than the members of the two car-oriented classes, monomodal drivers and carpoolers.

Table 12. Sample characteristics for the indicators and covariates, by traveler group (Sample Size N=1,069)

	Monomodal driver	Carpooler	Active traveler	Transit rider
Class size (n)	900	52	82	33
Class share (%)	84.2%	4.9%	7.7%	3.1%
Frequency per month				
For commute trips				
Car as a driver	**16.11**	8.53	5.06	8.04
Car as a passenger	0.43	**17.98**	1.45	1.92
Public transit	1.76	2.54	6.32	**22.24**
Active modes	0.35	2.10	**19.64**	3.21
Total	18.65	31.16	32.47	**35.41**
For leisure trips				
Car as a driver	**12.84**	10.47	6.93	7.87
Car as a passenger	2.02	**6.92**	2.54	5.28
Public transit	0.61	1.29	2.94	**22.96**
Active modes	2.13	4.44	**13.37**	12.28
Emerging modes	0.31	1.46	0.49	**5.25**
Total	17.92	24.58	26.26	**53.64**
Active covariates				
Travel patterns and mobility choices				
Commute days per week	4.49	**4.76**	4.57	4.26
Commute distance (mile)	8.99	**9.39**	3.73	5.46
Telecommuting frequency				
No	73.8%	70.7%	75.4%	**75.9%**
Less than once a week	17.4%	18.9%	**19.6%**	14.3%
At least once a week	8.8%	**10.4%**	5.1%	9.8%
Having a driver's license	**95.7%**	80.7%	71.4%	56.4%
Cars per household adult	**0.93**	0.74	0.59	0.64
Household composition				
Household size*	3.14	**3.42**	2.93	3.02
Living with parents*	19.9%	**32.3%**	29.3%	21.6%
Living with partner*	**64.7%**	63.5%	41.4%	40.4%
Living with own children	50.4%	41.7%	26.3%	**52.2%**
Work/study status				
Full-time student	8.3%	18.8%	6.4%	**20.8%**
Part-time student	1.3%	0.3%	0.2%	**6.9%**
Full-time worker	**73.1%**	66.7%	52.1%	63.4%
Part-time worker	16.7%	13.4%	**39.5%**	8.9%
Only doing unpaid work	0.6%	0.7%	**1.9%**	0.0%

	Monomodal driver	Carpooler	Active traveler	Transit rider
Class size (n)	900	52	82	33
Class share (%)	84.2%	4.9%	7.7%	3.1%
Educational attainment				
Decline to answer	0.1%	0.0%	**3.2%**	0.0%
Up to high school	9.3%	14.5%	**20.8%**	14.4%
Associate's degree	37.8%	**47.5%**	37.1%	28.2%
Bachelor's degree	**36.3%**	22.6%	21.8%	28.1%
Graduate degree	16.4%	15.3%	17.2%	**29.4%**
Household income*				
Decline to answer	5.2%	3.2%	**7.1%**	4.8%
$60,000 or less	35.1%	39.6%	38.6%	**55.4%**
$60,001-$120,000	35.4%	30.2%	**36.7%**	23.3%
More than $120,000	24.2%	**27.0%**	17.6%	16.4%
Attitudes and perceptions				
Car as a tool	-0.059	-0.075	**0.220**	-0.080
Pro environmental policies	0.056	0.273	0.592	**1.149**
Time/mode constrained	0.177	**0.296**	-0.568	-0.415
Pro exercise	**0.142**	0.068	0.057	-0.638
Personal vehicles				
Very bad	0.1%	**3.5%**	2.9%	0.0%
Bad	1.7%	2.1%	4.3%	**17.5%**
Neutral	12.8%	3.0%	**35.1%**	16.3%
Good	40.5%	34.1%	42.0%	**44.6%**
Very good	44.9%	**57.2%**	15.7%	21.6%
Public transportation				
Very bad	**14.0%**	10.6%	5.4%	0.0%
Bad	**25.4%**	23.0%	13.8%	2.8%
Neutral	**34.4%**	24.0%	17.4%	11.5%
Good	23.2%	28.4%	50.8%	**71.5%**
Very good	3.0%	13.9%	12.5%	**14.3%**
Active transportation				
Very bad	**12.1%**	6.6%	0.7%	5.3%
Bad	15.4%	**23.2%**	2.7%	4.7%
Neutral	**31.5%**	23.2%	11.2%	28.2%
Good	31.9%	32.0%	**50.7%**	38.2%
Very good	9.0%	15.1%	**34.7%**	23.6%
Land use attributes				
Activity intensity	0.114	0.206	0.506	**0.662**
Land use diversity*	0.222	0.033	0.301	**0.320**
Transit service quality*	10.557	13.786	16.870	**19.459**
Inactive covariates				
Demographics				
Age	**34.27**	33.70	30.00	33.76
Proportion of millennials	51.6%	47.0%	**74.0%**	56.8%

	Monomodal driver	Carpooler	Active traveler	Transit rider
Class size (n)	900	52	82	33
Class share (%)	84.2%	4.9%	7.7%	3.1%
Mobility choice				
Having a transit pass	11.3%	7.5%	33.3%	**73.6%**
Self-reported weekly VMD	**144**	115	47	64
Car availability [(a)]	**92.7%**	71.6%	50.7%	41.8%
Residential neighborhood type				
Central city	1.7%	2.3%	8.8%	**12.3%**
Urban	22.1%	24.1%	**43.1%**	36.7%
Suburban	**46.8%**	45.8%	33.4%	34.1%
Exurban	**20.7%**	19.0%	10.0%	11.6%
Rural	8.7%	**8.9%**	4.8%	5.4%

Notes: **Bold** values indicate the highest value for each row; * indicates a covariate dropped from the final specification due to statistical insignificance; † The counts of individual classes do not sum to the total due to rounding errors; and measures a self-reported car availability (0-100%), i.e., the percentage of time an individual has access to a private vehicle.

Class Membership Model

In addition to depicting the four classes of travelers based on summary statistics, we attempt to understand the factors affecting the probabilities of individuals belonging to these groups. Table 13. presents the estimates of active covariates that are statistically significant in the membership model. Here, the reference group is monomodal drivers (which is therefore omitted in the table), so we interpret the coefficients for the other groups in comparison to monomodal drivers. We test two hypotheses by including covariates that relate to millennials' limited economic resources and delayed life course events, as well as to their different preferences from the older cohorts. Moreover, we analyze the separate effects of the built environment, which most studies neglected.

Economic factors and related living arrangements affect class membership in various ways. First, not surprisingly, those without a driver's license are more likely to be carpoolers, active travelers, or transit riders than monomodal drivers. Having fewer cars per adult in the household is associated with belonging to carpoolers or active travelers. Those who do not have children living at home are more likely to be active travelers, suggesting they are less burdened by the childcare and housework duties that may make driving convenient or necessary. Interestingly, those who are students, either part-time or full-time, are less likely to be active travelers. Instead, it is a short commute distance that increases one's probability of belonging to the active traveler class. In the meantime, those with higher educational credentials are associated with a higher likelihood of using public transit. However, these factors do not present the full picture of millennials' multimodality. We also find separate associations of individual ***attitudes and preferences*** with class membership. In particular, those who think of a car as a mere "tool" (to reach a destination) rather than a desirable object in its own right are more likely to be active travelers than monomodal drivers. Those who share concerns over the environmental impacts of driving tend to travel more by public transit. Consistent with class-specific (probability-weighted) summary statistics in Table 12., those who do not see themselves constrained regarding trip schedules and mode choice tend to travel more by active modes or public transportation (the opposite is true for carpoolers, who feel constrained).

Land use attributes of one's place of residence help account for multimodality. Activity intensity, a composite measure extracted from a factor analysis on variables such as population and employment density in the place of residence, increases the likelihood of an individual being a public transit user. Dense neighborhoods, mostly located in or close to the central city, usually offer a transit-conducive environment and are well served by public transit. In comparison, we did not find statistical significance for land-use balance, a composite index measuring the balance between housing and employment. This finding suggests that the intensity of activities in a given neighborhood induces its residents to use alternative modes, while land-use balance in itself does not. After all, the same balance value (e.g., 1-to-1 between residential and commercial) may represent very different built environments (e.g., inner city or sprawled suburbs). We see the transit service quality measure is not significant because of its high correlation with the density measure.

Table 13. Class membership model (N = 1,069; Reference: Monomodal Drivers (84.2%))

Covariates	**Carpooler**		**Active traveler**		**Transit rider**	
Share	4.9%		7.7%		3.1%	
Travel pattern and mobility choices						
Natural log of commute distance	0.053		-1.052	***	-0.297	
Commute days per week	0.326	**	0.154		0.188	
Telecommute (reference: no telecommute)						
Less than once a week	0.451		0.081		0.135	
At least once a week	0.896		-2.073	**	0.260	
Has a drivers' license	-1.489	***	-1.264	**	-2.878	***
Cars per adult in the household	-1.342	**	-1.948	***	-0.722	
Household characteristics						
Living with own children	-0.124		-0.985	**	1.226	**
Student status (reference: not a student)						
Full-time student	0.570		-1.289	**	0.864	
Part-time student	-1.822		-4.004	***	1.904	
Educational attainment (reference: up to high school)						
Some college	0.068		0.004		-0.091	
Bachelor's degree	-0.422		-0.752		0.278	
Graduate degree	-0.037		0.364		1.718	**
Attitudes and preferences						
Car as a tool	-0.063		0.434	**	-0.400	
Pro-environmental	0.131		0.231		0.763	**
Time / mode constrained	0.322	*	-0.559	***	-0.400	*
Pro-exercise	-0.118		0.064		-0.901	***

Covariates	**Carpooler**		**Active traveler**		**Transit rider**	
Share	4.9%		7.7%		3.1%	
Overall rating for cars [(a)]	0.319		-0.737	***	-0.059	
Overall rating for public transit [(a)]	0.262		0.033		1.105	***
Overall rating for active modes [(a)]	-0.026		0.857	***	0.175	
Land-use attributes						
Activity intensity	0.051		0.003		0.990	**

Notes: * significant at the 10% level, ** significant at the 5% level, and *** significant at the 1% level; [(a)] denotes a single-item response (and not a factor score) for this attitudinal variable.

Generational Effects

To evaluate the effects of being a member of a certain generation on the adoption of multimodality, we control for one's age as an inactive covariate in the latent profile analysis, to investigate *subtler* differences among individuals belonging to the various groups (i.e., how they differ within and across generations). In fact, many studies attempted to measure generational effects by including a set of binary variables that indicate whether individuals are millennials or members of preceding generations in multiple regression models (Buehler and Hamre, 2014; McDonald, 2015). This approach may be effective for checking the existence of such effects, especially with panel or repeated cross-sectional datasets; however, it cannot reveal specific sources of the effects unless a rich set of qualitative attributes is also included. In contrast, we hypothesize that individuals' sociodemographic and economic conditions, living arrangements, and attitudes and preferences affect the type and intensity of travel multimodality. For instance, two same-aged people may travel in different ways because of the aforementioned factors being different (e.g., married or not), and two people with different ages may be very similar in their multimodal patterns, because of these factors being similar (e.g., similar preferences for urban lifestyles and active modes).

Figure 17 displays the share of each traveler group by age (note that the y-axis starts at 68 percent to clearly present the variation in the composition by age). Since we do not have sufficient cases for each age, we calculate five-year moving averages. As expected (in view of their large share), monomodal drivers dominate all age groups from 18-22 to 46-50; however, we see gradual changes, or even fluctuations, in the shares of the four traveler groups by age. The proportion of active travelers tends to decrease up to the age of 41 and slightly increase again after that age (probably because of the reduction in household obligations as children become older). Transit riders first peak in the early and mid 30s, gradually decrease to 0.7% at about 40 years old, and rebound among individuals in their mid to late 40s. Given that Figure 17 presents a one-time snapshot of the population, not a trajectory that follows the same individuals over time, young transit riders and older transit riders may differ in their characteristics. The largest proportion of active travelers are observed around an age of 29 years. In sum, treating one's age as an inactive covariate in the latent-class cluster analysis helps reveal nuanced, continuous, distributions of heterogeneity in multimodality by age, while we use individual attitudes and preferences, in addition to sociodemographics, to characterize the mobility styles of the members of the various latent classes. Still, how many millennials will continue to have multimodal travel patterns (as opposed to travel patterns more similar to those of the current older adults) as they age is an open question, which cannot be answered with the analysis of cross-sectional data.

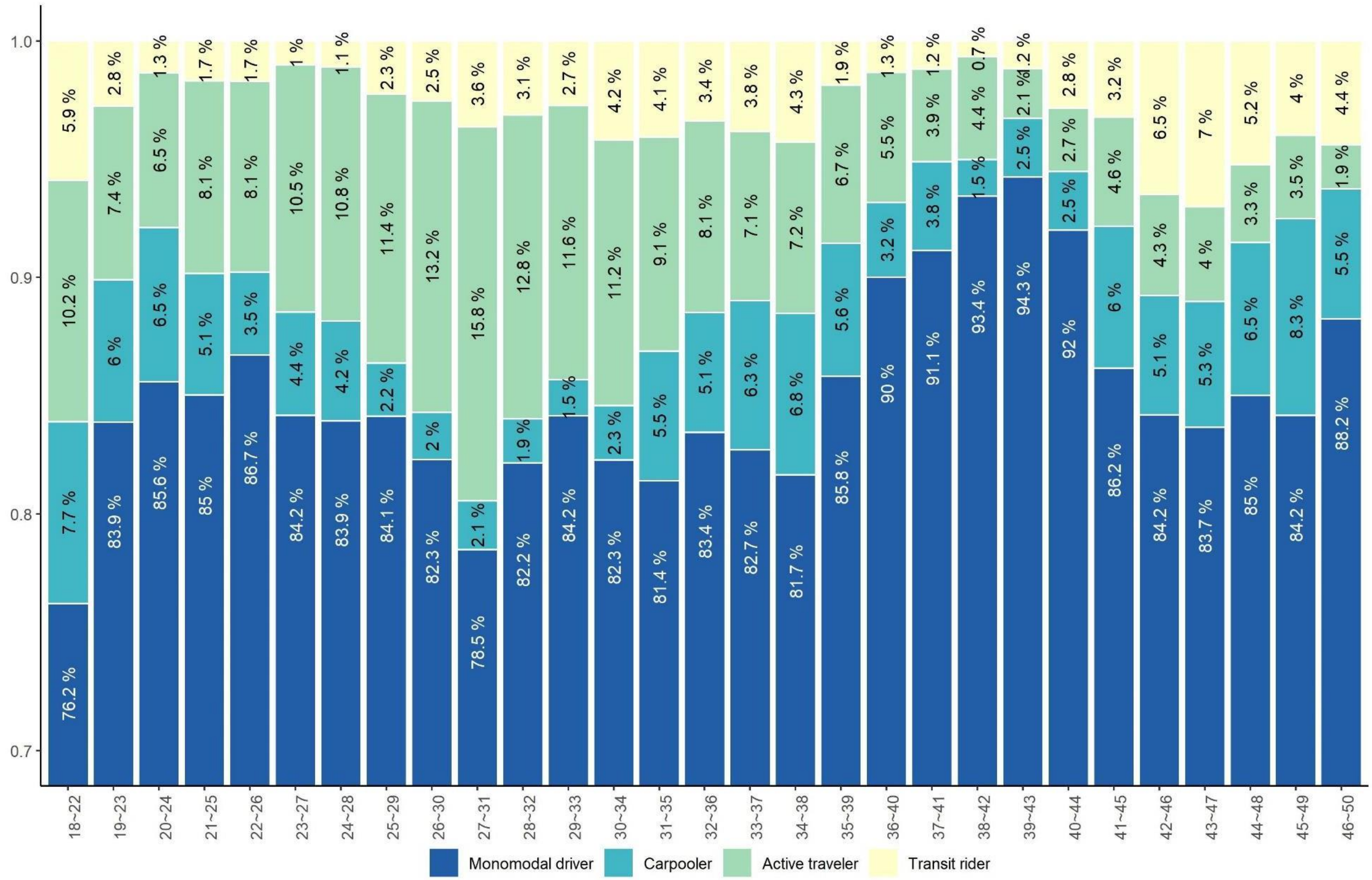

Figure 17. Shares of four traveler classes by age group Notes: Each bar presents the traveler group shares for cases within the specified five-year age range, with each bar advancing the five-year window by one year. Vertical axis truncated to clarify differences.

Conclusions

This study employs a latent-class model and a comprehensive set of variables to identify varying patterns of travel multimodality and the relationships of these patterns to individual attributes. By doing so, we reveal multiple classes of multimodal travelers. Our results suggest possible changes in the mode use patterns of millennials in coming years, which can inform policies to help millennials stay multimodal.

Unlike popular images of multimodal millennials in the media, our study shows that the majority of millennials in California are monomodal drivers, which is consistent with findings in a recent study that covers the entire US (Ralph, 2017). In contrast to the monomodal drivers, the three multimodal traveler classes have lower driver's licensure rates and limited car availability, as a result choose driving less often for commutes and leisure trips, and even though they drive occasionally, drive far fewer miles on a weekly basis. These traveler classes differ by several individual characteristics including household income, presence of children, and personal preferences. Not surprisingly, active travelers and transit riders more often reside in urban neighborhoods with high activity intensity, where public transit and non-motorized modes are viable alternatives. That is, land use facilitates, or inhibits, multimodality. Related to this, the combined share of the three multimodal travelers diminishes and that of monomodal drivers increases among individuals between 36 and 41 years old, ages at which people undergo marriage and childbearing, achieve increases in their earnings, and often relocate to the suburbs. Thus, to encourage individuals to maintain environmentally-beneficial behaviors and higher levels of travel multimodality, planners may take two approaches. First, they can spearhead plans for affordable residential alternatives (with decent public school quality) in the central parts of cities for those who *prefer* urban lifestyles, but also want to buy a home and raise children. Second, they can design and plan some suburbs with urban amenities (e.g., dense residential and commercial developments) for those who choose to relocate, to support more sustainable travel behavior.

This study presents a weighted analysis estimated with a relatively small sample from California. The travel patterns of the travelers included in this sample may differ from those in other regions or countries (for comparison see Heinen and Chatterjee (2015) for Great Britain, Molin et al. (2016) for the Dutch, and Kuhnimhof et al. (2012) for Germany). However, in view of California's position as a US leader in green energy production, greenhouse gas emissions reduction, and promotion of sustainable land use and transportation patterns, these results point to the difficulties in achieving sustainability goals at an aggregate level, even when the policy climate is favorable toward doing so. On the other hand, on average in California, proportionally more millennials belong to these three traveler groups than do the members of Generation X. Also, the membership model confirms that not only economic factors but also attitudes and preferences explain the likelihood of an individual to adopt travel multimodality. Thus, the current shares of the four traveler groups by cohort are likely to change in the future as millennials age and experience life course events (even if at a more delayed time in life), assuming they maintain their current attitudes and preferences (e.g., they continue to be more supportive of environmental policies and take more pragmatic approaches to car ownership and driving than older adults).

As for effective policies and interventions to encourage multimodality, studies suggest focusing on the *dynamic* nature of multimodality, which helps identify windows of opportunity during which individuals adjust their travel patterns to new social and physical environments (Scheiner et al., 2016). We find this strategy highly relevant to young adults in California, because many of those belonging to the active traveler and transit rider classes in this study appear to be in transition to full-fledged adulthood. Many active travelers work part time, live close to their schools or workplaces, and do not live with children of their own. Many of them earn incomes in the middle bracket, but live with low access to household vehicles in part because their lifestyles or urban locations may not demand frequent use of cars. Similarly, many transit riders are students either full-time or part-time while not making high incomes, but they do not necessarily perceive cars as merely a tool to get around (i.e., their demand for driving may be suppressed to some extent for now). Thus, when these young adults transition to next phases in the life cycle (e.g., relocation to less dense neighborhoods with low support for alternative modes), planners and policymakers should help them make an informed decision on mode choice by providing information on, and incentives for the use of, feasible alternatives in new circumstances (as well as improving the quality of such alternatives). By doing so, millennials may be both willing and able to keep being multimodal for a longer period of time.

This study analyzes cross-sectional data, which do not portray historic trends, so it cannot estimate the extent to which today's millennials will behave in coming years in the same way today's Gen Xers do. While researchers have attempted to understand generational differences by examining panel and repeated cross-sectional data (i.e., comparing millennials and Gen Xers at the same age) (Chatterjee et al., 2018), these data lack attitudes and preferences, factors behind different travel behaviors and mobility choices of different generations. To overcome this limitation, we are completing a second round of data collection with a larger sample, which includes some of the same individuals from the first survey as well as new respondents included to refresh the panel. With the two waves collected at a two-and-a-half-year interval, we plan to investigate the *dynamic* nature of multimodal travel patterns of the same individuals by employing a latent transition model. By the time of the second survey, these individuals are likely in a different life stage, they may have different attitudes and preferences, and the environments in which they live may have changed, while the quality of emerging transportation technologies and services may have substantially evolved in the meantime. Examining the ways that these various types of changes affect the travel multimodality of these individuals will help us better understand behavioral changes and produce practical insights for planning and policy.

Note that our final sample does not include non-commuting millennials (and Gen Xers). Given that non-commuters have zero commute trips by any travel mode, the latent-class cluster analysis is likely to assign many of them to a single class, while in fact there are some variations in mode choice (for non-commute trips) among them. Our chosen approach, taken to avoid insufficient differentiation across latent classes, has limitations: First, we cannot generalize the main findings of the study to non-commuters. Second, since work arrangements are changing over time (e.g., recent increases in flexible arrangements such as zero-hour contracts and telework (Le Vine, Polak, and Humphrey, 2017)), current commuters may behave differently from commuters in the previous and future years. Thus, any direct comparison between the current group of commuters and commuters in previous (or future) years regarding their travel behaviors requires careful approaches (note that this study does not attempt to do so because of the cross-sectional data). However, we believe it is worthwhile for future research to examine the extent to which millennials' commute (and non-commute) travel patterns are associated with their wider adoption of non-traditional work arrangements.

Factors Associated with the Adoption of Alternative Fuel Vehicles

Promoting the use of alternative fuel vehicles (AFV) has become a long-term transportation strategy in California, which has a broad range of social, economic, and environmental benefits. Based on a sample of 3,463 California residents from the 2018 California Panel Survey, this study explores the effects of socio-demographic characteristics, latent attitudes, and regional context of electric vehicle (EV) market on consumers' current vehicle fuel type choice and their future interest in purchasing or leasing an AFV. One joint integrated choice and latent variable (ICLV) model is estimated to understand the taste heterogeneity within different population segments. The results suggest that latent attitudes towards environmentalism, technologies, car-dependence and car-pragmatism play critical roles in individuals' adopting new vehicle technologies. Also, housing ownership and higher EV density has a significantly positive influence on AFV adoption, although public EV charging stations and related policy support have not found to be essential factors. Moreover, the study suggests that individual's current user experience in AFV has positive effect on their future interest in AFV. The findings offer detailed guidance on crafting California's transport policies based on the characteristics of statewide socio-technical system.

The following is a short version from a paper that was peer-reviewed and presented at 100th TRB Conference (Iogansen et al., 2021), and is currently in the process of peer review for a journal publication. Please use the following citation to cite the full paper:

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Introduction

Encouraging the adoption of alternative fuel vehicles (AFV) has emerged as a mainstream policy interest in California to control pollutants and greenhouse gas (GHG) emissions, and more broadly mitigate adverse environmental impacts related to the reliance on petroleum motor fuels. From customers' perspective, AFV reduce fuel costs and change the economy structure at the household level (Ogden, Williams, and Larson, 2004). In this chapter, vehicles that run on the following five alternative fuel powertrains are considered as AFV. Note that Flexible fuel vehicles (FFVs) run on a mixture of gas and ethanol and currently have the best network of fueling stations. They are usually considered as AFV, but given that many FFVs still dominantly use gasoline these days, we treat them as internal combustion engine vehicles in this study.

a) Hybrid electric vehicles (HEVs) combine a gas and electric propulsion system. The electrical generator either recharges the vehicle's batteries or directly powers its electric drive motors.
b) Plug-in hybrid electric vehicles (PHEVs) also have a gas and electric propulsion system yet having larger batteries than HEVs allows the car to run on electricity alone within a limited range, which is usually between 6 and 40 miles. HEVs and PHEVs are together referred as gasoline hybrid vehicle.
c) Battery electric vehicles (BEVs) run solely on battery power with a longer range than PHEV, which is commonly between 80 and 100 miles while a few models can run more than 250 miles. PHEVs and BEVs are together referred as plug-in electric vehicles (PEVs).
d) Hydrogen fuel cell electric vehicles (FCEVs) have on-board fuel cells that run on compressed hydrogen, with the advantage of zero tail-pipe emissions and high efficiency.
e) Natural gas vehicles (NGVs) run on compressed or liquefied natural gas and have cleaner emissions.

Established in January 2018, the California Zero-Emission Vehicle (ZEV) Action Plan set ambitious targets of supporting 1.5 million ZEVs, including a mix of PHEVs, BEVs and FCEVs by 2025, on the path to 5 million by 2030. Auto manufacturers are required to offer for sale specific numbers of the very cleanest cars available to their market (California Air Resources Board, 2020). Up to recent, more than 0.7 million ZEVs have hit the road in California, yet this figure will need to increase by more than sevenfold during the next decade to achieve the goal.

Policy makers and planning practitioners have advocated the usage of AFV for decades. Understanding what factors influencing individuals' current adoption, and usage of AFV would help policymakers evaluate what have worked and what have not, in order to develop more individually tailored policy interventions to encourage the market uptake. Since AFV, especially PHEV and BEV, were introduced to the broader consumer market in 2010, there has been a growing number of studies exploring consumers' motivations and barriers to their adoption (Javid and Nejat, 2017; McFadden, 1974; Rezvani, Jansson, and Bodin, 2015; Sierzchula, Bakker, Maat, and Van Wee, 2014).

Some studies have attempted to understand the factors that influence the adoption of AFV relying on theoretical frameworks, such as the theory of planned behavior (Moons and De Pelsmacker, 2012), the rational choice theory (Peters and Dütschke, 2014), the value-belief-norm-theory (Egbue and Long, 2012), the self-image congruency theory (Schuitema, Anable, Skippon, and Kinnear, 2013), the lifestyle theory (Axsen, TyreeHageman, and Lentz, 2012), socio-technical transitions theory (Steinhilber, Wells, and Thankappan, 2013), and the theory of diffusion of innovations (Lee, Hardman, and Tal, 2019). A common feature of this stream of literature is that attitudinal factors, such as knowledge, values, beliefs, norms are usually found to have the most direct influences on AFV adoption. For instance, the links between pro-environmental attitudes and the intention to adopt AFV have been widely discussed (Rezvani et al., 2015).

Other studies show that not only those current AFV users, but also many people who currently drive gasoline vehicles express great interest in buying or leasing a vehicle that runs on alternative fuels in the next few years (Rezvani et al., 2015; Shaheen, Martin, and Totte, 2020). Also, the adoption of AFV can be viewed as a proxy for the potential market penetration of more advanced technology-enabled transportation options, such as autonomous EV (Webb, Wilson, and Kularatne, 2019). It is likely that technology enthusiasts tend to be the early adopters of emerging transportation options (Alemi, Circella, Handy, and Mokhtarian, 2018; Egbue and Long, 2012). Studying the correlates between current and future fuel type choice can provide useful insights into the possible future of new vehicle technologies. Therefore, we believe a joint analysis between consumers' current and potential future behavior is of great interest.

By investigating empirical user data that includes 3,483 residents from California, the goal of this part of the research is two-fold. The first is to explore the factors that affect consumers' *current vehicle fuel type choice* and *interest in purchasing or leasing an AFV in the future*, respectively. We hypothesize that some factors may have common effects on both individuals' current choice and interest in the future, while others may have come into play in different ways. The second goal of this chapter is to decipher the interrelationship between individuals' current choice and their interest in the future. We hypothesize that current AFV users are more likely to indicate their interest in AFV in the future. In other words, individuals' existing user experience on AFV can bolster individuals' interest in continuing adopting AFV in the future and increase their future "stickiness" to AFV. We estimate a joint integrated choice and latent variable (ICLV) models to understand the source of preference heterogeneity among population segments, focusing on latent attitudes and neighborhood effects associated with residential characteristics, AFV facilities and policies.

Insights gained from this research will shed more light on the market penetration of ZEVs in California and guide policymakers in crafting transport policies based on the characteristics of statewide socio-technical system. This research will also provide guidance to transport professionals regarding the ways to incorporate consumer characteristics and preferences into infrastructure investments related to ZEVs.

Data and Preliminary Analysis

Current and Future Vehicle Fuel Type Choice

The data used for this analysis is from 2018 survey. In the survey, respondents indicated the fuel type of the vehicle that they currently used most frequently (*single choice out of seven fuel type options,* including gasoline, diesel, HEV, PHEV, BEV, FFV and FCEV), as well as their interest in buying/leasing an AFV in the future (*multi-choices out of four fuel type options*, including gasoline hybrid (i.e., HEV/ PHEV), BEV, FFV and FCEV). The original survey questions are listed below. In the remainder of the chapter, for convenience, we refer these two variables as "current vehicle fuel type choice" and "future interest in AFV", respectively. Since most current FFVs still heavily rely on gasoline/diesel, they may not require much behavioral change of the drivers and may not take as much effect on the environments as other categories of AFV, gasoline, diesel and FFV are thus all categorized into ICEVs in this study. Though hydrogen FCEV is one of the main interests of California ZEV Mandate, there is only one sample in our dataset, therefore it is excluded from the discussion. Observations from "other"/ "I do not know" categories are also excluded from consideration.

[Current vehicle fuel type choice]
What type of fuel does your most frequently used vehicle run on?

- ☐$_1$ Gasoline
- ☐$_2$ Hybrid (e.g., Toyota Prius)
- ☐$_3$ Plug-in hybrid (e.g., Toyota Prius Prime)
- ☐$_4$ Battery electric (e.g., Nissan Leaf, Tesla Model S)
- ☐$_5$ Diesel
- ☐$_6$ Flex-fuel vehicle (runs on gasoline or ethanol)
- ☐$_7$ Hydrogen fuel cell (e.g., Toyota Mirai)
- ☐$_8$ Other (please specify): _________________

[Future interest in AFV]
Would you ever be interested in buying or leasing a vehicle that runs on any of these alternative fuels?
Check here ☐$_0$ if not interested, otherwise please check ALL that apply.

- ☐$_1$ Gasoline hybrid (e.g., Toyota Prius)
- ☐$_2$ Battery electric (e.g., Nissan Leaf, Tesla Model S)
- ☐$_3$ Hydrogen fuel cell (e.g., Toyota Mirai)
- ☐$_4$ Flex-fuel vehicle (runs on gasoline or ethanol)
- ☐$_5$ I do not know
- ☐$_6$ Other (please specify): _________________

After removing cases with missing values on variables of interest, the final sample used for this analyses included 3,463 cases. The sample distribution of combined current and future fuel type choices is shown in Table 14.. ICEVs have been dominantly chosen by over 90% of the total samples as their most frequently used vehicle currently, and around 40% of them show no interest in AFV in the future. In contrast, most current AFV users, though only account for less than 10% of the total sample, are either willing to continue holding the same vehicle fuel type, or open to other alternative fuel options. In other words, people by and large show their future interest toward the same fuel type as their current vehicle, assuming they will still own/lease a. In fact, AFV users are "stickier" to their current fuel types than ICEV users and BEV users seem to be the most 'loyal' customers, with 82.2% of them continue showing interest toward BEV and one third of them (33.3%) actually only interest in using BEV in the future. Results from Pearson's Chi-squared test suggest that the future interest in alternative fuel is significantly correlated with current fuel type choice. In other words, people who use an AFV currently are more likely to have their interest in continuing to buy/lease an AFV, and also more likely to stick with the specific fuel type that they are running on now.

Table 14. Sample distribution of combined current and future fuel type choice

Current Vehicle Fuel Type	Sample Size (N)	Distribution (column-wise %)	Interest in purchasing/leasing an AFV in the future (row-wise %)							
				Has interest						
			No interest	HEV/ PHEV Only	BEV Only	Hydrogen FCEV Only	HEV/ PHEV & BEV	HEV/ PHEV & Hydrogen	BEV & Hydrogen	HEV/ PHEV & BEV & Hydrogen
ICEV (Gasoline /Diesel/ Flex-fuel)	3,150	91.0	40.3	16.6	6.3	0.9	18.2	1.5	1.8	14.3
HEV	221	6.4	10.4	26.2	6.3	0.9	28.5	2.3	0.9	24.4
PHEV	47	1.4	6.4	19.1	12.8	0.0	23.4	0.0	6.4	31.9
BEV	45	1.3	8.9	6.7	33.3	2.2	22.2	0.0	17.8	8.9
Total sample	3,463	--	1,301	594	235	30	657	53	69	524
% of total sample	--	100	37.6	17.2	6.8	0.9	19.0	1.5	2.0	15.1

One may concern that the individuals' vehicle fuel type choice is related to the environment, one of the socially sensitive topics that are likely to result in social desirability bias (SDB) in the survey responses when research subjects tend to give socially desirable responses instead of choosing responses that are reflective of their true feelings (Grimm, 2010). Comparing to their self-reported current vehicle fuel type choice, their stated future interest may be more subject to SDB. Nevertheless, we believe the issue is alleviated in our study, since (1) this is a self-administered survey without any presence involvement of an interviewer, and (2) the survey question only asks respondents' interest rather than immediate purchase intention, therefore they are less likely to provide answers under high pressure.

Given the complexity of the survey data structure, Figure 18 proposes a simplified modeling frame for this study. For current fuel type choice, PHEV and BEV are combined into PEV due to limited sample size, and besides, they share a number of commonalities in terms of vehicle features, user experience, requirements for infrastructure and policy regulations. Future interest in fuel type are condensed into a binary choice (i.e., no interest/ have interest). The current and future scenarios are modeled separately in two branches; however, their interrelationships will be discussed through detailed compare and contrast in Result section. More nuances contained within the dash frames below maybe explored in future research.

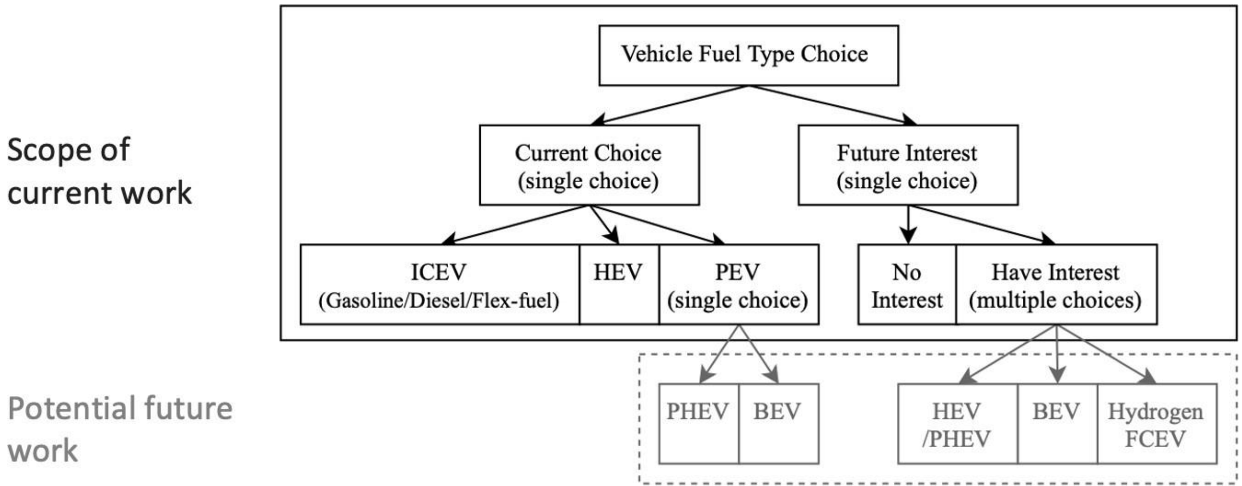

Figure 18. Modeling framework

Socio-demographics and Residential Built Environment Characteristics

Table 15. provides a comparison of exogenous socio-demographic variables and residential built environment characteristics between current AFV users and potential adopters in the future. For the current fuel type choice, people who are aged 35 to 54, white/Caucasian, male, non-student, employed, with high-income, living in urban area, owning a house and with private parking are more likely to adopt an AFV. While for the future interest, it is clear that majority of people from all socio-demographic categories and built environments are willing to shift to an AFV, yet substantial differences among population groups are also observed. For instance, although most current AFV is owned by population with annual income larger than $100,000, a sizable percentage of population among median- and low-income groups have shown their future interest. In another words, in contrast to their current relative-low AFV adoption rate, median- and low-income population may become the main momentum of future diffusion. Similar phenomenon exists according to other population groupings.

Local Context of EV Market

As this study gives special attention to the factors related to neighborhood effects related to EV infrastructure and policies, four additional variables were collected from external sources to reflect the local context of EV market for each survey respondent.

Density of EVs

The EV density is measured by the number of HEVs, PHEVs and BEVs per five square miles in each county in 2017. This processed data was collected from National Renewable Energy Laboratory (NREL) website by authors (National Renewable Energy Laboratory, 2020), while the original light-duty vehicle registration data was derived from HIS Markit 2017 by NREL. As Figure 19 illustrates, EVs are geographically concentrated within large metropolitan regions, with a much higher density of HEVs comparing to PHEVs and BEVs. Since the data is only available as ranges (e.g., 5-20 per five square miles), the median value of each range was calculated. Also, we kept the unit as number per five square miles as the original data collected instead of number per square mile. This variable is treated as a continuous variable during statistical modeling.

This variable is included in our model aiming to capture the potential "peer effects" in the EV market. As Rogers argued, peers adopting a new technology can send an approval signal to others, and conformity encourages those people to adopt similar behaviors and lifestyles (Rogers, 2010). We hypothesize that the higher the EV density in the region, the stronger positive peer effect will be on people's EV adoption living within the region. The density of each type of EV is assumed to impact differently on each group of EV users for their current fuel type choice, while the cumulative number of all EVs is assumed to impact their future interest in AFV in general.

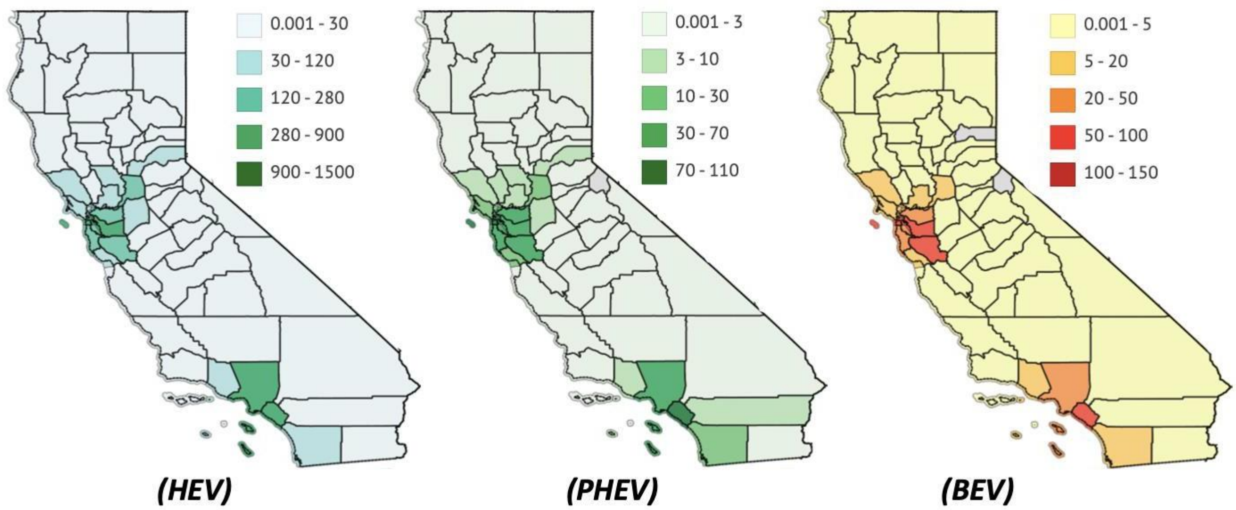

Figure 19. EV density in each county in California (unit: number of vehicles per 5 sq. mile)

Density of Public EV Supply Equipment (EVSE)

The EVSE density is measured by the number of EV charging stations in each blockgroup, combining Level1, Level 2 and DC Fast Charging, as Figure 20 plots. The original geolocation of each EVSE was collected from Alternative Fuels Data Center from U.S. Department of Energy website (US Department of Energy, 2020). By 2018 when the survey conducted, there were 23,818 individual charging outlets installed in 5,954 locations (i.e., stations) within California. This variable is included in the model with the goal of exploring the public EVSE network effects on consumers' propensity of owning/leasing an EV since studies found that public charging can compensate for the unavailability of home charging and alleviate some concerns of car buyers (Axsen, Kurani, and Burke, 2010; Zou, Khaloei, and MacKenzie, 2020). After trying different specifications in the model, this variable is transformed into a dummy variable during statistical modeling with "1" indicating there is at least one charging station within the blockgroup of each respondent's residential location, while "0" otherwise.

There is evidence that different types of EVSE have different effects, for example, fast chargers are more practical than slower chargers especially during long-distance travel above vehicles' single-charge range (Neaimeh et al., 2017) and some types of chargers (e.g., Tesla supercharger) are more exclusive than public chargers. However, considering this study focuses more on regular travel activities in neighborhood level which can be potentially fulfilled by charging events supported by each type of EVSE and the EVSE are still relatively sparse geographically across the state, we decide to aggregate all available EVSE in each blockgroup level without distinguishing their types.

According to an estimate of the U.S. Department of Energy (DOE), more than 80% of charging events take place at home, thus public EVSE perhaps matter less to those individuals with home chargers. In fact, availability of home chargers was found to be most influential for encouraging EV adoption (Hardman et al., 2018). Unfortunately, respondents in our survey did not directly indicate whether any home chargers are available to them. To tackle with this limitation, four pieces of information related to residential ownership and built environment characteristics, including their neighborhood type (i.e., rural, suburban, urban), housing tenure (i.e., own, rent), housing type (i.e., house, apartment/condo/others), and residential parking (i.e., private parking, on-street parking) that are included in the modeling stage are expected to capture some heterogenous propensity of having reliable home charging in the household. For instance, Lee et al. found in their study that more than 80% of PEV adopters from 2012 to 2017 in California were homeowners (Lee et al., 2019). Also, charging in a single-family home, usually with a garage, is generally more convenient, and allows EV owners to take advantage of incentives such as tax credit or rebates for home EVSE installation, and also obtain low, stable residential electricity rates for charging their vehicles in the long run. With comparison, charging at a multi-family residential complex can be less reliable and more similar to the experience of using public charging. In fact, only 20% of current EVs are owned by occupants of multi-family dwellings, who therefore mostly rely on public charging.

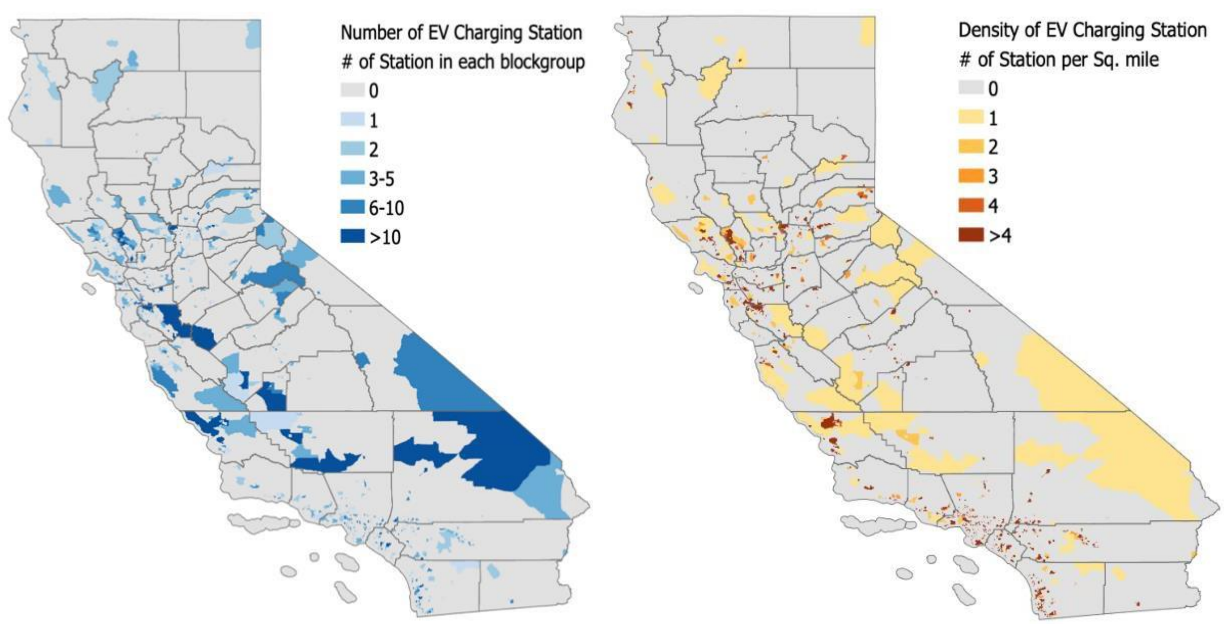

Figure 20. Count and density of EV charging station in blockgroup level

Accessibility to EVSE

The accessibility to EVSE is measured by the Euclidean distance (mile) to the nearest EVSE from the home location of each respondent, which is one aspect of EV readiness. Even though only those PEV owners are using those facilities, we assume their existence can play a role on impact each respondent's decision-making and utility of their current and future fuel type choice. In the final model, this variable is transformed into a dummy variable with "1" indicating less than 0.25 mile from the nearest charging station, while "0" otherwise. A quarter mile is usually regarded as a reasonable walking distance in urban planning, in the case when the EV users have to park and charge their vehicle in the charging station and walk home, for instance.

EV Promotion Policy

The U.S. DOE grants cities to coalitions that exhibit broad commitment to and support for implementing alternative fuels and advanced vehicle technologies (US Department of Energy, 2016). As Figure 21 plots, California Clean Cities Coalition Network is composed of nine such coalitions within 28 counties. Cities within the network may provide more incentives/ disincentives or take stronger measures to promote the adoption of cleaner vehicles in the region. We hypothesized that residents living within those regions may have higher awareness of policy, regulation and user benefits associated with cleaner vehicles, thus are more prone for EV adoption. The variable is measured as dummy variable in our model with "1" indicating living within the network, while "0" otherwise.

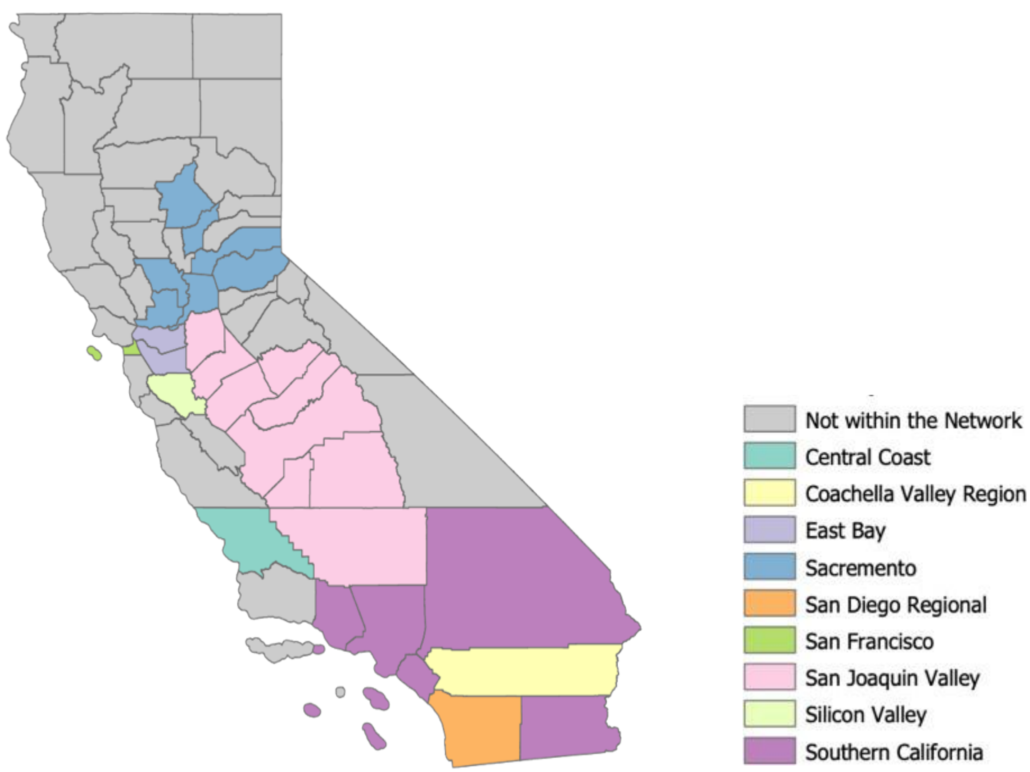

Figure 21. Clean City Coalition Network in California

Table 15. Comparison of socio-demographics and residential built environments across vehicle fuel type

Variables	Categories	# of Cases	% of Case (column-wise %)	Current Fuel Type Choice (row-wise %)			Future Interest in AFV (row-wise %)	
				ICEV	HEV	PHEV /BEV	No Interest	Has Interest
Age	18-34	743	21.5	93.1	4.8	2.0	65.5	34.5
	35-54	1267	36.6	89.9	7.0	3.1	66.3	33.7
	>= 55	1453	42.0	90.8	6.6	2.6	57.5	42.5
Race	Non-White	651	18.8	90.3	7.4	2.3	67.1	32.9
	White/Caucasian	2812	81.2	91.1	6.2	2.7	61.3	38.7
Gender	Not-Male	1843	53.2	91.9	6.2	2.0	58.5	41.5
	Male	1620	46.8	89.9	6.6	3.5	66.9	33.1
Student Status	Not-Student	3100	89.5	90.8	6.5	2.7	62.2	37.8
	Student	363	10.5	92.0	5.8	2.2	64.5	35.5
Employment	Unemployed	1298	37.5	92.8	5.6	1.6	54.5	45.5
	Employed	2165	62.5	89.9	6.8	3.3	67.2	32.8
Education	Below college degree	1465	42.3	95.8	3.4	0.8	50.7	49.3
	College degree or above	1998	57.7	87.4	8.6	4.1	71.0	29.0
Household Income	< $50,000	1019	29.4	97.2	2.3	0.6	50.5	49.5
	$50,000 to $99,999	1147	33.1	91.5	6.7	1.7	61.4	38.6
	>= $100,000	1297	37.5	85.6	9.3	5.1	72.7	27.3
Household Size	(mean)	3463	100.0	(2.7)	(2.6)	(3.0)	(2.7)	(2.6)
Neighborhood Type	Rural	808	23.3	94.2	4.5	1.4	53.1	46.9
	Suburban	1609	46.5	90.5	6.3	3.2	65.2	34.8
	Urban	1046	30.2	89.2	7.9	2.9	65.4	34.6
Housing Tenure	Rent	1220	35.2	93.5	5.2	1.2	59.3	40.7
	Own	2243	64.8	89.6	7.0	3.4	64.2	35.8
Housing Type	Apartment, condo or others	769	22.2	93.2	5.7	1.0	58.4	41.6
	Stand-alone/attached house	2694	77.8	90.3	6.6	3.1	63.6	36.4
Residential Parking	Unreserved, on-street parking	111	3.2	93.7	5.4	0.9	55.9	44.1
	Private/reserved parking	3352	96.8	90.9	6.4	2.7	62.6	37.4
Total Sample Size		**3463**	100					

Modeling Approach

Standard discrete choice model (DCM) based on random utility theory is widely used for modeling discrete choices, however, a number of researchers have argued that a hybrid choice model that integrates DCM and latent factors model generally performs better. The model has been found to better model unobserved heterogeneity, increase efficiency, gain predictive power, enhance behavioral representation, and extend policy relevance (Abou-Zeid and Ben-Akiva, 2014; Ben-Akiva et al., 2002; Vij and Walker, 2016; Walker and Ben-Akiva, 2011). Specifically, the ICLV model can incorporate psychometric latent factors (such as internal knowledge, opinion, perceptions and attitudes) as explanatory variables, thus yielding a more realistic model. It hypothesizes that both choice and attitudinal responses are influence by latent factors, directly or indirectly, while at the same time, those latent factors themselves are affected by experience and external factors, such as the characteristics of the decision-makers. The ICLV model has been widely applied in various contexts, such as vehicle type choice (Bolduc and Alvarez-Daziano, 2010), vehicle fuel type choice (Alvarez-daziano and Bolduc, 2009), shared mobility choices (Li and Kamargianni, 2020) and so forth.

One joint logit-kernel based ICLV model is constructed to model the effects of individual characteristics, latent perceptions/attitudes, residential built environments, and local context of EV market on respondents' current and future fuel type choice. The model is comprised of a multinomial discrete choice model with two dependent choice situations (i.e., current choice and future interest) and the latent variable model, with each sub-model consisting of a structural and a measurement component.

In the ICLV model, the utility in the discrete choice component depends on observed and latent characteristics of the alternatives and decision makers. The utility is modeled with random utility maximization theory. Based on respondents' self-reported vehicle ownership, different samples may have unequal choice sets. For instance, if a person only owns one vehicle and that is his/her most frequently used one, then we assume there are no other alternatives available within his/her choice set. It is worth noting that in this study, we assume the utility is indirectly affected by socio-demographic characteristics through the latent factors, thus they are not directly included in the utility function.

In the structural equation, each latent factor is expressed as a function of exogenous socio-demographic variables including age, gender, race, education degree, student status, employment status, household size, household income. A series of exploratory regression analyses are conducted in advance to detect any potential relationships between these attitude dimensions and individual characteristics, based on which the structural equation for each latent factor is then specified in the ICLV model.

In the measurement equation, those unobservable latent factors are manifested by a total of 21 indicators from the survey where respondents rate their level of support for or opposition to / agreement or disagreement to different attitudinal and preference statements. The indicators help the identification of the latent factors and increase the efficiency in estimating the choice model. The number of latent factors and model specification is suggested by the estimated factor loading from an exploratory factor analysis (EFA). The larger factor loadings correspond to a stronger relationship between the indicator and the corresponding latent factor. In the end, five factors were extracted, which are hypothesized to significantly impact people's EV adoption. They are 1) pro-environment; 2) tech-savvy; 3) car-dependent; 4) car-utilitarian; 5) pro-urban. The final model specification depends on their statistical significance in the optimized ICLV model.

In this model, since the structural equation and measurement equation are estimated based on the same sets of socio-demographics and indicators from one-time observation through the survey, we hypothesize that specifications related to latent factors in these two equations will stay identical no matter which choice situation was presented to respondents. However, we hypothesize that those latent factors and other observed variables will have different effects on individuals' current choice and future interest. In other words, we will generate one set of parameters from structural equation and measurement equation, yet two sets of parameters from utility equation, one for current choice and one for future interest. Moreover, the correlation between current AFV user experience and future interest in AFV is also reported.

Figure 22 illustrates the flowchart of ICLV model for current fuel type choice and future interest with our hypothesized relationship based on initial factor analysis and regression models for measurement model and structural model, respectively. We use the *Apollo* library in R for performing maximum simulated likelihood estimation (Hess and Palma, 2019). The final model results will be presented in the next section.

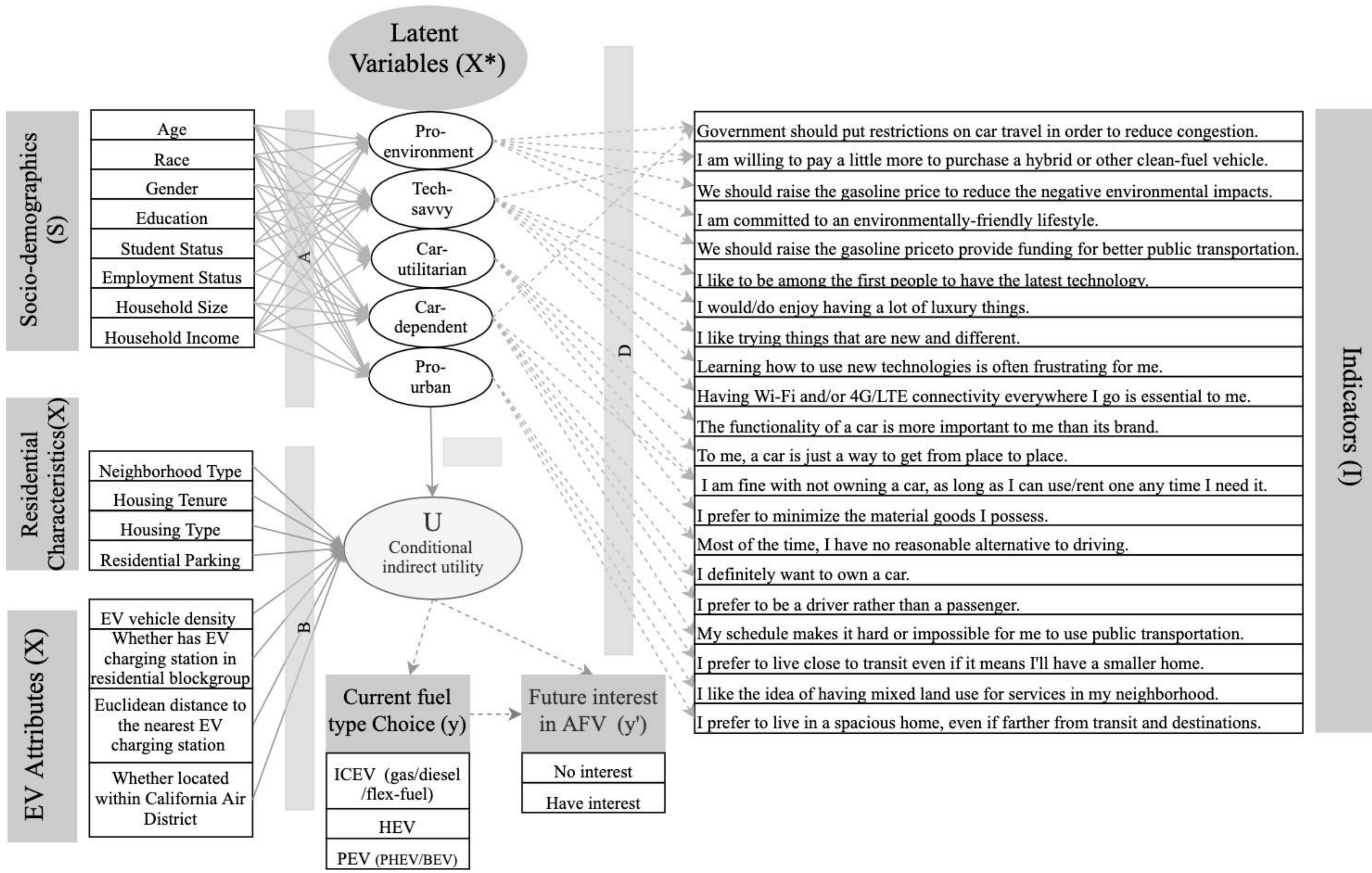

Figure 22. Flowchart of ICLV model for current and future fuel type choice

Results and Discussion

Multiple model specifications with different number of latent factors were tested. The final model presented below has the highest goodness-of-fit with a large number of significant coefficients at the 95% level (i.e., p-value less than 0.05). It is partially in accordance with our hypotheses shown in Figure 22. Although all the equations in an ICLV model are calibrated simultaneously, we present the results separately for each sub-model, i.e., vehicle fuel type choice model, the latent variable structural model, and the latent variable measurement model. Please note again that the **current** and **future** fuel type choice are modeled independently, but their results are presented here at the same time to compare and contrast the similarities and differences of the effects of different variables.

Structural Model

Measurement Equation

Table 16. shows the coefficients of each indicator in the measurement equation, which suggest the relation between each latent variable and their corresponding indicators. They are comparable to the factor loadings from the EFA and all statistically significant.

The *pro-environment* factor encompasses people's attitude towards all types of governmental environmental regulations as well as personal environmentally friendly lifestyle. The *tech-savvy* variable reflects people's familiarity/proficiency with new technologies and their curiosity/openness to new experience. The *car-utilitarian* factor pertains to people's value on the pragmatic aspects of a vehicle, such as taking more seriously on its functionality instead of its brand. In addition, *car-dependent* factor indicates people's dependence on and attachment to their vehicle on daily life. Finally, the *pro-suburban* factor manifests people's preference on living in suburban areas to gain more and spacious living environment, even in the exchange of better neighborhood services and public transportation.

Structural Equation

Table 17. shows the estimated coefficients for the structural equation, which confirms our hypothesis that exogenous socio-demographic attributes significantly influence people's perceptions and attitudes.

People who are from younger generation, with higher education, higher income, under student status and with small household size and are more *pro-environment* than their counterparts. Many of the above characteristics look alike among *tech-savvy* people, expect that male, people under employment status and people with larger household size are also found to be more *tech-savvy*. Non-white people are also more tech-savvy, after controlling the potential correlation between younger generation being more racially diverse than the older generation. This is consistent with some signs suggesting a potential digital transformation among younger and more diversified population (Enni, Ar, and Als, 2016). The findings for *car-dependent* factor are all within expectation. People from older generations, who are with high income and with large household size are more car-dependent. In contrast, students, and people with higher education are less car-dependent. Regarding *car-utilitarianism*, the pragmatic aspects of a vehicle seem to be less a concern for males and high-income people, potentially because they are more driven by other aspects of a vehicle, such as its representation of social status, while older people and people with higher education tend to care more in this aspect. On the other hand, older people and people with higher education pay more attention to the pragmatic components of a vehicle. Finally, in terms of residential location preference, the white, those with higher income and with larger house income and with larger household size are more *pro-suburban*, while students, employees, people with higher education are less.

These findings help build the clusters of population and to predict values of the unobserved latent factors that are used in the choice model. An important policy implication of understanding the heterogeneity among population is to understand how individuals will react to a policy which can be used to support the design of efficient policies tailed for certain group of population.

Table 16. Estimation results from the measurement equation

	Latent Factors									
	Pro-environment		Tech-savvy		Car-dependent		Car-utilitarian		Pro-Suburban	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
1. We should raise the price of gasoline to provide funding for better public transportation.	**1.14**	**(49.16)**								
2. We should raise the price of gasoline to reduce the negative impacts on the environment.	**1.09**	**(52.62)**								
3. I am willing to pay a little more to purchase a hybrid or other clean-fuel vehicle.	**0.56**	**(24.46)**	**0.30**	**(11.74)**						
4. The government should put restrictions on car travel in order to reduce congestion.	**0.55**	**(23.89)**			**-0.38**	**(-14.42)**				
5. I am committed to an environmentally-friendly lifestyle.	**0.41**	**(23.43)**								
6. Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.			**0.57**	**(21.45)**						
7. I like to be among the first people to have the latest technology.			**0.56**	**(20.76)**						
8. I would/do enjoy having a lot of luxury things.			**0.37**	**(16.02)**					**0.22**	**(5.76)**
9. I like trying things that are new and different.			**0.37**	**(19.12)**						
10. Learning how to use new technologies is often frustrating for me.			**-0.50**	**(-20.62)**						
11. Most of the time, I have no reasonable alternative to driving.					**0.50**	**(11.34)**				
12. My schedule makes it hard or impossible for me to use public transportation.					**0.43**	**(8.44)**				
13. I definitely want to own a car.					**0.39**	**(15.94)**				
14. I prefer to be a driver rather than a passenger.					**0.32**	**(9.65)**				
15. I am fine with not owning a car, as long as I can use/rent one any time I need it.					**-0.58**	**(-16.69)**	**0.35**	**(8.32)**		
16. To me, a car is just a way to get from place to place.							**0.60**	**(15.77)**		
17. The functionality of a car is more important to me than its brand.							**0.42**	**(12.99)**		
18. I prefer to minimize the material goods I possess.							**0.36**	**(11.2)**		

	Latent Factors									
	Pro-environment		**Tech-savvy**		**Car-dependent**		**Car-utilitarian**		**Pro-Suburban**	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
19. I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.									**-0.70**	**(-18.9)**
20. I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.									**-0.46**	**(-13.9)**
21. I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.									**0.53**	**(10.57)**

Note: bold indicates statistical significance at 95% confidence interval.

Table 17. Estimation results from the structural equation

Social-demographic Characteristics	Category	Latent Factors				
		Pro-environment	Tech-savvy	Car-dependent	Car-utilitarian	Pro-suburban
Age	35-54	**-0.27**	**-0.43**	0.00	0.00	-0.12
(base: 18-34)		**(-4.12)**	**(-6.09)**	(-0.04)	(0.02)	(-1.59)
	>= 55	**-0.25**	**-1.07**	**0.41**	**0.20**	0.02
		(-3.87)	**(-13.02)**	**(4.86)**	**(2.57)**	(0.23)
Race	White/Caucasian	-0.06	**-0.24**	**0.14**	-0.09	**0.15**
(base: Non-white)		(-1.12)	**(-3.91)**	**(2.10)**	(-1.32)	**(2.24)**
Gender	Male	0.06	**0.11**	-0.01	**-0.17**	0.05
(base: Not-Male)		(1.31)	**(1.98)**	(-0.21)	**(-2.6)**	(0.76)
Student Status	Student	**0.22**	**0.43**	**-0.40**	0.12	**-0.35**
(base: Not-Student)		**(2.71)**	**(5.06)**	**(-4.21)**	(1.14)	**(-3.49)**
Employment	Employed	-0.03	**0.37**	0.00	0.00	**-0.19**
(base: Unemployed)		(-0.62)	**(6.35)**	(-0.07)	(0.02)	**(-2.97)**
Education	College or above	**0.46**	**0.33**	**-0.27**	**0.29**	**-0.48**
(base: Below college)		**(9.46)**	**(5.67)**	**(-4.45)**	**(4.19)**	**(-6.88)**
Household Income	$50,000 to $99,999	0.01	0.06	0.06	**-0.17**	**0.16**
(base: < $50,000)		(0.18)	(0.91)	(0.85)	**(-2.29)**	**(2.11)**
	$100,000 or higher	**0.18**	**0.28**	**0.28**	**-0.38**	**0.34**
		(2.91)	**(3.61)**	**(3.39)**	**(-4.31)**	**(4.04)**
		-0.03	**0.06**	**-0.07**	0.03	**0.06**
Household Size	(mean)	**(-1.95)**	**(3.43)**	**(-3.59)**	(1.38)	**(3.27)**

Statistics: Coefficients (t-statistics)
bolded: statistically significant at 95% confidence interval

Fuel Type Choice Model

Table 18. reports the results from the logit model with two interrelated dependent variables, one for current fuel type choice and the other for future interest in AFV. The alternative specific constants (ASCs) are negative for current choice, suggesting that both HEVs and PEVs are less likely to be chosen compared to ICEVs if all other variables are constant. This is reflected by the fact that more than 90% of current users are using ICEVs in our sample. In contrast, the positive ASC for future interest indicates that people are more likely to have interest in AFV in the future if all other variables are constant, however the difference is not statistically significant, which is explained by a much-balanced market share in our sample.

Latent Factors

The results suggest that environmental consciousness plays an important role on EV adoption. People who are more *pro-environment* have been found to be more prone to become current EV users and show potential interest in the future, as they are more motivated to support green technology and environmentally friendly lifestyle.

Tech-savvy persons are more likely to currently use a PEV comparing to an ICEV, yet no significate relationship with current adoption of a HEV. This may be because the features and functionalities of an HEV are somewhat similar to that of an ICEV, while a PEV might require adopters' substantial knowledge of new vehicle technologies as well as behavior changes. As expected, *tech-savvy* is statistically significant and positively associated with individuals' future interest in an AFV.

Instead, *car-utilitarian* is a significant and positive predictor of choosing a HEV currently, yet not significantly associated with the future interest of PEV. A possible explanation is that a HEV usually outperforms an ICEV in terms of fuel efficiency through regenerative braking, and do not require additional battery charges like an PEV, thus people who value the pragmatic aspect of a vehicle will find them more compelling. With comparison, even though an PEV should perform better in some perspectives, their relatively high costs, limited driving ranges and tediousness of charging requirement might still be major barriers to consumers. Interestingly, despite of current barriers, people who are car-utilitarian stay positive on future AFV, potentially because they believe AFV will become more practical as the technology, market and infrastructure are all in place in the future.

In our model, *car-dependent and pro-suburban* are not significantly associated with current fuel type choice. Based on the results of the measurement model, we may infer that these people heavily rely on driving in daily life, thus they might just treat a vehicle as a way of moving them around and tend to pay less attention with the technologies. The insignificance of *pro-suburban* latent variable suggests that at least among our samples, built environment characteristics play a less important role on their decision-making when it comes to their fuel type choice. Interestingly, based on our observation from the dataset (Table 15.), the HEV market uptake is faster among urban residents (7.9%) comparing to suburban residents (6.3%), yet PEV market uptake is faster among suburban residents (3.2%) comparing to urban residents (2.9%), and the EV market seems to lag in rural area in general. This distribution may have correlate with other factors, such income. In contrast, the market share of future interest in AFV is much balanced geographically. Notwithstanding the foregoing, those who are car-dependent tend to indicate their interest in AFV in the future.

Residential Characteristics

Housing ownership is found to be positively associated with both current and future AFV adoption. As discussed previously, owning a house can make EV charging activities much more convenient and reliable. It is highly likely that this variable is correlated with the rest of three variables reflecting residential characteristics and built environments (e.g., people who owning a house tend to have private parking garage). This may partially explain why they are not found significant in the model. Nevertheless, the sign of the coefficients does suggest that locating in more urban environment, living in a house, and having dedicated parking space near residential location can promote the AFV adoption, in general.

Local Context of the EV Market

The positive sign of the EV density variable suggests that people living in regions with higher density of EVs are more likely to become current EV users and also have higher interest of future adoption. The findings of this study confirm Rogers's argument about "peer-effects". Government can leverage the social-geographic peer effects and economy of scale to promote EV adoption in regional level.

Somewhat surprisingly, the rest of variables from supply side including density of EV charging station, distance to the nearest charging station and whether located within California Clean Cities Coalition Network are not significant in both current and future model (at $p\text{-value} < 0.05$ level), and the sign of their coefficients suggest conflicting effects on individuals' current choice and future interest. Following are several potential reasons. (a) Through we a decent sample size in our model, HEV and PEV users only account for less than 10% of total observation, thus the power of analysis is heavily restricted. (b) From statistical sense, one potential reason is that current EV density is highly correlated with these factors, as the 'chicken-and-egg' dilemma implies, which results in the rest of variables insignificant within one model. (c) From practical sense, over 80% of EV charging happens at home and many drivers can also charge at their workplaces, thus the public charging may not play an essential role. And for the future decision, we would not expect many of those who does not currently own an EV or are not seriously considering purchasing/leasing an EV to have good knowledge or even be aware of EVSE. (d) Given the early phase of the EV market and infrastructure deployment, it is likely that those current users and potential adopters are more driven by other internal factors, such as values, attitudes and perceptions associated with owning an EV as discussed above, instead of the direct utility from these external factors.

Current User Experience

One important finding from the model is that people's current user experience with both HEV and PEV are positively correlated with their continuing interest in AFV with strong statistically significance. This suggests a promising future of expanding (or at least maintaining) of the AFV market from current EV users. Increasing people’s knowledge and experience of EV, especially those that have not used AFV ever before, is critical strategy for market uptake.

Table 18. Results from discrete choice models

Variables	Categories	Current Fuel Type Choice (ICEV as baseline) HEV	PEV (PHEV/BEV)	Future Interest in AFV (No interest as baseline) Has interest
Constants		**-3.15**	**-5.50**	0.01
		(-5.28)	**(-4.08)**	(0.03)
Latent Factors				
Pro-environment		**0.48**	**0.77**	**0.56**
		(4.96)	**(5.85)**	**(10.17)**
Tech-savvy		0.10	**0.68**	**0.51**
		(0.98)	**(4.74)**	**(9.09)**
Car-dependent		-0.06	0.27	**0.17**
		(-0.47)	(1.27)	**(2.78)**
Car-utilitarian		**0.40**	0.13	**0.11**
		(2.67)	(0.97)	**(1.75)**
Pro-suburban		-0.21	0.12	-0.08
		(-1.43)	(0.69)	(-1.30)
Residential Characteristics				
Neighborhood type	Suburban	0.19	0.52	**0.19**
(base: rural)		(0.73)	(1.47)	**(1.77)**
	Urban	0.17	0.33	0.08
		(0.57)	(0.82)	(0.62)
Housing tenure	Own	**0.42**	**0.86**	**0.22**
(base: rent)		**(2.06)**	**(2.54)**	**(2.38)**
Housing type	Stand-alone/attached house	0.04	0.48	0.16
(base: Apartment, condo or others)		(0.15)	(1.06)	(1.56)
Residential parking	Private/reserved parking	-0.07	0.20	0.11
(base: Unreserved, on-street parking or others)		(-0.13)	(0.18)	(0.50)
EV Market and EV Infrastructure				
EV density		**0.0014**	0.0029	0.0001
		(2.16)	(1.37)	(0.24)
Whether has an EV charging station within the residential blockgroup	Yes	-0.39	-0.35	0.06
(base: no)		(-1.54)	(-1.11)	(0.48)
Euclidean distance to the nearest EV charging	Longer than 0.25 mile	0.03	0.35	-0.10

Variables	Categories	Current Fuel Type Choice (ICEV as baseline) HEV	PEV (PHEV/BEV)	Future Interest in AFV (No interest as baseline) Has interest
station from residential location (base: 0.25 mile or shorter)		(0.15)	(1.14)	(-0.88)
Located within CA Clean Cities Coalition Network	Yes	-0.16	-0.18	0.09
(base: no)		(-0.57)	(-0.48)	(0.60)
Current User Experience				
Current user	HEV user	----	----	**1.45**
(base: ICEV user)		----	----	**(6.15)**
	PHEV/BEV user	----	----	**1.74**
		----	----	**(3.75)**
# of Observation			3,463	3,463
		(ICEV:HEV:PEV= 3150:221:92)		(No: Yes= 1281:2182)
LL(0,choice)			-2826	-2400
LL(final, choice)			-931	-2126
Adjust Pseudo R^2			67%	11%

Statistics: Coefficients (robust t-statistics)
bolded: statistically significant in 95% confidence interval

Conclusions

Understanding the factors associated with current vehicle fuel choice and future interest in AFV can help policymakers and transport professionals properly allocate public resources with the purpose of increasing the market share of advance vehicle technologies. AFV is improving fuel economy, reducing GHG emissions, and saving consumers' expense on fuel. Using data collected from the 2018 California Panel Survey, this study contributes to the literature on exploring how latent attitudes and supply-side determinants on the adoption of AFV. The findings have timely implications on infrastructure and policy provisions.

The survey data reveals that more than 90% of respondents choose traditional fuel vehicles. As expected, these people who use AFV currently are more likely to show higher level of interest in purchasing or leasing an AFV in the future. We further find that median- and low-income groups may be the main momentum of gaining market share of new vehicle technologies. Automotive companies and transportation planners could proactively think of tailored strategies for disadvantage communities. Nevertheless, more research is needed regarding actual actions. Embracing the emerging trend in discrete choice modeling towards incorporating perceptual/attitudinal factors into the behavioral representation of the decision process, this study constructs an ICLV model to jointly model current vehicle fuel type choice and future interest in an AFV. The modeling results suggest that people who are pro-environment, tech-savvy and car-utilitarian are more likely to choose an AFV currently as well as in the future. Car-dependent people are also found to be more likely to adopt an AFV in the future than their counterparts. We suspect that they are interested in an AFV for quite distinct reasons from the other groups.

Among the four factors representing the local context of the EV market, EV density is the only one that has a significant relationship with the adoption of an AFV. The density and level of accessibility of public EV charging facilities have not found to be significant in our model, but this does not necessarily deny them as critical factors in people's decision-making in reality or in the near future. After all, only 9% of our samples own an EV, which represents a small group of population. Probably most of those early adopters have had a dedicated home charger that the near future. After all, only 9% of our samples own an EV, which represents a small group of population. Probably most of those early adopters have had a dedicated home charger that minimizes their utilization of public chargers. Although there is no doubt that home chargers fulfill the majority of charging events currently, for many buyers, the small probability that they might need public charging under certain circumstances may have a disproportionately key role in evaluating the adoption decision. Thus, improving public charging network could be significant in removing people's psychological barriers.

Another notable finding of this study is that current user experience in AFV has positive impact on consumers' future interest, therefore, increasing people's knowledge and experience of EV, especially those that have not used AFV ever before, is critical strategy for market uptake.

The results of this study can be seen as a baseline for understanding the market share of different type of vehicle technologies. Policymakers and other stakeholders can design efficient policy provisions and marketing efforts regarding heterogeneity taste among population segments.

Exploring the Factors that Affect the Frequency of Use of Ridehailing and the Adoption of Shared Ridehailing

In this chapter we explore the factors that affect the use of ridehailing services (Uber, Lyft) as well as adoption of shared (pooled) ridehailing (UberPOOL, Lyft Share) using data collected in California in fall 2018 using cross-sectional travel surveys. We estimate a semi-ordered bivariate probit model using this dataset. Among other findings, the model results show that better-educated, younger individuals who currently work or work and study are more likely to use shared ridehailing services compared to other individuals, and in particular members of older cohorts. Being white and living in a higher-income household is associated with a higher likelihood of being a frequent user of regular ridehailing but does not have statistically significant effects on the likelihood of adopting shared ridehailing. With respect to the factors limiting the use of shared ridehailing services, we found that increased travel time and lack of privacy decreases the likelihood of adoption of shared ridehailing. We also find evidence that some land use features affect the likelihood of using both types of services. While the likelihood of using both ridehailing and shared ridehailing is higher in urban areas, residents of neighborhoods with higher intersection density are found to be more likely to only adopt shared ridehailing. However, some of the land-use variables become insignificant after introducing individuals' attitudes related to land-use into the model. This is an indication of residential self-selection, and the potential risk of attributing impacts to land-use features if individual attitudes are not explicitly controlled for.

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Introduction

Travel demand in the U.S. has been going through a structural change since the last 15 years. Total and per-capita vehicle miles traveled (VMT) increased during the 20th century and until the mid-2000s, when total VMT almost became stagnant, and there was a decline in per-capita VMT. However, since 2015, there has been an increase in both VMT and per-capita VMT (Circella, 2016). This change is reflected in the vehicle ownership which reached a 'peak' in 2008 (with 243 million vehicles), followed by decline of 4 million vehicle in the period of 2008-2011, before rebounding again to 241 million by 2013 (Circella, 2016).

Several possible explanations have been proposed to these changes in travel behavior. Some of them include fluctuations in fuel prices, change in household compositions, the economic recession, change is lifestyle, and new mobility services enabled by information and communication technology (Circella, 2016; Newman and Kenworthy, 2011). On one hand, the information and communication technology made it possible to share real-time locational data and provided access to internet through smart phones. At the same time, the so-called sharing economy, allows individuals to share resources without the need to own. Together they have introduced new ways to travel which do not include a fixed cost of vehicle ownership, provide cheaper options of travel, and reduce travel uncertainty.

The new shared mobility services have brought a range of services to the market. These include fleet-based carsharing services, bikesharing, e-scooter sharing, and ridehailing services. Ridehailing, also known as ridesourcing (SAE, 2018) or the services provided by transportation network companies (TNCs) such as Uber and Lyft, brings together the supply and demand typical of taxi services through modern smartphone apps. The matched drivers pick up the users from their location and drive them to desired destinations in exchange of monetary compensation. Ridehailing is quickly gaining popularity in the U.S. and other markets around the world. By the end of the year 2017 Uber announced the completion of 1 billion trips, and in 2019 the number reached to 5 billion (Uber 2019). Nearly 10% of the U.S. population has reported that they use ridehailing at least once a month, according to the recent National Household Travel Survey (NHTS) data (Conway, Salon and King, 2018). In San Francisco, ridehailing services account for nearly 15% of the trips made within the city. This translates to almost 20% of the total VMT with in the city. In New York City, ridehailing services accounted for 600 million VMT in the period of 2014-17 (Schaller, 2017).

After a few years of experimentation, in 2014, Uber launched UberPOOL and Lyft launched Lyft Line (later rebranded to Lyft Share). The purpose of these services is to enable unacquainted riders, travelling in same direction, to share rides. The computer algorithm optimizes the route of their vehicles in real time to allow new pickups along a trip by minimizing the detours for each rider. In exchange of increased travel time and the disutility of sharing the ride with a stranger, the riders are offered a discount of up to 40-50% (Sperling, 2018). These services are only offered in dense urban areas such San Francisco and New York City. Shared ridehailing or pooling services bring together public interest of promoting high occupancy vehicles with private business interests. For the service providers, shared ridehailing brings in new prospects of increasing profits by increasing the utilization rate of resources (labor and capitol). By decreasing the costs of the trips, they can make ridehailing more accessible to various segments of the market and for new trip purposes. Shared ridehailing services provide an avenue to increase efficiency of a trip (as opposed to a trip made by a single occupant vehicle). However, overall, these services may have positive, neutral or negative impact on the VMT in the transportation system depending on the modes replaced and how successfully multiple passengers are matched in single trip without much detours (Alemi, 2018). This builds a case to further investigate the adoption and impacts of shared ridehailing in more detail. In order to increase the market share of shared ridehailing it is important to understand the right balance of decreased costs and increased disutility for various segments of the market.

The objective of this chapter is to understand the factors that affect the frequency with which travelers living in California use ridehailing and their eventual adoption of shared ridehailing services. We identify the differences in the factors that encourage the use of each type of service, through the estimation of a semi-ordered bivariate probit model of the adoption of shared ridehailing and frequency of use of ridehailing as dependent variables. Since shared ridehailing is not available everywhere in California, we focus on the subsample of individuals living in regions of the state where shared ridehailing services are available.

Literature Review

Traditional carpooling has been often promoted as a strategy to reduce the number of vehicles on the roads. It allows travelers to share a ride to a common destination, and has numerous societal benefits such as reductions in VMT, greenhouse gases (GHG) emissions, congestion and need for parking infrastructure (Shaheen et al., 2018). The share of carpooling to work reached its maximum in 1970s (20% of all commute trips), during the energy crisis, which lead to a 23% reduction in VMT. The main takers of carpooling were households with low income and more workers than vehicles in the household (Shaheen and Cohen, 2019). Younger individuals, immigrants and blue-collar employees in the U.S. are still more likely to carpool than other demographics (Blumenberg, 2010; Neoh et al., 2017). Reduction in congestion, environmental concerns, reduction in travelling costs, incentives from the employers, access to special parking spots and HOV (high occupancy vehicles) lanes, and an opportunity to socialize are some of the motivating factor which have led to adoption of carpooling. The other factors that lead to more carpooling are situational variables such as having a fixed commute schedule and residence in urban areas. Typically, carpooling is more successful for commute trips as opposed to non-commute trips which require extensive coordination and planning (Neoh et al., 2017; Cools et al., 1998; Ferguson, 1997). Carpooling saw a sharp decline as a mode of transportation in 1980s—soon after the end of shortage of oil in the U.S. (Ferguson, 1997). There are many reasons which have made Americans stop carpooling. Perhaps some of the most important barriers are the difficulty in coordinating the time of trip with other non-households members, the difficulty (and anxiety) about sharing a ride with strangers (Cools, 1998), and the low-density patterns of U.S. cities, which make origins and destinations not convenient for pooling. Strategies which penalize driving alone such as congestion pricing have been unsuccessful in promoting carpooling in American households (Baldassare, 1998). Therefore, ever since 1980's single occupancy vehicles have been the most preferred mode of transportation in the US.

Information and Communication Technology (ICT) solutions along with the application of the shared economy to transportation have now opened doors to new ways of travel, including the ability to share rides with others in a more efficient way. Ridehailing is probably the most relevant type of new mobility services in this regard. Some studies have explained how ridehailing can potentially be used as a travel demand management strategy (Rodier et al., 2016). On average, the use of ridehailing is much higher in mid-sized and large US cities (Conway et al., 2018). The users of ridehailing services are young individuals with medium to high income (Conway et al., 2018; Alemi et al., 2018, Alemi, 2018). Individuals who make frequent long-distance trips are more likely to use such services, possibly to access and egress airport. Moreover, individuals with pro-environment attitudes and those who easily embrace new technologies are more likely to use such services (Alemi et al., 2018).

But a bigger debate has been on do ridehailing services help reduce VMT and congestion, or do they further increase them? Certainly, the answer lies in how ridehailing interacts with other modes of transportation and the way users adjust their activities and travel schedules as a result of the use of ridehailing. Babar and Burtch (Babar and Burtcg, 2017) examined public transit ridership data in the U.S. and showed how ridehailing on one hand replaces the services provided by city buses but compliments the services provided by subway and commuter rail. Another study analyzing the NHTS dataset in the U.S. reported that in the absence of ridehailing services many trips currently made using ridehailing would have been completed using public transit (15-50%) or active modes (12-24%), or they would not have been made at all (2-22%) (Schaller, 2018). At the same time, ridehailing replaces private modes in areas with high parking charges (Schaller, 2018). At this point there is not much consensus on the impact of ridehailing on transportation, as well as, more particularly, its impact on VMT and GHG emissions. Li et al. (Li et al., 2016) analyzed the traffic congestion data in cities of the U.S. before and after introduction of ridehailing services and found evidence that ridehailing could reduce congestion by reducing vehicle ownership. But there has also been evidence from simulation and survey based studies suggesting that the introduction of ridehailing leads to an increase in VMT in the transportation system (Schaller, 2017; Tirachini and Gomez-Lobo, 2019; Henao and Marshall, 2018; Anderson, 2014). Many reasons have been cited to explain such an increase in VMT: the deadheading of drivers in search of passengers, eventual induced travel and replacement of trips to be made by transit and active modes (Tirachini and Gomez-Lobo, 2019; Henao and Marshall, 2018). For example, Erhardt et al. (2019) analyzed data scrapped from API services of Uber and Lyft, and show how ridehailing services have led to increase in congestion and VMT in San Francisco.

Ridehailing companies also provide a platform for sharing the ride without much effort through their shared (pooled) services: this may lead to a higher vehicle occupancy leading to an overall reduction in VMT and per-capita emissions of greenhouse gases (Sperling, 2018; Tirachini and Gomez-Lobo, 2019), depending on the conditions in which services are "consumed" by travelers. Still, so far the acceptance of shared ridehailing services has been low—13% to 20% of the trips made using the online ridehailing platform (Tirachini and Gomez-Lobo, 2019; Gehrke et al, 2018). To authors' knowledge, not many studies have investigated the barriers to using shared ridehailing services. Lavieri and Bhat (Lavieri and Bhat, 2019) conducted a survey in Dallas, Texas and jointly modeled the usage of shared ridehailing services in present and future preference of shared autonomous vehicles. The study showed that there are two main factors affecting the use of shared vehicles—extra time with new passenger and presence of a new passenger in the car. In the current chapter we analyze how factors influencing the adoption of shared ridehailing services differ from frequency of use of regular ridehailing—which has been very popular so far. In the next section we describe the dataset used to answer this question.

Data Description

Dependent variables: in the survey we asked respondents to report how frequently they used ridehailing and shared ridehailing services by asking them to choose one option from—"I am not familiar with it", "It's familiar but I've never used it", "I used it in the past, but not anymore", and several categories for "I use it…" "…less than once a month", "…1-3 times a month", "…1-2 times a week", and "…3 or more times a week".

We use two dependent variables in our model—adoption of shared ridehailing (binary variable) and frequency of use of ridehailing services (ordinal variable). We grouped respondents who reported that they have never used or heard about shared ridehailing services into 'non-users' category, and those who reported they had used service in past but not anymore, use it less than once a month, 1-3 times a month, 1-3 times a week or more than 3 times a week were categorized as 'users'. Nearly one-third of the respondents from the selected counties reported to have used shared ridehailing services at least once. We want to point out that initially we wanted treat this as an ordinal variable. However, very few numbers of respondents (less than 5%) reported using shared ridehailing on weekly basis. Thus, we collapsed this into a binary variable.

For the frequency of use of ridehailing, respondents who had never heard about or used it, or had used in past but not anymore were regrouped as 'never'. Individuals who responded by saying they used it less than once a month were categorized as 'occasional' users. The 'monthly' category is for individuals who said they use ridehailing for 1 to 3 times a month. Finally, respondents who claimed they use ridehailing services for more than once a week were all grouped together as 'weekly' users. About 7.6% of the respondents from the selected counties reported using ridehailing on a weekly basis. The proportion is twice higher in comparison with the entire dataset. Nearly 46% of the respondents in the subsample used for this analysis said they never used ridehailing services. This number is as high as 60% for the entire 2018 California dataset.

To identify the factors that affect the use shared ridehailing and ridehailing, we first explored the differences between specific groups of users and non-users of these services by examining the distribution of potential explanatory variables in each group. We divided these explanatory variables into four main groups (socio-demographics, built environment, lifestyle and personal attitudes), and we tested different variable transformations in each group to identify the variables most closely associated with the use of shared ridehailing and ridehailing services.

Table 19. summarizes the distribution of these variables in the eight selected counties and in entire California. The four groups of variables are as follows:

Socio-demographic variables: we conducted chi-square tests on various socio-demographic variables such age, gender, race, education, income and country of birth with the hypothesis that these variables impact the frequency of use of ridehailing services and adoption of shared ridehailing services. The result of these exploratory tests showed that age, income, education and race were statistically significant in explaining the variation in the frequency of use of these services. For age, we have three categories: 'Millennials and younger', 'Gen X' and 'Baby Boomers and older'—with all three categories having an equal representation in the selected subsample used for this analysis. We define 18 to 37 years old as 'Millennials and younger'; 38 to 53 years old as 'GenX; and 54 years or older as 'Baby Boomers and older'. We use a dummy variable (White or not) to control for race; a categorical variable to control for household income that consists of three levels low-income household (household with annual income of less than $50k), medium-income household (household with annual income of $50k to $100k), and high-income households (households with annual income of more than $100k); a dummy variable for the level of education based on information on the highest attained educational level (we define individuals with a bachelor's degree or more as highly-educated individuals). We found that respondents living in the eight counties of interest are more likely to be higher educated and to live in high-income households. This was expected because the selected counties represent affluent regions of California, in and around San Francisco, Los Angeles and San Diego.

Lifestyle: the lifestyle of an individual can be measured in different ways. For example, Salomon and Ben-Akiva (Salomon and Ben-Akiva, 1983) describe individual's lifestyle in form of their participation in the work force, household formation and how they spend time in leisure activities. This definition has been used widely in many transportation related studies (Van et al., 2014; El Zarwl et al., 2017 Kitamura, 2009). We tested many indicators, which serve as a measure of lifestyle, which could explain individuals' choice of using ridehailing services. These included: presence of children in the household, household size, interaction of age and gender with employment. We found that variables describing the employment status and student status of the respondents could statistically explain their behavior of using these services. In the selected subset of the sample, 70% of the respondents have a full-time, part-time job, or they do some volunteering work. The same sample has about 10% of the respondents who are students and also have a job.

Built environment: the location where the respondent lives and work have a high association with their travel choices (Van et al., 2014; Sisson et al., 2006; Nazari et al., 2018; Tiwari et al., 2016; Lee and Handy, 2018; Handy et al., 2014; Guerra, 2014). Thus, it is important to control for built environment characteristics of the neighborhood where the respondent lives. We geocoded the home location of the respondents using the Google API (Google Developers, 2019). We used this geocoded information to obtain the census tract and block group ID of the home locations using the census API (Recht, 2019). We then used external datasets to bring in information about the built environment to our final dataset. One of these additional data sources was the classification of various neighborhoods, developed by Salon (Salon, 2015) who classified all census tract in California into five neighborhood types—central city, urban, suburban, rural-in-urban and rural. We collapsed these five levels to three levels—urban (central city and urban), suburban, and rural (rural-in-urban and rural). About half of the selected subset of the sample lives in suburban neighborhoods and nearly 40% of them in live in urban neighborhoods. The other dataset that we integrate to our final dataset is the Smart Location Database maintained by the US EPA which includes information on land use density, diversity, destination accessibility, network and design for each block group in US (U.S.EPA, 2019).

We collected the walkability of the place of residence of the respondent using Walkscore.com API service (Walkscore, 2020). Walkscore ranges from 0 to 100. Where 100 indicates an extremely pedestrian friendly neighborhood, where most of the errands can be performed by walking.

Personal Attitudes: a number of studies have shown the importance of individual attitudes in predicting behavior (Ajzen,1991; Paulssen et al., 2014). We use the factor scores obtained from EFA described above.

Table 19. Distribution of data in the selected counties and entire California

	Counties with Pooling services (n=1,654)	Complete Dataset (n=3,767)
Dependent Variable		
Usage of ridehailing services		
Never	46.31%	59.42%
Occasional	28.84%	24.59%
Monthly	17.17%	11.43%
Weekly	7.68%	4.56%
Usage of shared ridehailing		
Non-User	67.90%	80.36%
User	32.10%	19.64%
Socio-Demographics		
Age		
Millennials and younger (18-37 yrs. old)	31.68%	28.53%
GenX(38-53 yrs. Old)	32.41%	31.03%
Baby Boomers and older (54 yrs. or older)	35.91%	40.44%
Race		
White	74.18%	80.51%
Other	25.82%	19.49%
Household Income		
Less than $50,000	25.88%	31.18%
$50,000 - $99,999	30.29%	32.06%
More than $100,000	43.83%	36.76%
Education		
Bachelors or Less	34.28%	43.23%
More than Bachelors	65.72%	56.77%

	Counties with Pooling services (n=1,654)	Complete Dataset (n=3,767)
Lifestyle		
Employed		
Yes	70.62%	65.18%
No	29.38%	34.82%
Employed and Student		
Yes	10.10%	65.18%
No	89.90%	34.82%
Built Environment		
Employment Entropy		
Low [0,0.27]	20.56%	20.35%
Medium (0.27,0.65]	29.99%	29.61%
High (0.65,1]	49.46%	50.04%
Intersection Density		
Low [0,58]	26.00%	38.22%
Medium (58,1.5e+02]	58.10%	51.41%
High (1.5e+02,5.2e+03]	15.90%	10.37%
Neighborhood Type		
Urban	36.70%	19.24%
Suburban	50.67%	45.28%
Rural	12.64%	35.48%
Walkscore*	60.24 (27.87)	49.33 (29.35)

Model Estimation

In this chapter, we jointly model the adoption of shared ridehailing services (binary) and the frequency of ridehailing services (ordinal) using a semi-bivariate probit modelling approach. We suggest readers to read the full paper (Malik et al. 2021) for details on the modelling. The model estimation results are discussed in the next section.

Results and Discussion

Table 20. presents the results of the estimation of the semi-ordered bivariate probit models with and without attitudes. The estimated value of ρ for the model without attitudes is 0.70 and the value for the model with attitudes is 0.65. Both are significantly different from 0, allowing us to reject the null hypothesis (ρ = 0) and confirming that the error terms in the two equations are indeed correlated. The significance of the likelihood ratio test of independence of the two equations also show that the two equations are indeed correlated. This means that the effects of the unobserved variables on the adoption of shared ridehailing are highly correlated with those affecting the frequency of use of ridehailing. However, the reduced magnitude of ρ in the model with attitudes indicates that a part of the shared error component between the adoption of shared ridehailing and the frequency of ridehailing usage in the first model (without the attitudes) is attributable to individual attitudes (pro-urban, tech-savvy, car dependent and pro-multitasking).

We found that younger individuals are more likely to use ridehailing frequently than middle-aged and older individuals. The younger generation is also more likely to adopt shared ridehailing services than the members of the older generations. Among other sociodemographic variables, higher household income is associated with a higher frequency of using ridehailing, however household income is not a significant predictor of the propensity to adopt shared ridehailing. Our previous research studies (Alemi et al., 2018) found a similar relationship among ridehailing, age and household income of the respondents. Individuals who self-identify as white are more likely to use ridehailing services frequently (compared to other races). However, this does not affect the propensity to adopt shared ridehailing. Lavieri and Bhat (Lavleri and Bhat, 2019) found white individuals to be more reluctant than those of other races to share rides with strangers due to privacy concerns. Higher education has positive significant coefficients for both ridehailing frequency and shared ridehailing adoption in the model without attitudes. Other studies (Conway et al., 2018; Slkder, 2019; Rayle et al., 2016) also found that individuals with higher education (more than Bachelors' degree) are more likely to use ridehailing services. However, our study offers an added insight by comparing the results from models with and without attitudes. We observe that the education of an individual is not significant anymore when we add the tech-savvy factor in the model. Thus, it seems that education was acting as proxy variable for individuals who are more comfortable with using new technology, with the true effect being that individuals with such attitudes are more likely to use ridehailing services.

Among the lifestyle indicators, employed respondents are more likely to adopt shared ridehailing and to use ridehailing more frequently. It is interesting to note that employment still has a significant effect on the frequency of using ridehailing (but not on adoption of shared ridehailing) even after controlling for income in the model. As pointed out by Dias et al. (2017) this indicates that ridehailing services are possibly used for work related activities. Individuals who are employed and are students are found to be more likely to frequently use ridehailing in the model without attitudes. However, being employed and a student is not found to have significant impacts on the frequency of using ridehailing after adding the pro-multitasking attitude in the model.

Table 20. Bivariate models with and without attitudes

	Without Attitude		With Attitude	
	Ridehailing Frequency	Shared Ridehailing Adoption	Ridehailing Frequency	Shared Ridehailing Adoption
Socio-demographics				
Age (Ref = Millennials and younger)				
GenX	-0.3885*** (0.0705)	-0.5909*** (0.0844)	-0.3160*** (0.0708)	-0.5118*** (0.0856)
Baby Boomers and Older	-0.6507*** (0.0774)	-0.8350*** (0.0921)	-0.4964*** (0.0790)	-0.6627*** (0.0951)
Household Income (Ref = Less than $50,000)				
$50,000 to $99,999	0.3839***(0.0742)		0.4219*** (0.0742)	
$100,000 or more	0.6134***(0.0756)		0.6450*** (0.0720)	
Race (Ref = Other)				
White	0.2560*** (0.0595)		0.2899*** (0.0609)	
Education (Ref = Bachelors' or less)				
More than Bachelors'	0.1842*** (0.0668)	0.1274* (0.0769)		
Lifestyles				
Employed (Ref = No)				
Yes	0.3644*** (0.0743)	0.3612*** (0.0899)	0.3769*** (0.0763)	0.3459*** (0.0941)
Employed and Student (Ref = No)				
Yes	0.2956*** (0.0846)			
Built Environment				
Neighborhood type (Ref = Urban)				
Suburban	-0.2619*** (0.0723)	-0.2555*** (0.0785)	-0.1795*** (0.0599)	
Rural	-0.1332 (0.1198)	-0.1896 (0.1326)	-0.1128 (0.0922)	
Employment Entropy (Ref = Low)				
Medium	0.1170 (0.0829)	0.0501 (0.1025)	0.1408* (0.0830)	0.0625 (0.1041)
High	0.1775** (0.0766)	0.1691* (0.0929)	0.2473*** (0.0758)	0.1951** (0.0948)
Intersection Density (Ref = Low)				
Medium		0.0008 (0.0859)		-0.0318 (0.0806)
High		0.3715*** (0.1128)		0.3541*** (0.1048)
Walkscore	0.0032** (0.0014)			
Attitudes towards Shared Ride*				
Longer Travel Time		0.2298*** (0.0364)		0.2228*** (0.0381)
Safety/Privacy		0.1088*** (0.0363)		0.0821** (0.0379)

	Without Attitude		With Attitude	
	Ridehailing Frequency	Shared Ridehailing Adoption	Ridehailing Frequency	Shared Ridehailing Adoption
General attitudes				
Pro-Urban			0.1968*** (0.0270)	0.2169*** (0.0332)
Tech-savvy			0.2058*** (0.0266)	0.1426*** (0.0332)
Car Dependent			-0.0602** (0.0247)	-0.0548* (0.0305)
Pro-Multitasking			0.0712*** (0.0238)	0.0818*** (0.0297)
Constants				
μ_1	0.6928*** (0.1599)		0.6773*** (0.1215)	
μ_2	1.5814*** (0.1626)		1.6103*** (0.1251)	
μ_3	2.4160*** (0.1674)		2.4904*** (0.1321)	
δ_1		0.4411*** (0.1551)		0.7105*** (0.1368)
ρ	0.6958*** (0.0437)		0.6485*** (0.0440)	
Model Specification and Goodness of Fit				
Log likelihood(null)	-2679.04		-2589.75	
Log likelihood(model)	-2539.70		-2471.428	
Degrees of Freedom	30		32	
AIC	5139.39		5006.857	
BIC	5301.72		5180.007	
LR test of indep. eqns. (chi2)	278.68***		236.63***	
Observations	1,654		1,654	

*Note: Standard errors in parentheses; level of significance: *** p<0.01, ** p<0.05, * p<0.1*

** Please keep in mind that the statements associated with these factor scores are measured on a five-point Likert scale - ‘Very Limiting’ to ‘Very Encouraging’*

As expected, built environment characteristics of the home location of the respondents did have some impact on the use of new mobility services. Residents of urban neighborhoods are found to be more likely to use ridehailing often than the residents of suburban and rural neighborhoods. This effect of the neighborhood type is not significant for the adoption of shared ridehailing when the factor pro-urban is included in the model. Among the specific characteristics of the neighborhood, the Walkscore of the neighborhood is significantly associated with the frequency of use of ridehailing in the model without attitudes; but this variable becomes insignificant after including the pro-urban factor in the model. This is an indication of residential self-selection. Previous studies have found evidence of individuals' travel choices and their residential choice being driven by same underlying attitudes. Both studies Kitamura et al. (1997) and Cao et al. (2009) followed a strategy similar to ours—they observed how land-use variables lost their significance in predicting trip frequencies by specific modes after adding attitudinal factor scores (related to residential choice) to the models. To our knowledge, none of the studies so far has examined the impact of residential self-selection while estimating demand for ridehailing services using built environment variables. This could be potentially problematic from planning perspective as it could lead to overestimation of the effect of land-use on demand for ridehailing (a form of residential self-selection bias). For instance, Yu and Peng (2019) observed a positive relationship between sidewalk density (which is another measure of walkability) of a block group and the aggregated demand for ridehailing in that block group. However, the study, by design, could not control for residential self-selection.

Further, we also evaluate the association among employment entropy (a measure of diversity), intersection density (a measure of design) of a neighborhood, and the two dependent variables (Ewing and Cervero, 2010). High employment entropy of the block is associated with a higher frequency of using ridehailing and a higher propensity to adopt shared ridehailing services. Possibly, a diversity in attractive destinations in a neighborhood induces more trips, and some of these trips are made using ridehailing services. Yu and Peng (2019) and Sabouri et al. (Sabouri, 2020) reached a similar conclusion in their analyses about the demand for ridehailing. Intersection density can be defined as the number of intersections per acre in a block: our models show that individuals living in a neighborhood with high intersection density are more likely to adopt shared ridehailing services. High intersection density leads to easier movement of automobiles, decreasing the wait time for shared ridehailing vehicles (and increasing their popularity). It is likely that this variable also acts as a proxy for central locations where many trip origins/destinations can be found, thus increasing the likelihood of reaching the critical mass to make the shared ridehailing service attractive.

Individuals who see longer waiting time and lack of privacy in shared ridehailing services as barriers are less likely to adopt shared ridehailing services. Similar conclusion was reached by Lavieri and Bhat (2019). Our study shows how individuals who easily embrace new technologies are more likely to both adopt shared ridehailing and to frequently use ridehailing.

A Deeper Investigation into the Role of the Built Environment in the Use of Ridehailing for Non-Work Travel

Ridehailing has become a main-stream mobility option in many cities around the world. Many factors can influence an individual's decision to use ridehailing over other modes, and the growing need of policy makers to make built-environment and regulatory decisions related to ridehailing requires an increased understanding of these. This chapter develops a model that estimates how the built environment affects the decision to choose ridehailing for making non-work trips, while carefully accounting for a variety of confounding effects that could potentially bias the results (if ignored or improperly incorporated). These include: total number of trips, supply differences between urban and non-urban areas, residential choice (urban versus non-urban), and household choice of whether to own a vehicle. We use individual-level data from a California travel survey that includes detailed attitude measurements to estimate an integrated choice and latent variable (ICLV) model to properly specify these effects. We include accessibility measures used elsewhere (e.g., Walkscore) plus measures developed for this chapter. Our analysis estimates the effect of these measures on ridehailing mode share, and how they differ between urban and non-urban areas. We also confirm that failure to take into account, e.g., latent preferences for residential location can lead to biased results. This analysis results in two major findings: 1. individuals living in vibrant and walkable neighborhoods replace other modes (possibly active modes) with ridehailing, 2. previous studies may have overestimated the complementary or supplementary relationships between public transit and ridehailing by ignoring confounding effects.

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Introduction

Ridehailing services (e.g., Uber/Lyft) have become a mainstream mobility option in many cities around the world. Uber, one of the leading ridehailing service providers, launched in 2009 had provided one billion trips by 2017. The number grew fivefold in just two more years, and it currently operates in 900 cities around the world (Uber, 2019). Other service providers such as Lyft, DiDi and Ola have experienced similar trends (Tirachini, 2019). It is estimated that nearly ten percent of the U.S. population uses a ridehailing service at least once a month (Conway, Salon, and King, 2018). Policymakers in the U.S. and other countries want to regulate these services to increase the positive benefits while minimizing the negative externalities (e.g., congestion). For instance, Seattle introduced a fare of $0.51 on ridehailing trips originating in the city to reduce congestion in core urban areas and fund public transportation (Hightower, 2019). Understanding the factors affecting demand for these services can be very helpful in designing effective regulations.

With this objective in mind, a growing number of studies have aimed to improve understanding of users of these services and the factors influencing their decisions to use them (Alemi, 2018; Alemi, Circella, Handy, and Mokhtarian, 2018; Alemi, Circella, Mokhtarian, and Handy, 2019, 2018; Dias et al., 2017). Over the past few years, a number of studies have reported evidence of a link between use of ridehailing and the built environment, after controlling for differences in socio-demographics. A majority of these studies have used aggregated data on ridehailing demand from service providers such as Uber and RideAustin. Studies have explored the associations between demand for ridehailing and the built environment using measures at the census tract, TAZ or a similar aggregated levels (Gerte et al., 2018; Lavieri et al., 2018; Sabouri et al., 2020; Yu and Peng, 2019). In contrast, Alemi, Circella, Handy, et al., (2018), Alemi, Circella, Mokhtarian, et al., (2018) and Alemi et al., (2019) explored these effects using individual-level datasets collected through surveys of individuals in California. However, few studies have focused on the role of the built environment, even though past research has shown strong evidence that the built environment affects overall travel demand, including the choice of mode and trip distances (Handy, 1992). We therefore expect that the built environment also influences the demand for ridehailing services, and that this factor should therefore be taken into account when developing models and performing analyses to support policy decisions. A small number of studies examining this link have indeed found significant effects (Sabouri, Park, Smith, Tian, and Ewing, 2020; Yu and Peng, 2019). However, as explained in detail later, these studies present mixed findings which are not consistent with each other.

This paper investigates the influence of the built environment on—1) the total demand for travel for non-work purposes, and 2) the degree to which ridehailing services are used to meet this demand. We use accessibility measures to characterize the built environment, including some measures that are new additions to the literature. Finally, we develop a modeling approach that takes into account latent or difficult-to-observe effects—e.g., residential self-selection, affinity for owning a personal vehicle, and shorter waiting times for ridehailing services in urban areas—that are potentially confounded with more directly-observable factors that may affect the decision to use ridehailing services. Presence of these latent/unobservable effects may bias model estimation results if not taken into account, yielding incorrect conclusions. This chapter uses individual-level data from a travel survey of California respondents conducted in 2018 by a research team at the Institute of Transportation Studies, University of California, Davis. We employ Integrated Choice Latent Variable (ICLV) models to address methodological issues and answer the research questions identified in this chapter.

There have now been a number of ridehailing studies examining the behavior of users and exploring factors related to the decision to use ridehailing. Many of these focus on sociodemographic effects, but more recently some studies have started to explore the role of the built environment in influencing the use of these services. As already noted, the influence of the built environment on travel behavior has been well established, but the currently available evidence for how it influences ridehailing is less clear. Studies so far provide some evidence of a connection, but the measures used to characterize the built environment are limited, and the possibility of self-selection has not been adequately addressed.

Methodological Issues

To our knowledge, studies so far have not addressed the following factors which may have led to inaccurate conclusions about the effect of the built environment on use of ridehailing:

- Dependent variables: Among previous studies, the dependent variables are either the total number of ridehailing trips at the aggregated level or frequency of use of ridehailing services by individuals. The effect of the built environment variables on these dependent variables is then examined using various modelling techniques. This is problematic because the total number of trips by ridehailing (at the aggregated or individual level) is the product of total number of trips and the fraction of trips made by ridehailing services (mode share). After controlling for socio-demographics, different dimensions of the built environment affect various aspects of travel behavior. More particularly, presence and proximity to attractive destinations leads to a high travel demand which leads to a high trip frequency. The choice of mode for a trip is influenced by distance to destinations and the infrastructure which determines the 'cost' to reach a destination by a particular mode—see Handy (1992). Thus, when examining the effect of the built environment on use of ridehailing, it is important to separate the effect of the built environment on total number of trips from the degree to which ridehailing services are used to meet that demand.
- Residential self-selection (RSS) bias: Previous studies have shown that an individual's travel choices and their choice of residential location may be driven by the same underlying attitudes (Cao, Mokhtarian, and Handy, 2009; Kitamura, Mokhtarian, and Laidet, 1997). Failure to address these effects can lead to overestimation of the influence of the built environment on travel behavior, possibly leading to misguided policy recommendations. To our knowledge the effect of residential self-selection has not yet been explored in the literature on the built environment and ridehailing use.
- Supply effect: A study by Hughes and MacKenzie (2016) shows how the average wait time for ridehailing vehicles was much lower in the urban downtown regions of Seattle as compared to non-urban regions in the outskirts. It is likely that the quality of

ridehailing service will be much better in urban areas in California as well. The higher quality of service can have a direct effect on the use of ridehailing services. Since urban areas also tend to have better accessibility to activities, it is possible that we might overestimate the effect of the built environment on travel behavior if we do not correct for this 'supply' effect of ridehailing services.

- Measures of the built environment: most studies on this topic so far have characterized areas (census tracts, block group) by measuring indicators of the built environment at an aggregated level. Such studies find statistical evidence that use of ridehailing changes with the aggregated measures of the built environment in these areas. But such measures make it difficult to identify the specific aspects of these areas that influence travel behavior (Handy, 1996). It is more meaningful to evaluate the destination options offered to an individual and the 'cost' of reaching them as a function of the built environment. In other words, accessibility (potential for travel) is a more appropriate type of measure for modeling the impact of the built environment on travel behavior. This is still a gap in the literature when understanding the use of ridehailing services as a function of the built environment.

In this section, we explain how we construct our dependent variables and the built environment variables to correct for the issues. We then explain how our modeling approach accounts for long-term effects such as residential self-selection and vehicle ownership, and the supply effect of ridehailing services.

Even though our main analysis is on the California Panel 2018 Survey dataset, we use another dataset (detailed travel diary) to empirically support how we define our hypotheses and, construct dependent variables and the built environment variables used in the models. The Sacramento Area Council of Governments (SACOG) conducted a household travel survey in 2018 in the six counties of California which come under their jurisdiction—Yolo, Sacramento, El Dorado, Placer, Sutter, and Yuba. The survey consisted of detailed trip level information of a representative sample of 4,010 households living in the region, collected over seven days. This information was collected using a smartphone app installed in the mobile phones of the respondents. The app collected passive information of each trip—origin, destination, time—and prompted respondents to enter other information such as mode used and trip purpose at the end of each trip (SACOG, 2018). For the current analysis we used a subset—only ridehailing trips—of this large dataset. We would like to point out that travel patterns in the SACOG region may be different from other regions in California. We use the SACOG travel diary dataset only to construct hypotheses which are ultimately tested using the main dataset.

Variable Selection

In this sub-section we summarize our rationale for constructing and selecting the dependent variables, the built environment variables, socio-demographics and attitudinal variables. Table 21. summarizes the distribution of these variables by urban and non-urban areas.

Dependent Variables

The analysis uses six dependent variables. First, we model two types of binary choices for all respondents: residential location type (urban or non-urban), and car ownership (yes or no). The remaining dependent variables were of two types: total number of trips (made using all modes) for non-work purposes, and the share of these trips made by ridehailing. We modeled these responses conditional on type of the neighborhood of the home-location of the respondents' (urban or non-urban). This yields four dependent variables, where only two of the four are actually observed for each respondent.

We focus on non-work trips because travelers usually have more flexibility in deciding the destination/time for discretionary trips (trips made for social, recreation, shopping and errand purposes rather than commuting). Due to this flexibility, discretionary trips are most likely to be affected by the built environment. A descriptive analysis of ridehailing trips from the California Panel 2018 study and SACOG household travel survey (see SACOG (2018) for details) from 2018 shows that a majority of trips made using ridehailing are for discretionary purposes (see Table 21. and Table 22.).

The survey asked respondents to report how frequently they use private modes, active modes, public transportation and ridehailing for non-work purposes. In all, respondents were shown 12 modes. For each mode, they could select an option from a seven-point ordinal scale: 'Never' (0 days), 'Less than once a month'(0.5 days), '1-3 times a month' (2 days), '1-2 times a week' (6 days), 3-4 times a week' (14 days) and '5 times a week' (20 days). For analysis, we used a variable coded in units of "days per month" and treated it as continuous (Lee, Circella, Mokhtarian, and Guhathakurta (2019) used the same technique).

Let N be the total number of (non-work) trips estimated by summing the days-per-month frequency variables for all modes. Two of our dependent variables are ln(N) for urban and non-urban respondents, respectively. As a measure of ridehailing mode share, we adopt a variable specification used by Kitamura et al., (1997) (—see this reference for more details). Let Nm be the frequency of mode m. Rather than use mode share ($^{N_m}/_{(N)}$) directly, we first compute the odds of using a mode versus all other modes [$^{N_m}/_{(N-\ N_m)}$], and then take the natural log, yielding the log-odds variable:

$$LogOdds_m = \ln\left(^{N_m}/_{(N-\ N_m)}\right).$$

This log-odds transformation yields a continuous variable that resembles a normal distribution, suitable for a linear-in-parameters specification. If Nm = 0, then 0.5 is added to both numerator and denominator to avoid infinite values under the log-transformation. Kitamura et al. (1997) estimate multiple models for all the modes they were studying. In our models we are focused on the case where m = ridehailing.

Respondents were assigned to a home location type based on the detailed home address requested by the survey. We geocoded this home address to get the corresponding latitudes/longitudes using the Googleways (Cooley, 2018) package in R. We then identified the census tract number for the home location using the Censusapi (Recht, 2019) package in R. To assign each respondent a home location type, we relied on Salon (2015), who classified all census tracts in California into five categories—central city, urban, suburban, rural-in-urban and rural. For simplicity, we collapsed these five levels to two levels—urban (central city and urban) and non-urban (suburban, rural-in-urban and rural). This is the binary dependent variable in our analysis representing residential location choice. The survey asked respondents to report if their household owns a vehicle or not, the other binary dependent variable in our model.

Built Environment Variables

In studying travel behavior, it makes sense to evaluate the built environment from the perspective of the traveler. That is, the built environment should be evaluated with respect to the choices it offers individuals as to potential destinations and the cost, broadly defined, of reaching them (Handy, 2017). Accessibility measures provide a way to do this, though assumptions must be made about the distance over which destinations are relevant. Thus, while developing specific hypotheses about the influence of the built environment on use of ridehailing, it is important to rely on empirical data to get a sense of the length of the trips made by ridehailing services (and other modes) and the kinds of destinations accessed by them. Data from the SACOG Household Travel Survey (HHTS) described above provide an indication of the limit for most ridehailing trips (see Table 21.): 75% of ridehailing trips for social/recreational purposes (including visits to restaurants/cafes) in the SACOG region had trip lengths less than 5.72 miles (median 2.62 miles), while 75% of ridehailing trips for shopping/errands had trip lengths less than 7.88 miles (median 3.48 miles). In our survey (in the state of California) we asked respondents to report the trip duration of the last trip made using ridehailing services (Table 22.). It is interesting to note that the distributions of trip duration by trip purpose in the California-2018 survey follow a very similar pattern to those from the SACOG HHTS.

Based on these numbers and our understanding of the link between travel behavior and the built environment, we hypothesize that individuals who live in vibrant neighborhoods (with destinations within walking distances) will have higher trip frequencies for non-work purposes. Moreover, these individuals can meet many of their travel needs for purposes such as eating out or visiting cafes by walking. Thus, the overall mode share of ridehailing services (for discretionary trips) will be lower for these individuals. Again, we rely on the SACOG survey to get an estimate of typical walking distances in California (although the dataset is only available for Sacramento). We observed a differential between the median lengths of home-based non-work-related walking trips in urban areas (0.48 miles) and non-urban areas (0.62 miles).

We also hypothesize that individuals who do not live in vibrant neighborhoods but have attractive destinations in the range of one to eight miles from their home locations will have the highest mode share of ridehailing services for trips with discretionary purposes. These individuals have attractive destinations in a close enough range to induce trips, but these destinations are not close enough to be reached by walking. If the neighborhood where these individuals reside does not have good transit service, we hypothesize that they will have an even higher mode share of ridehailing services.

Table 21. Ridehailing trip duration and length recorded by smartphones in SACOG HHTS

Trip Purpose	Percentage of Trips	Trip Duration and Length					
		First Quantile		Median		Third Quantile	
		Trip Duration (min)	*Trip Length (miles)*	Trip Duration (min)	*Trip Length (miles)*	Trip Duration (min)	*Trip Length (miles)*
Work/School	23.5%	10.8	*1.9*	15.0	*3.3*	23.1	*8.2*
Shopping/Errands	22.6%	9.4	*1.7*	13.9	*3.5*	23.8	*7.9*
Social/Recreation	50.1%	8.6	*1.5*	12.6	*2.6*	19.3	*5.7*
Connect with other modes	3.8%	14.0	*3.0*	15.6	*5.9*	24.6	*14.7*
Trips for all purposes (N)	864	9.4	*1.6*	13.9	*3.2*	21.4	*7.0*

Table 22. Self-reported ridehailing trip durations from CA Panel dataset

Trip Purpose	Number of trips	Trip Duration in Minutes		
		First Quantile	Median	Third Quantile
Work/School	15.3%	10.0	18.0	30.0
Shopping/Errand	16.2%	10.0	15.0	25.0
Social/Recreation	45.8%	10.0	15.0	20.0
Connect with other modes*	25.6%	15.0	20.0	30.0
Trips for all purposes (N)	1968	10.0	15.0	25.0

*Other modes include airplanes

To test these hypotheses about the effects of the built environment on ridehailing mode share for discretionary trips, we need measures that capture the vibrancy of the residence neighborhood, the presence of attractive destinations within a medium-distance range, and connectivity to destinations by alternative modes of transportation. A closer look at the detailed purposes for which ridehailing services are used (from the SACOG household travel survey), Figure 23 reveals that 22% of discretionary trips are made to access restaurants. Visits to movie theaters also form a large percentage (16%) of such trips. Trips for shopping form 7% of the discretionary trips. We used the Googleways (Cooley, 2018) and Spatial Points packages (Bivand, Pebesma, and Gómez-Rubio, 2008) in R to build the following accessibility measures for the reported home addresses:

1. Vibrant neighborhoods:
    a. For non-urban neighborhoods, our measure of vibrancy is calculated as the sum of the inverse of distance to restaurants within 1 mile of the place of residence:

$$\sum_{j=1}^{J} 1/d_{ij}$$

dij = Distance (Euclidean) to restaurant j from the home location of individual *i*

J = number of restaurants within a 1-mile radius of the home location of individual i

If an individual has a good variety of restaurants in close proximity, we expect them to make more non-work trips within the neighborhood by walking and rely less on alternative modes (such as ridehailing) to reach these destinations.

b. For urban neighborhoods, we observed that most home locations in our sample had a restaurant within 1-mile radius. Thus, for urban areas we include a dummy variable (0 or 1) which takes the value '1' if the home-location has a restaurant within a 0.5-mile radius (this corresponds to the threshold we observed in SACOG dataset).

c. We also include a commercial third-party measure of neighborhood accessibility: Walkscore. Walkscore is another measure of neighborhood accessibility that essentially indicates how easily an individual can perform errands by walking (Walkscore, 2020). For each address, Walkscore analyzes hundreds of walking routes to nearby amenities, and awards points based on a decay function of the distance required for reaching them. Amenities within 5 minutes of walking receive maximum points while those beyond 30 minutes receive no points. The Walkscore ranges from 0 to 100, where 100 indicates an extremely pedestrian-friendly neighborhood with destinations in very close proximity, where most errands can be performed by walking.

2. Destinations visited occasionally by an individual, such as department stores (e.g., Target) or movie theaters, can induce more trips if they are located within a 'close' distance. But such destinations are not usually within walking distance, so it is possible that trips to these destinations will be made via ridehailing services, even more so in the absence of links via transit. We measure the following as indicators of accessibility to non-work-related activities beyond the neighborhood:

   a. Distance (Euclidean) to the nearest department store from the home location of the respondent. We specify it as a categorical variable with three levels—less than 0.65 miles, between 0.65 miles and 8 miles and more than 8 miles—for department stores in non-urban areas.

   b. All urban home locations in our sample had a nearest department store within a distance of 8 miles. Thus, for urban areas we include a dummy variable which measures if the home-location has a department store in less than 0.65 miles (again, cutoffs based on home-based non-work-related trip lengths by walking and ridehailing in SACOG dataset).

   c. We also measure distance to the nearest movie theater from the home location. For non-urban areas, we categorize it into three levels - less than 0.65 miles, between 0.65 miles and 8 miles and more than 8 miles.

d. For urban areas we include dummy variables which measures if the home-location has a movie-theater in 0.5-mile distance. Table 23. summarizes the distribution of these variables.

3. Finally, it is also important to evaluate how well served the residence neighborhood is by transit. We hypothesize that individuals living in neighborhoods with good access to destinations via transit will have a lower mode share of ridehailing services. The accessibility laboratory at the University of Minnesota has calculated the number of jobs accessible through transit in each block group in the U.S. (Owen and Murphy, 2017). We link this information to the block groups of the home locations of the respondents in our survey.

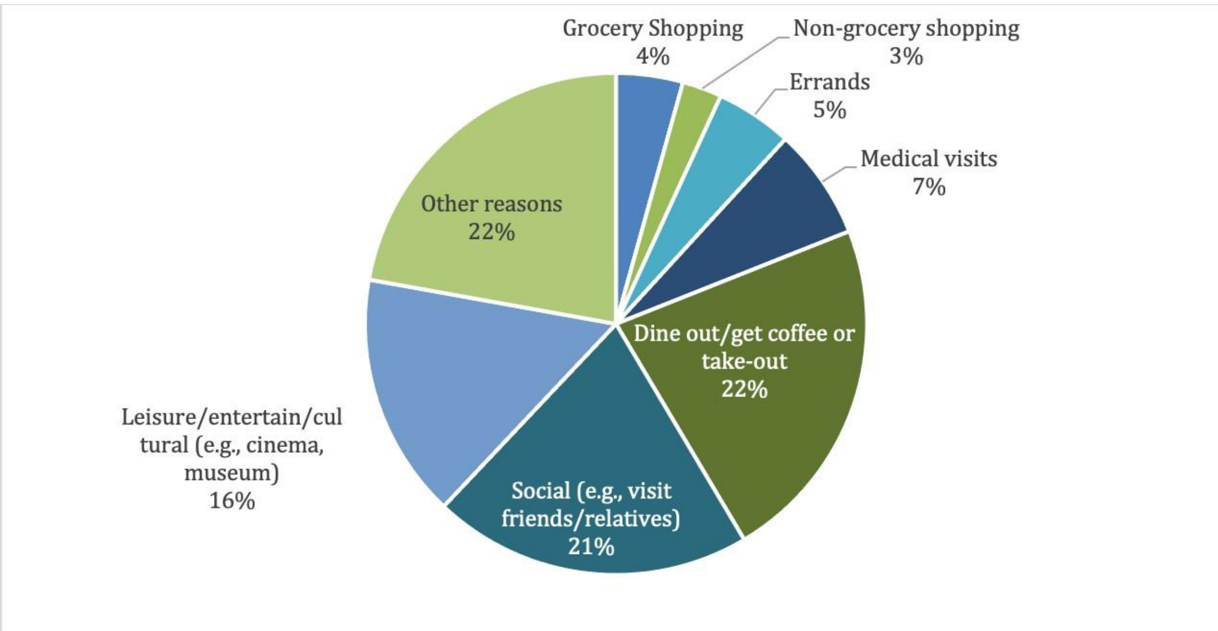


Figure 23. Detailed trip purposes for discretionary trips using ridehailing (n=628 trips made by 302 individuals), Source: SACOG HHTS

Socio-Demographics and Attitudes

The survey asked respondents to report their key socio-demographics—gender, age, gross household income, race and highest education degree. We also asked them to report their employment status, if they are currently a student, and if they have any household members below the age of 18 living with them. At the beginning of the survey respondents were presented with 30 attitudinal statements and asked to indicate their agreement with the statement on a five-point Likert scale from Strongly Disagree (1) to Strongly Agree (5). The intention here was to measure underlying constructs about choice of home location, attitudes about modes of transportation, technology and internet connectivity, and the built environment. In the next subsection we explain how we use these variables to explain our dependent variables.

Table 23. Description of the variables used in the model

	Urban (n=624)	Non-urban (n=2,445)
Dependent Variable		
Odds of ridehailing	0.27 (2.30)	0.09 (0.19)
Log odds of ridehailing	-2.71 (1.28)	-3.03 (1.05)
Total number of non-work trips	26.92 (22.60)	19.72 (15.94)
Log of total number of non-work trips	2.97 (0.89)	2.64 (0.94)
Socio-Demographics		
Age		
Millennials (18–34 yrs.)	39.6%	30.2%
GenX (35–54 yrs.)	37.8%	33.3%
Baby boomers (55 yrs. or older)	22.6%	36.5%
Gross Annual Household Income		
Less than $50,000	29.3%	32.4%
$50,000 to $100,000	30.3%	32.4%
More than $100,000	40.4%	35.1%
Gender		
Male	48.2%	44.2%
Female	51.8%	55.8%
Race		
White	71.5%	81.6%
Other	28.5%	18.4%
Employed		
Yes	80.3%	69.6%
No	19.7%	30.4%
Student		
Yes	14.7%	12.1%
No	85.3%	87.9%
Education		
More than Bachelors	69.2%	52.9%
Bachelors' or less	30.8%	47.1%
Children in the Household		
At least one	20.7%	21.7%
None	79.3%	78.3%
Built Environment		
Inverse sum restaurant in 1miles		27.58 (69.53)
Restaurants within 0.5 miles		
Yes	97.6%	
No	2.4%	
Walkscore	82.07 (14.33)	42.09 (26.33)
Movie theater within 0.5 miles		
Yes	9.5%	
No	90.5%	

	Urban (n=624)	Non-urban (n=2,445)
Distance to the nearest movie theater		
Less than 0.65 miles		6.1%
Between 0.65 miles to 8 miles		75.5%
More than 8 miles		18.4%
Distance to the nearest department store		
Less than 0.65 miles	38.9%	21.1%
Between 0.65 miles to 8 miles	61.1%	68.1%
More than 8 miles		10.8%
Type of house		
Stand Alone	44.1%	
Apartments/others	55.9%	
Jobs available via 30 min transit ride		7543.95 (10496.62)
Vehicle Ownership		
Zero Vehicle Households	8.8%	7.3%
Households with Vehicles	91.0%	92.6%

Limitations

Even though our choice of variables and modeling approach address the issues raised, this chapter does not completely resolve all of the gaps in the literature on ridehailing and the built environment. First, we can only observe how the built environment features associated with the home-location might affect respondents' use of ridehailing and their total number of trips. This is a limitation because people also make non-home-based trips that would be included in the dependent variable measures. Given the flexibility and the on-demand availability of ridehailing services it is possible that it is also used at locations other than homes, e.g., work location.

Second, our analysis is limited to understanding the effects of the built environment on trip frequency and mode share of ridehailing. The built environment also has an effect on trip length, which is not accounted for in this chapter. Moreover, the combination of the built environment and use of ridehailing services can influence activities in which people engage. In this chapter we analyze cross-sectional survey datasets, which prevents us from conducting an in-depth analysis and restricts our analysis to trips rather than tours and activities. In future, we plan to analyze the travel diary dataset from SACOG for a more exhaustive analysis.

Finally, by simultaneously estimating the effect of a variable on log-odds of ridehailing and total number of trips, we can discern the underlying reasons for, e.g., an observed change in ridehailing frequency (the dependent variable in many previous studies on ridehailing) due to a change in that variable. Recall, trips made by ridehailing by an individual depends on odds of using ridehailing (over other modes) and total number of trips made by the individual. For instance, if a variable has a positive coefficient for log-odds of ridehailing but negative or no effect on total number of trips made by an individual, then that variable is associated with ridehailing replacing other modes of transportation. However, if ridehailing frequency were to increase due to an increase in ridehailing mode share, we cannot comment with surety which mode (active/public transit/private) is being replaced by ridehailing. This is a limitation of our current modelling approach. In future studies models can be extended to estimate the trade-off between other modes and ridehailing.

Results and Discussion

In Table 24., we present model estimation results for the ICLV model which includes (sub-) models for both log-odds of ridehailing services and total number of trips for non-work purposes. In the following subsections we first discuss the implications of the estimated signs and significance of coefficient estimates for latent attitudinal constructs and socio-demographics. We then explain the implications of the unbiased estimated effects for the built environment variables.

Latent Variables and Random Effects

Table 25. shows the values and the significance of the coefficients associated with the latent variables—Pro-Urban, Car Lover, and Technology Averse—in explaining the eleven indicator variables in the measurement model. As a reminder to the readers, in order to account for the possibility of residential self-selection bias, we use the Pro-Urban latent variable to simultaneously explain log odds of ridehailing in urban and non-urban areas, and residential choice of urban/non-urban neighborhood. The significance of this latent variable, and the direction of the effect in all three sub-models shows that, indeed, underlying attitudes drive the decision to choose an urban home-location and to choose ridehailing services over other modes of transportation. We observe that younger individuals and individuals with lower household incomes have higher Pro-Urban attitudes, possibly because of better access to jobs and other activities in urban locations. Students and respondents with more than bachelors' degrees also have a higher Pro-Urban attitude.

An increase in the Car Lover latent variable decreases the log odds of ridehailing services in non-urban areas. This makes sense because this attitude captures an individual's desire to own or drive a personal vehicle. We simultaneously estimate the effect of Car Lover on vehicle ownership, and the coefficient estimate is positive and significant (as would be expected). Thus, we believe that the Car Lover attitude captures a source of (otherwise) unobservable correlated effects on both vehicle ownership and this travel behavior choice. At the same time, we find that some variation in this attitude is explained by demographics: younger individuals and those with low household incomes have a lower than average Car Lover attitude. It is possible that their stage in life and economic constraints influence this attitude. Moreover, having a high level of education is also associated with lower than average Car Lover attitude.

Finally, we also find that a Technology Averse attitude is associated with less travel in general in both urban and non-urban areas. However, we found no evidence that this attitude also influences log odds of ridehailing. Previously, Alemi et al. (2019) found that a tech-savvy attitude positively influences the frequency with which individuals use ridehailing services. However, since frequency of ridehailing is a function of both mode share (log odds) and total number of trips, it is possible that the observed relationship is primarily due to the effect of this variable on total number of trips, and not a preference for ridehailing. The Technology Averse attitude is observed to be higher in older individuals, with low household income and low levels of education; women and respondents with children (below the age of 18 yrs.) are also more technology averse.

These results illustrate one of the known advantages of ICLV models: we have been able to incorporate additional information on attitudes to specify and estimate structural models that capture what would otherwise be unobservable, correlated effects on multiple travel-related choices. However, there could also be unobserved effects that are not related to any of the attitudes for which we have measures, but that also are correlated across travel choices. When developing our models, we discovered evidence of an unobserved random effect that negatively affects log odds of ridehailing while also causing the total number of trips to increase, and that this effect exists for individuals in both urban and non-urban locations. Because none of the variables in our dataset could explain this variable, it was necessary to represent it as an additional underlying error component. From a modelling standpoint, it was important to include this variable because excluding it essentially caused the measurement model for the three latent variables to be miss-specified. Without it, the estimated measurement coefficients (essentially 'factor loadings') diverged from what we knew to be true from the factor analysis, and magnitudes and significance of coefficients on the latent variables in the behavioral models were both diminished. There could of course be a variety of other unobservable effects that remain unaccounted in our model.

Socio-Demographic Variables

The models show the impact of socio-demographics on log odds of ridehailing and total number of trips through two pathways. The first pathway is indirect, where the impact of socio-demographics on travel behavior is mediated through attitudes, as discussed in the previous subsection. In the second, we study the direct effects of socio-demographics after controlling for the indirect effects.

Our estimates indicate that younger individuals are more inclined to use ridehailing, as has been found in almost every study on ridehailing services. In our approach, age is an important variable in predicting log odds of ridehailing (in both urban and non-urban areas) and total number of trips (in non-urban areas), showing both direct and indirect impacts on travel choices. The ICLV approach adopted here provides a more detailed behavioral interpretation for these effects than in other types of models that ignore the effect of attitudes. The effect of age on log odds of ridehailing and number of trips (for non-urban individuals) appears to be a direct effect of age in this model. However, these direct effects lose significance in Table 25., because the effect of age becomes an indirect effect through its influence on attitudes.

With regard to other demographic effects, we observe that individuals with high household income make more trips for non-work purposes. However, in urban areas, individuals with low-household incomes have a higher mode share for ridehailing services. In our model, we find that employed respondents have a higher mode share for ridehailing services but made fewer trips than unemployed respondents. The signs of these two coefficients imply that employed individuals replace other modes with ridehailing services for non-work travel (possibly originating at their work locations due to time constraints).

Built Environment

After controlling for the socio-demographic variables, and the effect of home-location and vehicle ownership with the help of latent variables, we observe the unbiased estimated effects of the built environment on ridehailing mode share and number of non-work trips in Table 25..

Notably, the signs and significance of the estimated coefficients of the built environment variables change between the urban and non-urban models. This suggests that there is a difference in the way the built environment influences the log odds of ridehailing and total number of trips in the two kinds of areas. Yu and Peng (2019) had a similar observation when they analyzed aggregated data using geographically weighted regression.

We hypothesized that individuals who live in vibrant neighborhoods with plenty of restaurants in close proximity (walking distance) would have a lower mode share for ridehailing. However, the urban model showed that if individuals have at least one restaurant within a half mile of their residence, they will have a higher mode share for ridehailing services. Moreover, they make fewer trips for non-work purposes than those who do not live in such neighborhoods (the opposite of our original hypothesis). Even in non-urban neighborhoods, having more restaurants within a one-mile radius is associated with higher ridehailing mode share and lower total number of trips. The increase in the mode share of ridehailing and decrease in total number of trips could be an indication that ridehailing replaces other modes (possibly walking) for individuals who live in areas with close proximity to restaurants. It seems counter-intuitive that lower non-work trip-frequencies are associated with the presence of restaurants within a walkable distance. It may be that a more detailed model that also takes into account the role of individuals' underlying activity patterns may be required when examining the effect of the built environment on ridehailing and trips.

We also examine the effect of the Walkscore for the home locations of respondents on their ridehailing mode share and total number of non-work trips. In urban areas, a higher Walkscore is associated with a higher ridehailing mode share; in non-urban areas the mode share for ridehailing decreases with Walkscore. In urban areas, where ridehailing service is available at much shorter waiting times (as compared to non-urban areas) it is possible that ridehailing replaces walking trips. The fact that the increase in mode share for ridehailing with Walkscore is not accompanied by an increase in total number of trips for non-work purposes is also consistent with this interpretation. The differential effect of Walkscore on mode share and number of trips may help to explain why previous studies, which have examined the effect of land-use mix on the number of ridehailing trips, have found both positive effects (Sabouri et al. 2020; Yu and Peng. 2019) and negative effects (Alemi et al. 2019).

The ease of reaching destinations that are not necessarily available in all neighborhoods, but that people still visit occasionally, can have an impact on travel behavior. We found that individuals living in non-urban areas have a higher mode share of ridehailing if the nearest movie theatre is in the range of 0.65 miles to 8 miles from their home locations, as opposed to those who either live closer (less than 0.65 miles) or further away (more than 8 miles). This finding is consistent with our hypothesis that this range of distances is close enough for movie theatres to attract trips even though they are not close enough to reach by walking. In urban areas, living in a home which has a nearest movie theater in a distance between 0.5 miles to 8 miles is associated with higher mode share of ridehailing as compared to living in a home which has a movie theater within 0.5 miles.

The presence of a department store in a medium range distance (0.65 miles to 8 miles) from the home location induces more trips but the effect on the mode share of ridehailing is not significant. This makes sense because as observed in Figure 23, only 7% of the ridehailing trips were made to department stores.

To understand if our ICLV approach mitigates potential issues with, e.g., the effect of RSS bias on estimated effects of the built environment variables, we formulated a model without latent variables and random effects. This model indicates a significant effect of living in a stand-alone house (in urban areas), and also high neighborhood transit accessibility (in non-urban areas) on mode share of ridehailing services. Previously, Yu and Peng (2019), who did not control for RSS, also found a positive relationship between job access by transit and use of ridehailing services. They speculated that this could be an indication of ridehailing serving as a first- and last-mile connection with transit. However, the significance of both these effects goes away in the ICLV model, indicating that RSS bias could indeed be a problem when attempting to ascertain the effect of the built environment.

Table 24. Main models and structural models from the ICLV model

	Main Models												Structural Models					
	Urban				Non-urban				Residential choice		Vehicle Ownership		Pro-Urban		Car Lover		Tech averse	
	Log Odds		Total Trips		Log Odds		Total Trips											
	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.
(Intercept)	-3.83	-10.06	2.92	27.07	-2.83	-29.79	2.39	25.87										
Asc. Non-urban									1.83	20.00								
Asc. Zero Vehicle HH											3.20	20.42						
Age (ref=Millennials)																		
GenX	-0.36	-3.29			-0.09	-1.31	-0.07	-1.19					-0.13	-2.05	0.03	0.34	0.51	7.70
Baby boomers	-0.56	-4.51			-0.10	-1.50	0.04	0.54					-0.40	-5.65	0.43	5.08	1.13	14.26
Gross Annual Household Income (ref=Less than $50,000)																		
$50,000 to $100,000	-0.27	-1.87	0.31	3.02			0.13	3.45					-0.23	-3.59	0.17	2.13	-0.10	-1.31
More than $100,000	-0.01	-0.10	0.19	1.92			0.18	4.53					-0.29	-3.89	0.35	4.04	-0.28	-3.32
Gender (ref=male)																		
Female			-0.19	-2.92			-0.07	-2.39									0.14	2.61
Race(ref = other)															-0.18	-2.44		
White			0.24	3.16			0.15	4.00										
Employed (ref=no)																		
Yes	0.57	4.21	-0.45	-4.59	0.15	2.44	-0.17	-3.12							0.12	1.70	-0.40	-6.21
Student(ref = no)																		
Yes			0.14	1.30	0.11	1.76							0.27	3.47			-0.45	-5.73
Education (Ref = Bachelors' or less)																		
More than Bachelors					-0.18	-3.40	0.14	3.02					0.54	8.76	-0.27	-3.94	-0.15	-2.33
Children in the HH (ref=none)																		
At least one			0.20	2.12													-0.28	-4.10
Built Environment																		
Inverse sum restaurant in 1miles					5.14E-04	1.89	-5.31E-04	-2.06										
Restaurant within 0.5 miles (ref = Yes)																		
No	-0.49	-2.38	0.36	3.43														
Walkscore	0.01	2.41			-2.59E-03	-2.25	3.75E-03	3.82										
Movie theater within 0.5 miles (ref = Yes)																		
No	0.27	1.62																
Distance to the nearest movie theater (ref = between 0.65 miles to 8 miles)																		
Less than 0.65 miles					0.02	0.28												
More than 8 miles					-0.13	-3.36												

	Main Models												Structural Models					
	Urban				Non-urban				Residential choice		Vehicle Ownership		Pro-Urban		Car Lover		Tech averse	
	Log Odds		Total Trips		Log Odds		Total Trips											
	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.	Est.	t-rt.
Distance to the nearest department store (ref = between 0.65 miles to 8 miles)																		
Less than 0.65 miles	-0.17	-1.60	0.15	2.16	0.05	0.86	-0.11	-1.90										
More than 8 miles					0.16	1.68	-0.19	-2.29										
Type of house (ref = Apartments/others)																		
Stand Alone	-0.15	-1.60																
Jobs available via 30 min transit ride					3.16E-06	1.57												
Attitudes																		
Pro Urban	0.23	2.18			0.13	4.99			1.35	11.43								
Car Lover					-0.14	-5.83					1.47	8.24						
Techaverse			-0.19	-4.80			-0.15	-6.57										
Error Component	-0.59	-7.47	0.45	8.37	-0.90	-31.68	0.78	27.78										
Model Fit																		
LL(start)	-90820.24																	
LL(final, whole model)	-60753.95																	
AIC	121703.9																	
BIC	122294.7																	
Number of estimated parameters	98																	
N	3,066																	

Table 25. Estimates from measurement model

Pro Urban	Estimate	T-ratio
I prefer to live in a spacious home, even if it is farther from public transportation and many places I go.	-0.37	-15.91
I prefer to live close to transit even if it means I'll have a smaller home and live in a more crowded area.	0.51	32.15
I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	0.41	21.50
Car Lover		
I definitely want to own a car.	0.42	13.75
I prefer to be a driver rather than a passenger.	0.37	16.83
I am fine with not owning a car, as long as I can use/rent one any time I need it.	-0.43	-19.25
Tech Averse		
I like to be among the first people to have the latest technology.	-0.43	-25.42
Having Wi-Fi and/or 4G/LTE connectivity everywhere I go is essential to me.	-0.41	-24.95
I like trying things that are new and different.	-0.38	-18.55
Learning how to use new technologies is often frustrating for me.	0.30	15.56
I try to make good use of the time I spend commuting.	-0.34	-17.28
My commute is a useful transition between home and work (or school).	-0.28	-14.67

Conclusions

Ridehailing services have become a mainstream mobility option in many cities across the world. Planners and policymakers want to ensure that ridehailing is a net positive in the transportation system, that it increases mobility options for travelers but does not replace sustainable modes of transportation such as active modes and public transit. Ridehailing and its impacts has been much studied by the academic community, but research on the effect of the built environment on the use of ridehailing services has notable gaps.

In this study, we take the view that accessibility measures based on behavioral considerations are potentially a more effective way to measure the effect of the built environment than, e.g., the more common "D-measures' (density, diversity, design, etc.). We employ measures from existing sources (Walkscore and jobs accessibility) as well as measures we developed ourselves for this study. We also employ a modeling framework that allows us to test whether the effect of the built environment is different in urban and non-urban neighborhoods, a difference that could be driven by a better supply of ridehailing services in urban areas. Because it is well known that residential self-selection (RSS) can bias estimates of built environment effects on travel behavior, we explicitly incorporate the effect of attitudes and other unobserved variables using an ICLV modeling framework to address this issue. Estimation of a simpler model indicates that RSS bias is indeed a problem.

Two notable policy implications emerge from our analysis. The first implication is that, if the goal is to discourage ridehailing from replacing active modes, pricing should be employed to discourage short distance ridehailing trips. We found that the mode share of ridehailing services is higher when destinations are within walkable distance of the home location. Since the total number of trips made by individuals in not positively associated with an increase in the accessibility (by walking) of the neighborhood they live in, we speculate that ridehailing replaces active modes in such neighborhoods. More studies examining trip lengths and trip chains using travel diary datasets are required to confirm this speculation. It is undesirable from a policy perspective if this increase in mode share of ridehailing comes at the expense of walking, which is a more sustainable and cleaner mode of travel than ridehailing, in addition to its direct benefits. In order to prevent replacement of walking trips by ridehailing services it is important to appropriately price short distance trips made by ridehailing services in urban areas.

Second, the relationship between ridehailing and public transit has been central to many studies in the past few years. Some suggest that ridehailing services act as a first- and last-mile connection to mass transit services (Yan, Levine, and Zhao, 2019; Yu and Peng, 2019) while others find that ridehailing may be replacing public transit (Schaller, 2018). Our model indicates that after controlling for individual attitudes about where they choose to live and their perceptions about public transit, this relationship becomes insignificant. Interestingly, a recent study by Malalgoda and Lim (2019), which instead of relying on the total number of trips made using ridehailing (like most other studies) focused on transit ridership and availability of ridehailing service in cities around the U.S. over the past decade, found no evidence of a linkage between the two. It is possible that other studies may have overestimated the linkage between transit ridership and ridehailing due to lack of control for residential self-selection.

This study provided new insights into the relationship between the built environment (at the home-location) and use of ridehailing services for non-work purposes. As the research on this topic evolves, future studies can explore how the built environment affects decision to use ridehailing for non-home-based trips. The use of ridehailing for commute purposes has also not been examined closely. Finally, analyzing data collected through travel diary surveys focusing on tours and activities rather than trips can reveal new insights into the link between ridehailing services and the built environment.

Modal Impacts of Ridehailing: A Latent Class Analysis with Shared Ridehailing Distal Outcome

This chapter investigates the latent patterns in the modal impacts of ridehailing services in a sample of California ridehailers, and how shared ridehailing adoption and usage (in addition to their determinants) are associated with these ridehailing modal impact patterns. Using a dataset collected in Fall 2018, we use a latent class with distal outcome approach to firstly identify the latent classes of ridehailing modal impacts, and then analyze the relationship between the identified latent classes and *shared* ridehailing adoption and usage while controlling for other factors that directly influence the adoption and usage. Our analysis points to three latent classes of ridehailing modal impact. In our first class, where ridehailers are younger, lower income, and more urbanite, a majority/plurality report a decline in the usage of taxi cabs and transit services. In our second and third classes, where ridehailers are relatively older and higher income, a majority of ridehailers report no change in their use of other modes, with the difference that Class 3 ridehailers also report being users of transit (as opposed to Class 2, who are not), but ridehailing usage does not impact their transit usage. Analyzing the association between these latent classes and shared ridehailing adoption and usage, we find Class 1 to have the highest adoption rate and usage frequency of shared ridehailing. Moreover, we conclude that 30% of the total shared ridehailing adopters, and 50% of the frequent users (weekly users), in our sample are associated with Class 1 of ridehailing modal impact. This analysis helps provide a more detailed picture of how ridehailing interacts with other transportation modes in different population segments, and further investigates the sustainability promise of shared ridehailing by identifying its association with different modal impacts.

The following section contains an extract from Dr. Ali Etezady's PhD dissertation which is currently in the process of peer review for a journal publication. Please use the following citation to cite the PhD dissertation:

> *Etezady, SeyedmohammadAli. Transportation in an Era of Disruption: How Generational Differences And New Transportation Technologies Are Influencing Travel Behavior. PhD Dissertation, Georgia Institute of Technology, 2021.*

Introduction

Uber and Lyft, as the main representatives of the gig and platform economy in the U.S. transportation sector, have revolutionized the daily mobility of many travelers, with their array of services ranging from private and shared on-demand rides to bicycle/scooter sharing and food delivery. These services have consequently disrupted and challenged some longstanding transportation models and policies, a research subject of great interest to numerous studies that have aimed to unravel these services' impacts on travel demand and their interactions with other mobility choices. A number of studies, for instance, have pointed to the negative relationship between ridehailing (RH) and vehicle ownership (Hampshire et al., 2017; Ward et al., 2019), while a number of others point to the opposite conclusion (Gong, Greenwood, and Song, 2017; Schaller, 2018). Several other studies have investigated the interaction of such services with public transit, with some pointing to circumstances where a complementary effect exists (e.g., Feigon and Murphy, 2016), while others discuss circumstances with negative impacts (Graehler Jr, Mucci, and Erhardt, 2018)—results which have fed into a growing concern for sustainable mass mobility options being downgraded or eliminated in the future. Such apparent divergence in conclusions and results may partly arise from heterogeneity in the RH relationship with other elements of travel behavior, therefore calling for further research that better incorporates heterogeneity into the analysis.

Furthermore, and in light of the importance of ridehailing impacts on the transportation sector, many studies have aimed to better understand the growing market for these services, with several of them trying to identify the factors influencing these services' adoption and usage. As a result, literature often reports age, income, education level, land use, and personal attitudes as significant correlates of adoption and usage (Alemi et al., 2018). Most such studies, however, have focused on RH services in general, not differentiating among the different services offered by the transportation network companies (TNCs). One such service, shared RH, has significantly grown in availability and adoption since its limited introduction (in the United States) in late 2014. Considering that such shared rides are often considered and proposed as a more sustainable alternative to private rides or driving alone, a better understanding of the driving factors behind their usage and their impact on other modes can help modelers and planners better incorporate them in their analyses and understand their usage.

The main goal of this chapter, therefore, is to investigate the heterogeneity in the impact of RH services on other travel modes, and how the adoption and use of *shared* RH and its determinants are related to the different modal impact patterns of RH. To achieve this goal, we use a travel survey dataset collected in California in Fall 2018, and employ a latent class (LC) with distal outcome modeling framework in our analysis. Using this approach, we firstly identify the patterns of modal impacts of *any* RH usage among different segments (latent classes) of the population, and then examine the relationship between *shared* RH adoption and usage (as the distal outcomes) and the identified latent patterns. We will, therefore, also be able to partially assess the sustainability promise of shared RH services through examining for which segments of the population these services tend to replace the less sustainable modes of transportation such as personal car.

Literature review

Over the past several years, the concept of the sharing and platform economy, propelled by recent leaps in information and communications technology (ICT), has gained a strong foothold in the global market and has grown significantly in popularity among various segments of the population (Hamari, Sjöklint, and Ukkonen, 2016; Jin, Kong, Wu, and Sui, 2018; Kenney and Zysman, 2016; Zervas, Proserpio, and Byers, 2017). The appeal of such business models, owing largely to their convenience of use and lower costs (Nadler, 2014), has also impacted the transportation sector, with companies such as Uber and Lyft having changed the usual balance in the sector. Such businesses operate on the premise of providing on-demand rides by connecting willing suppliers (drivers) to consumers (passengers) all through an easy-to-access digital platform (e.g., smartphone app). To better cater to different needs and segments of the population, the RH companies (also known as transportation network companies) have also diversified their services, not only providing economy and premium private rides, but shared rides as well. The adoption of these services has been a topic of interest in the literature over the past few years.

Rayle et al. (2016), using evidence from intercept surveys collected in the city of San Francisco, reported the appeal of such on-demand ride services to be stronger among younger, well-educated individuals, who like to avoid the longer wait times and inconveniences of driving and finding parking in the city. Alemi et al. (2018) investigated the adoption of RH services over a larger area (state of California), estimating adoption models for RH and finding that higher-educated older millennials tend to be among the more frequent adopters of these on-demand ride services, with living in a more mixed land-use area and having more long-distance travel further propelling this adoption. Clewlow and Mishra (2017) obtained similar findings on a more diverse scale (seven major US cities), reporting the rate of adoption among college-educated, affluent Americans to be twice that of the rest, and those living in urban neighborhoods to be significantly more likely to adopt. Young and Farber (2019) investigated RH usage in the City of Toronto using a large-sample household travel survey, and concluded RH to be a “wealthy younger generation phenomenon”. In general, most studies point to Millennials or the younger generation as the demographic with a higher adoption rate of RH services.

In addition to studies on the adoption of RH services, another body of literature has investigated the impacts of such services on other travel modes and urban conditions. Such impacts seem to differ based on the type of services, local context, and users’ characteristics (Circella and Alemi, 2018). Hall, Palsson, and Price (2018), for instance, studied the impact of Uber on public transit using a difference-in-difference design, with results pointing to Uber acting as a complement for the average transit agency, although they comment that their reported average effects do not necessarily portray the existing heterogeneity well. A number of other studies have used the 2017 U.S. National Household Travel Survey (NHTS) to investigate the modal impacts of RH services and point to a positive relationship between RH and public transit usage (Conway, Salon, and King, 2018; Grahn et al., 2019), although causality inference from such analyses is not possible. On the other hand, de Souza Silva et al. (2018), studying RH in Brazilian cities, and Tang et al. (2020), studying the same topic in China, concluded that the majority of RH trips replace those otherwise taken by taxis and public transit.

Considering the extent of studies on different aspects of RH in general, the literature contains fewer studies that more specifically focus on shared RH. Among the latter, Krueger et al. (2016) used an SP survey to explore the adoption of shared *autonomous* vehicles (SAVs), concluding that travel cost, travel time, and waiting times may play a critical role in the adoption of SAVs, and that younger and multimodal individuals are more likely to be among the adopters. In another study, Lavieri and Bhat (2019) used both RP and SP data and developed a willingness-to-share concept to investigate individuals' willingness to share trips in an AV future. Their results point to a lower sensitivity to sharing commute trips with strangers compared to doing so on leisure trips, and indicate that the longer travel time of shared rides may be more of a barrier than exposure to strangers for the adoption of shared trips. Alonso-Gonzales et al. (2020) studied the different factors that influence an individual's decision to share rides using an SP dataset of Dutch urbanites. They report that willingness to share rides is clearly subject to population heterogeneity, and (similarly to Lavieri and Bhat) that a time-cost trade-off plays a more important role in shared ride usage than the potential disutility related to sharing space with strangers.

The importance of further studying shared ridehailing services lies in their promise of a more efficient and sustainable transportation system, where a higher vehicle occupancy, as some simulation studies show (Martinez and Viegas, 2017), may help relieve congestion and reduce the overall carbon footprint of the transportation industry. The sustainability promise of such services, however, hinges on the assumption that shared rides replace private rides, as opposed to public and active modes of transportation. Therefore, a more in-depth study of the interaction of shared RH and other travel modes, in addition to the characteristics of its users, can help inform TNCs, planners, and policy makers.

In this chapter, we aim to extend the existing literature on the modal impact of RH services by exploring the heterogeneity in the reported impacts of RH on other travel modes, and how these different impact patterns relate to the adoption and use of shared RH services and their determinants. This chapter will, therefore, contribute to the exisiting literature by shedding light on how shared RH usage is associated with different RH modal impacts, and what user characteristics tend to bolster the adoption and usage of these services.

Overview of the dataset and methodology

Empirical context and chapter scope

Since the goal of this chapter is to investigate the modal impacts of RH and how they relate to shared RH usage, we narrowed down the total sample to only RH users, and ultimately worked with a sample of 1288 respondents. Moreover, and although the research team developed sample weights to better project the complete dataset onto the population at large, we decided against using any sample weights in the current chapter. The main reason behind this decision was that, as mentioned, the population of interest to the present chapter is that of ridehailers only. Since data on the distributions of various characteristics in the population *of* *ridehailers* is not available, we could not develop weights appropriate for this chapter. Accordingly, we conducted the analysis on the *unweighted* sample, while controlling for a number of sociodemographic characteristics in our model.

Investigating the heterogeneity of the modal impacts of ridehailing usage

Reported impacts of ridehailing on personal use of other travel modes

Asking respondents how using RH services in general has impacted their use of other travel modes, the survey recorded their responses on a five-level ordinal scale from *much less* to *much more* for each of six other modes. In addition to these five levels, respondents could also report if they "did not use [a mode] before, and do not use it now", or if "[they] have changed how [they] use [a travel mode] but not *because of* RH". To obtain a simpler and easily usable set of categories, in addition to having enough responses for each level, we recoded this variable into four categories by merging some of the options. In the final recoded variable (used in categorical format), 1 indicates that RH has resulted in using the given mode much less or less; 2 indicates that RH has *not* resulted in a change in the use of the mode (no change or no change due to RH use); 3 indicates that RH has resulted in an increased use of the mode (more and much more); and 4 indicates that a respondent did not use the mode in the past and present (not a user). Figure 24 shows the distribution of these categories in our sample.

RH services, as expected, have had the strongest negative impact on taxi cabs, with about 39% of RH users in our sample reporting a lower use of this mode. Approximately 22% report that their use of taxi cabs has not changed due to RH usage, and the share of those reporting that they use taxis more often as a result of using RH services is the smallest at about 1.3%. Such respondents perhaps have used taxi cabs instead of RH as a result of longer travel times, surge pricing, etc. for specific trips. Their low share, however, points to the relative scarcity of such instances. Approximately 22% of RH users in our sample report a lower use of personal car, while a majority of 66% report no RH impact on their personal car usage. In addition, 3% of the sample report a higher use of this mode due to RH services. This can possibly be either due to a complementary use of RH services, where travelers use RH for part of the trip where parking, for instance, might be more difficult to find, or cases where respondents get a ride from a family member for one leg of a trip and use RH for the return trip. Similar to the taxis' case, their low share points to the relative scarcity of these cases.

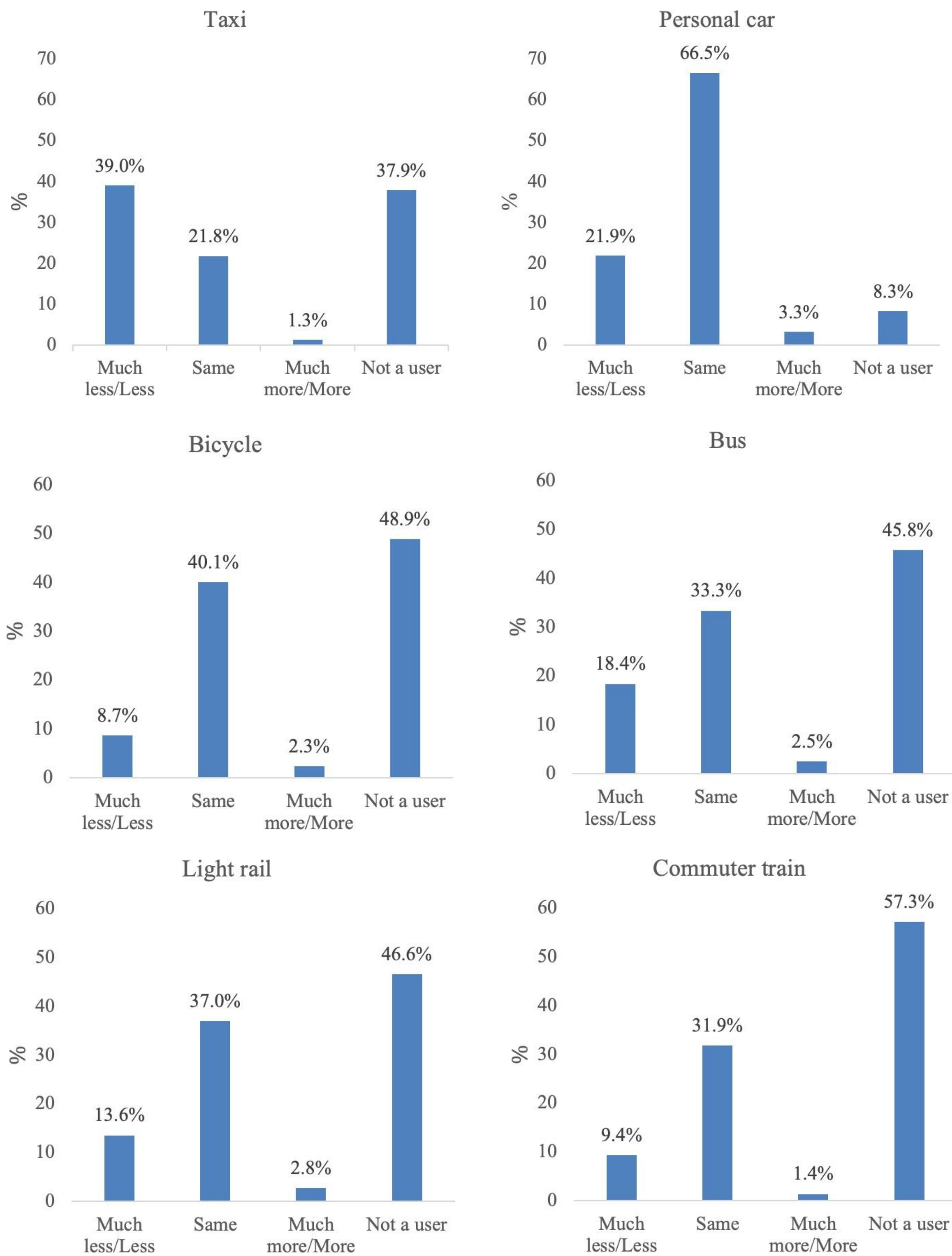


Figure 24. Distribution of the impacts of RH services on traditional travel modes (N=1268)

Bicycling, as an active mode of travel, appears to have had the smallest impact from RH services compared to the other modes, with only 11% of the sample reporting a different usage frequency (either increased or decreased). With respect to public transportation, the negative impact of RH on these modes (bus, light rail/subway, commuter train) in our sample is the strongest for bus, with approximately 18% reporting a lower usage (34% of those who use bus), while this share is comparatively smaller at 14% and 9% (25% and 22%) for light rail and commuter rail modes, respectively. This observation, perhaps, draws attention to bus as the most afflicted transit mode, specifically considering how RH can provide a faster and more convenient alternative to its user group, while light rail and commuter train seem to have been impacted relatively less. Moreover, the share of those reporting a higher transit usage, at around 1-3%, is quite small, indicating that the substitution impact of RH services far outweighs their complementary effect on transit modes in our sample.

Latent classes of ridehailing modal impacts

In choosing the optimal number of classes, we compared the log-likelihood (LL) statistics of different class numbers in addition to the interpretability of the results. Table 26. shows the different Information Criteria (IC) used to determine the optimal number of classes. The three-class solution has the minimum value for all the ICs (Bayesian IC (BIC), Akaike IC (AIC, AIC3), and Consistent AIC (CAIC)), suggesting that this model is an optimal solution with respect to the LL statistics.

Table 26. Summary of model estimation ICs by class number

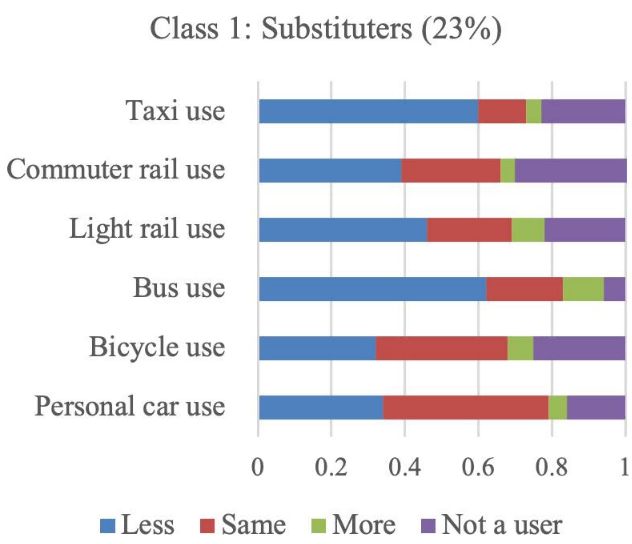
Solution	LL	BIC	AIC	AIC3	CAIC	No. of parameters
1-Cluster	-7928.2	15985.0	15892.4	15910.4	16003.0	18
2-Cluster	-6904.3	14073.0	13882.6	13919.6	14110.0	37
3-Cluster	-6330.8	13383.3	12863.6	12964.6	13484.3	101
4-Cluster	-6355.7	13440.3	12915.5	13017.5	13542.3	102
5-Cluster	-6391.7	13455.0	12971.3	13065.3	13549.0	94

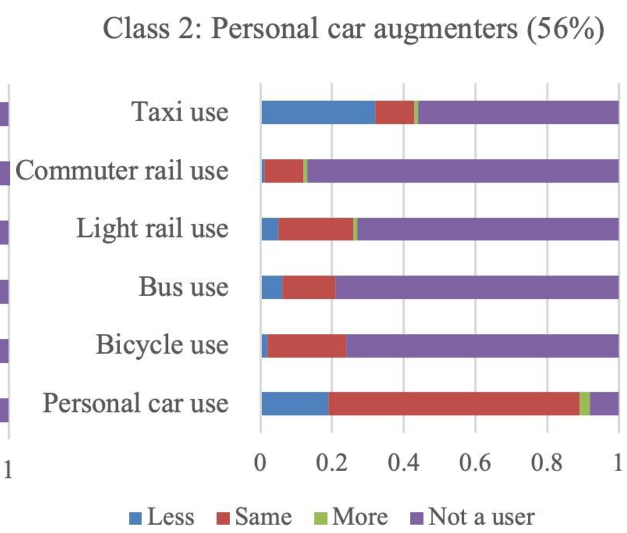
To better investigate the three-cluster solution, Figure 25 presents a summary of the three-cluster membership model results. As may be seen, the largest cluster (Class 2) includes 56% of the sample, with the rest of the sample roughly equally divided between the other two classes.

In Class 1, or the Substituters, RH usage has the strongest negative impact on the use of public transit modes and taxi cabs, with a plurality or majority of the ridehailers in this class reporting a lower use of these modes. A sizeable portion of this class—especially when compared to the other classes—also reports a lower use of personal cars and bicycles, although these shares do not constitute a majority or plurality. For this latent class of ridehailers, therefore, RH in general acts as a substitute mode, with this effect being more prominent for non-personal modes of transportation. With respect to the sociodemographic characteristics of this latent class of ridehailers, we see that they are on average the youngest (average age of 40 years old) of the three classes. In addition, the shares of lower incomes (those living in households earning less than $50K/year) and those living in households without a personal vehicle, at 47% and 25% respectively, are the highest for this class. In terms of education, we see a comparatively higher share of ridehailers with only a high school diploma or less (14%), and a lower share of ridehailers with bachelor's or higher degrees (59%). This class, in addition, contains a comparatively larger share of Hispanic ridehailers (27%), while the difference in the shares of other race groups is less pronounced. We also investigate each latent class with respect to attitudes and lifestyles, since these traits have also been found to impact the use of RH services. This class on average scores the lowest on the pro car and pro-suburban construct, indicating that ridehailers of this class, in line with some of their sociodemographic characteristics as discussed above, tend to have a more urban mindset and a lifestyle that favors or necessitates a lower rate of car ownership. In addition, members of this class have on average the strongest pro sustainability attitude.

Class 2, or the Personal car augmenters, is largely composed of those who are not users of non-personal or active modes of transportation. RH in this class seemingly acts as a complement to the personal car for the majority of cases, while acting as a substitute for taxi and personal car in a comparatively smaller share of cases. Ridehailers in this class tend to be the oldest (with an average age of 48 years old) compared to the other two classes, and are also higher educated (with a 72% share of bachelor's degrees or higher) than ridehailers in Class 1. This class includes a lower share of low incomes (32%) than Class 1, with the share of those living in households without personal vehicles also considerably lower at 7%. With respect to attitudes, members of this class are on average the most pro car, as well as being the strongest pro suburban ridehailers. Moreover, the members of this class also have the lowest average score on the pro sustainability construct.

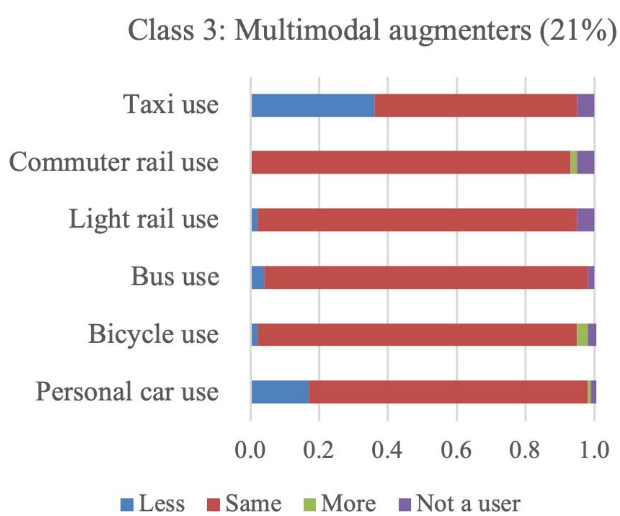
Finally in Class 3, or the Multimodal augmenters, a strong majority of ridehailers, unlike those in Class 2, are users of public transit and active modes of transportation. However, their use of RH has not impacted (reduced or increased) their use of these modes, implying little to no substitution or bolstering effect of RH on these modes for this class. Similar to Class 2, a majority of ridehailers in this class report that their use of personal car or taxi cabs has not changed due to RH usage, although, again similarly to Class 2, a comparatively smaller share report a lower use of these two modes due to RH usage. In terms of sociodemographics, ridehailers of this class are on average older (average age of 45 years old) than those in Class 1, but younger than those in Class 2. In addition, members of this class are somewhat higher educated than those in Class 2, with 78% having a bachelor's degree or higher. The share of higher and lower income households, at 53% and 30% respectively, points to this class as being slightly higher income than Class 1. In addition, the share of those living in households without personal vehicles is approximately similar to Class 2 at 6%. In terms of attitudes, this class scores, on average, between Classes 1 and 2 on car enthusiast, pro suburbia, and pro sustainability constructs.





SED: The youngest, lowest income, lowest education level, fewest vehicles owned, and with the highest share of living in urban areas
Attitudes: Most pro sustainable, least pro car and pro suburban

SED: The oldest, higher income and higher educated than Class 1, and with the lowest share of living in urban areas
Attitudes: Most pro car and pro suburban, least pro sustainable



SED: Average age between Classes 1 and 2, slightly higher income and higher educated than Class 2

Figure 25. Latent profiles of the modal impacts of ridehailing on other travel modes (x-axis shows the share in a class reporting a specific impact) (N=1268)

Shared ridehailing and its association with different ridehailing modal impact classes

It was relevant to identify modal impact latent classes for all ridehailers, and therefore the analysis in the previous section was performed on all such individuals, including those who lived in areas where shared RH service was not available. Now, however, we wish to relate the modal impact classes to the usage of *shared* RH, and therefore it becomes important to determine what portion of our overall sample could reasonably be said to have access to shared RH services. To make this determination, we initially used the geocoded home addresses of the respondents in conjunction with the Uber API, and identified 1308 respondents (out of the total 3835) who lived where shared RH services were available. An additional 208 respondents, whose home addresses did not fall within geographies where shared RH services were available, indicated that they use shared RH services. Considering that the majority of these cases used these services with low frequency (less than once a month), we believe they generally represent those who travel long-distance to areas where shared RH is available. We decided against including these respondents in our analysis, since we could not reasonably include a counterpart group who did *not* use shared RH given the same conditions, and doing otherwise could possibly bias our analysis. Moreover, we excluded cases who reported they were not familiar with shared ridehailing, since not being a user for them could not be considered as a *conscious choice.*

Based on this exploration, therefore, the restricted sample we used to conduct this portion of the analysis included those ridehailers who lived in areas where shared RH was available and who were familiar with the option of shared RH (N=496). We kept the same latent clusters, and checked to see if this sample restriction changed any of the class characteristics or overall patterns. All the classes kept their identified characteristics and patterns, with only negligible changes in average values. We also performed a separate LC cluster analysis only on the restricted sample and obtained similar results, further assuring that the sample restriction did not distort our identified latent clusters.

In the following subsections, we respectively present the distribution of shared RH adoption and usage, explain the methodology employed to assess the relationship of these variables with the identified latent profiles of RH modal impacts in the previous section, and report the results of this analysis.

Adoption and usage frequency of shared ridehailing services

Table 27. shows the descriptive statistics of shared RH adoption and usage in our restricted sample. The shared RH adopters constitute approximately 52% of the sample, with those who use this service on a regular basis (more frequently than “less than once a month”) forming about 29% of the total sample.

Table 27. Descriptive statistics of the adoption and usage of shared ridehailing among ridehailers having shared RH available (N=496)

Variable	N	%
Shared ridehailing adoption		
Adopters	258	52.0%
Non-adopters	238	48.0%
Shared ridehailing usage frequency		
Not a user	238	48.0%
Less than once a month	115	23.2%
1-3 times a month	98	19.8%
1-2 times a week	34	6.9%
3 or more times a week	11	2.2%

Results

Shared ridehailing adoption

Table 28. shows the distribution of shared RH adoption within and across the identified latent classes. Based on the within-class distribution statistics, we see that Class 1 has the highest rate of shared RH adopters, with the other two classes having fairly similar adoption rates. But more importantly, by looking at the across-class distributions, we see that 30% of the shared RH adopters in our sample belong to Class 1 (Substituters), where RH largely impacts public transit and taxis. On the other hand, 49% of adopters in our sample belong to Class 2, the Personal car augmenters who largely do not use public or active modes of transportation, with another 21% belonging to Class 3, the Multimodal augmenters for whom RH largely does not impact public transit usage. In other words, 70% of shared ridehailers in our sample are associated with RH modal impact patterns where RH appears to have minimal impact on active and public modes (more sustainable modes), while the remaining 30% are associated with the modal impact cluster where public transit's usage has been substantially weakened.

Table 28. Distribution of shared ridehailing adoption within and across the identified latent classes (N=496)

Descriptive statistics type	Class (share) / Adoption category	Class 1: Substituters (26%)	Class 2: Personal car augmenters (51%)	Class 3: Multimodal augmenters (23%)
Distribution *within* class (Average $p(d_i \mid c, z_i)$)	Non-adopters	0.40	0.49	0.51
	Adopters	0.60	0.51	0.49
Distribution *across* classes (Average $p(c \mid d_i, z_i)$)	Non-adopters	0.21	0.54	0.25
	Adopters	0.30	0.49	0.21

In addition to the association of shared RH and identified latent classes, we further investigated other direct determinants of shared RH and how they differ based on the identified latent classes. Table 29. shows the binary logit models of shared RH adoption with the explanatory variables including sociodemographics, built environment, and attitudinal factors (statistically insignificant coefficients have been constrained to zero). Overall, we see that Class 2 is associated with the highest number of explanatory variables, likely due to its largest size and the existence of more heterogeneity than for the two smaller classes.

Table 29. Distal outcome model (binary logit) of shared ridehailing adoption (N=496)

Variables	**Class 1: Substituters**		**Class 2: Personal car augmenters**		**Class 3: Multimodal augmenters**	
	Coef.	P-value	Coef.	P-value	Coef.	P-value
Age (years)	-	-	-0.041	0.002	-	-
High income household (> $100K/yr)	-	-	-0.883	0.019	-1.517	0.002
Urban dweller	1.135	0.022	0.639	0.062	-	-
Frequency of long-distance leisure air travel[1]	-	-	0.111	0.043	0.218	0.069
Transit meets my needs[2]	0.039	0.047	-	-	0.357	0.042
FS[3] open to interaction with strangers	0.467	0.086	0.955	<0.001	-	-
FS pro sustainability	-	-	0.417	0.013	-	-
Constant	-1.048	0.094	1.695	0.010	-0.511	0.340
Distal outcome model statistics: *LL_{EL}=-343.80, LL_{MS}=-343.40, LL_{β}=-295.60* *ρ_{EL}=0.140, ρ_{MS}=0.139*						

[1]Transformed to a continuous per month variable from the original ordinal variable using this logic: "5 or more times a week"= 5 times a week (20/month), "3-4 times a week"= three and a half times a week (14/month), ''1–2 times a week''=1.5 times a week (6/month), ''1–3 times a month'' = 2 times a month (2/month), "less than once a month" = 3 times per year (0.25/month), and "Never" = 0/month.
[2] Ordinal five-level Likert-type variable.
[3]Factor score generated based on the exploratory factor analysis using Bartlett method.

Among the sociodemographic variables, as Table 29. shows, we found age and household income to be significant predictors of shared RH adoption. In our Class 2 (Personal car augmenters), age is negatively associated with shared RH adoption, indicating that younger ridehailers in this class are more likely to be among the adopters. Although the coefficients of age in the other two (younger, on average) classes were also negative, we did not find them to be statistically significant, and therefore constrained those coefficients to zero. With respect to income, we see that ridehailers of Classes 2 and 3 who live in high-income households are less likely to be among the adopters, while the influence of income is insignificant in the Substituters Class, whose members already live in relatively lower income households.

The built environment is significantly correlated with shared RH adoption in our first two classes, with those living in urban areas more likely to be among the adopters than suburbanites. This effect is more significant in Class 1, which has a larger share of younger ridehailers whose use of transit has been negatively impacted, while this variable's impact in the two Augmenter Classes is of lower statistical significance. Moreover, a higher frequency of long-distance leisure air travel is positively associated with using shared RH in the two Augmenter Classes.

With respect to opinions and attitudes, we see that ridehailers in Classes 1 and 3 who indicate that public transit meets their needs are more likely to be among adopters, while this effect is insignificant in Class 2, where a majority of ridehailers are not users of public transit. In addition, we see that an openness to interaction with strangers on rides, as expected, is positively associated with shared RH adoption in Classes 1 and 2. This association is strong in our older car-centric users (Class 2), but considerably weaker in our younger classes whose other characteristics are more in line with using shared rides. Finally, pro sustainability ridehailers in Class 2, a class in which pro sustainability is on average the lowest, are more likely to adopt shared RH.

Shared ridehailing usage frequency

Although it is important to understand what factors influence the adoption of shared RH services, it is even more important to study the determinants of the usage frequency of these services, as that would provide us with more insight into the impact of shared RH. As presented in Table 27., usage frequency of shared RH in our dataset has 5 ordered levels; however, considering that the “3 or more times a week” usage level has a low number of cases, we merged it with the previous level, and named the new level the “frequent users”. Subsequently, the monthly users are considered moderate users, those using this service “less than once a month” are considered infrequent users, and those not using shared RH are considered “non-users”. Following this definition, therefore, we consider this 4-level ordered usage frequency of shared RH as the new distal outcome and use an ordered logit framework in conjunction with the identified latent classes. Table 30. shows the distribution of the usage frequency of shared RH in and across the identified latent classes.

Table 30. Distribution of the shared ridehailing usage frequency within and across the identified latent classes (N=496)

Descriptive statistics type	Class (share) / Usage category	Class 1: Substituters (26%)	Class 2: Personal car augmenters (51%)	Class 3: Multimodal augmenters (23%)
Distribution within class	Non-users	0.38	0.50	0.53
	Infrequent users	0.24	0.22	0.27
	Moderate users	0.23	0.21	0.16
	Frequent users	0.14	0.07	0.04
Distribution across classes	Non-users	0.21	0.53	0.25
	Infrequent users	0.27	0.46	0.27
	Moderate users	0.28	0.55	0.17
	Frequent users	0.50	0.41	0.09

As the within-class distribution part of Table 30. demonstrates, the Substituters Class (with younger, more urbanite ridehailers) has the highest shares of frequent and moderate shared RH users. In addition, this class has the lowest share of non-users. Considering that the majority/plurality of ridehailers in this class report a lower use of transit services, we may confirm that: (1) the younger and lower income class of ridehailers is associated with a higher use of shared RH services, and (2) a higher impact on transit usage is associated with a higher usage of shared RH services. The within-class distribution of usage frequency in the Personal car augmenters Class is relatively higher than that of the Multimodal augmenter Class with the share of frequent users 3 percentage points, and the share of moderate users 5 percentage points, higher than those of the Multimodal augmenters. In both classes, moreover, the share of non-users is fairly similar, with approximately half the ridehailers in each class reporting not having used shared RH services.

The across-class distribution of shared RH usage shows that approximately 50% of the frequent, and 28% of the moderate, shared ridehailers in the total sample belong to the Substituters Class, with younger urbanite members. This result further confirms the uneven distribution of different usage frequencies, and how the class of ridehailers with a higher share of reported lower usage of transit is associated with a bigger share of frequent shared RH users, results that cast doubt on the overall sustainability promise of shared ride services. We further conclude that 50% of the frequent, and 71% of the moderate, shared ridehailers in the total sample belong to the Augmenters Classes, where active and public modes of transportation are the least affected.

We now turn to the other direct determinants of shared RH usage frequency and how they differ in each latent class of users. As shown in Table 31., age is a significant predictor of usage frequency in our oldest class of ridehailers (Class 2), indicating that the younger ridehailers within that class tend to use shared RH more frequently. Similar to the result for adoption (Table 5.), however, the age effect is not significant for the other two classes, who are relatively younger to start with. Car ownership and income status also influence usage frequency across the classes; those ridehailers in Class 1 who do not own (or lease) a car tend to use shared RH more frequently. Among Class 2 and Class 3 ridehailers, moreover, those who live in higher income households tend to use shared RH less often, a result in line with that of the adoption model.

Urban environment influences usage frequency only in Class 2 (as opposed to the adoption model where it also played a role in Class1), indicating that the ridehailers in this class who live in urban areas tend to use shared rides more frequently. This built environment effect is probably more pronounced in this class (as opposed to the other two classes) since it already comprises the smallest share of urban dwellers.

With respect to opinions toward using shared RH, we see that, as expected, a higher tolerance toward longer travel times and interaction with strangers on shared rides is associated with a higher usage of shared RH, although the former showed a statistically insignificant association with the adoption of these services. Specifically, Class 2 ridehailers who are more open to interaction with strangers on rides tend to use shared RH more often, while ridehailers in Classes 1 and 3 who are less bothered by the longer travel times of shared rides are likely to use it more often. This result further underlines the importance of an openness toward the "sharing" economy in our oldest class, as opposed to the younger ones, in adopting and using these services. In addition, we see that those in Class 2 with a stronger pro-sustainability attitude tend to use shared rides more often, and ridehailers in Classes 1 and 3 who express that public transit meets their needs tend to use shared rides more often.

Finally, and similar to the adoption model, we see that those in the Augmenters Classes who take more leisure trips by air tend to use shared RH more often, while this effect is insignificant for Class 1 ridehailers.

Table 31. Distal outcome model (ordered logit) of shared RH usage frequency (N=496)

	Class 1: Substituters (26%)		Class 2: Personal car augmenters (51%)		Class 3: Multimodal augmenters (23%)	
	Coef.	P-value	Coef.	P-value	Coef.	P-value
Age (years)	-	-	-0.028	0.005	-	-
High income household (> $100K/yr)	-	-	-0.449	0.051	-0.631	0.022
Not a car owner	1.117	0.011	-	-	-	-
Urban dweller	-	-	0.710	<0.001	-	-
Transit meets my needs[1]	0.227	0.040	-	-	0.167	0.097
Frequency of long-distance leisure air travel[2]	-	-	0.0694	0.021	0.015	0.001
FS[3] open to interaction with strangers	-	-	0.336	<0.001	-	-
FS tolerant of longer trip time	0.246	0.044	-	-	0.260	0.070
FS pro sustainability	-	-	0.336	0.001	-	-
Constants						
Moderate user | frequent user	0	-	0.803	-	0	-
Infrequent user | moderate user	-0.966	0.012	0.3328	0.45	-0.6858	0.075
Non-user | infrequent user	-1.775	0.0015	0	0.32	-1.5289	0.014

Distal outcome model statistics:
LL_{EL}=-686.22, LL_{MS}=-609.03, LL_{β}=-533.33
ρ_{EL}=0.223, ρ_{MS}=0.124

[1] Ordinal Likert-type scale variable.
[2] Transformed to a continuous per month variable from the original ordinal variable using this logic: "5 or more times a week"= 5 times a week (20/month), "3-4 times a week"= three and a half times a week (14/month), ''1–2 times a week''=1.5 times a week (6/month), "1–3 times a month" = 2 times a month (2/month), "less than once a month" = 3 times per year (0.25/month), and "Never" = 0/month.
[3] Factor score generated based on the exploratory factor analysis using Bartlett method.

Discussion

The analyses in the previous sections highlight different aspects of ridehailing and their interaction with other travel modes. As expected, we see the taxi industry as the most strongly impacted mode due to ridehailing services, with all three of our latent classes also showing a substantial negative impact on the use of taxi cabs. Whether taxi cabs are a "greener" or more efficient mode of transportation is up for argument. While ridehailing services use advanced algorithms to minimize empty miles, and in the case of shared ridehailing match passengers on similar routes, taxi fleets in some areas like San Francisco have been converted to alternate fuel vehicles (SFMTA, 2014), hence reducing their impact on the environment and air quality.

The second most strongly hit mode due to RH in our analysis is personal cars, with approximately a quarter of the sample reporting a lower use of this mode. A lower use of personal cars may be counted as a positive impact of ridehailing services, since it can help reduce some urban maladies such as unwarranted parking spaces in urban areas (Zhang, Guhathakurta, Fang, and Zhang, 2015). Such a benefit, however, may not positively materialize for other dimensions such as congestion and VMT, as multiple studies point out that RH services appear to have an adverse effect on these measures (Erhardt et al., 2019; Henao and Marshall, 2019; Tirachini and Gomez-Lobo, 2020).

With respect to transit, our sample shows the negative impact of ridehailing to be considerably stronger than its positive impact. Although a small portion of our ridehailers reported a higher use of transit as a result of using RH, their share is too small to even influence the formation of a distinct latent class where its members generally report a complementary effect of RH on transit. In this respect, our analysis is more in line with previous work which points to a stronger RH substitution effect on transit rather than a bolstering impact (de Souza Silva, de Andrade, and Alves Maia, 2018; Tang et al., 2020). In addition, active modes of transportation, represented by bicycling in our data, show to be the least impacted by RH, with only 10% of the sample reporting a lower usage level, and perhaps point to the low competition between this mode and ridehailing, especially considering its smaller usage group and intended distance range.

Our latent classes of ridehailing modal impact further shed light on how ridehailing impact differs among various population segments. While taxi cabs, as mentioned, show a substantial share of usage decline in usage across all the three classes, in our younger, lower income, and more urbanite class of ridehailers it is transit that also shows a sizeable share of usage decline as a result of using ridehailing. In contrast, in the older and higher income classes of ridehailers we see a decline in personal car usage in addition to taxi cab usage while public and active modes of transportation do not see a noticeable impact. We, in addition, see signs of generational divide among the classes. Our younger class, who is earning less, exhibits a higher pro sustainable attitude, in addition to being less pro suburban and pro car, attitudinal patterns that an earlier analysis on a similar data set collected in 2015 has shown to be present in the younger generation (Etezady, Shaw, Mokhtarian, and Circella, 2020).

The adoption rate and usage of shared ridehailing, moreover, is also higher in the Substituters Class, which has younger and more urbanite ridehailers (Class 1). This observation agrees with other studies on sharing economy consumption (Winkle et al., 2018), with the younger generation often reported as avid partakers of the sharing economy. It is, however, important to notice that based on our analysis, the younger generation usage of shared ridehailing tends to also come at the expense of transit, which is still a more sustainable travel option. Especially, we see that the ridehailers in this class (and also in Class 3) who indicate that transit can meet their needs are more likely to be among the adopters of shared ridehailing, further underlining the competition between transit and shared RH among ridehailers who are also users of transit.

We, moreover, see a strong influence of sociodemographics and built environment in the adoption and usage of shared RH in all our classes. Lower age and income, fewer owned vehicles, and being an urbanite tend to be positively associated with shared RH adoption or usage in one or all of the classes. We further see that a stronger attitude toward sustainability increases the likelihood of higher adoption or usage only in our older class of ridehailers. Although our younger classes are on average more pro-sustainable, we see insignificant evidence of the role of this attitude in the adoption and use of these services among those ridehailers.

One psychological impediment in the adoption and usage of shared ridehailing is sharing the vehicle space with another passenger. We see the effect of this factor (in the form of being open to interacting with strangers) strongly in our older car centric class (Personal car augmenters), while such an effect is considerably weaker in statistical significance among the younger classes. This observation, as mentioned, further underlines a generational divide with respect to the sharing economy, where the older generations tend to be more concerned about collaborative consumption, and this factor plays a more important role in their decision toward partaking in the sharing economy.

Conclusion

In this chapter, we focused on uncovering how ridehailing modal impacts differ across population segments, and how shared ridehailing usage frequency is associated with the identified modal impact patterns. To achieve these goals, we first estimated a latent class cluster model with self-reported RH modal impacts used as the indicators of latent class. The resulting three classes showed distinctly different impacts: transit and taxis showed sizable shares of usage decline among the younger, lower income, and urbanite ridehailers, while higher income, older ridehailers tend to belong to classes where RH is largely supplemental to their use of other modes, but when there *is* an impact, it tends to be a reduction in the usage of personal cars and taxi cabs.

To investigate the association of *shared* ridehailing and the identified latent classes, we used a latent class model with distal outcome approach, thereby analyzing a bias-adjusted joint association between the latent classes and our distal outcomes. We concluded that shared RH adoption rate and usage frequency are higher in our Substituters Class, where transit and taxis see sizable shares of usage decline as a result of using RH services. Moreover, 30% of the total number of shared RH adopters in our sample and 50% of the frequent users (more than once a week) are associated with this class. On the other hand, 72% of the moderate users and 73% of the infrequent users are associated with the two (Augmenters) classes having a negligible impact on active and public modes of transportation. These results, as discussed, cast doubt on the overall sustainability of shared ride services, considering that the large share of frequent users associated with the Substituters Class.

Furthermore, we saw a strong influence of SED variables, in addition to attitudes and perceptions, on the adoption and usage of shared RH. In general, we concluded that a younger age and lower income level are associated with a higher adoption and usage level of shared rides, while a stronger pro-sustainability attitude and an openness to interaction with strangers on rides more significantly influences the adoption and usage of shared RH among the older more car centric ridehailers.

Among the limitations of the current chapter, we can point to the geography of our dataset, which covers only the state of California. Future studies, therefore, should focus on different geographies to better investigate the impacts of shared ridehailing. Moreover, although our modal impact variables captured the *direction* of impacts, they did not measure the *magnitude* of impacts on other modes. Further, since we did not know whether respondents in our sample had access to shared ridehailing in their region, we used the Uber API to identify those with access to shared rides. This approach is not perfect, but still provides a reasonable way to filter out those respondents who cannot use these services due to a lack of access. Finally, since this study's dataset was collected before the impact of COVID-19, this analysis offers few insights into the impacts of this pandemic on these services or the longevity of the impacts. Additional studies need to be conducted to assess such impacts.

Linkages Between Frequency of Ridehailing Use, Vehicle Availability, and Expectations to Change Vehicle Ownership

In this study, we propose a trivariate latent-class modeling framework to jointly study ridehailing usage frequency, vehicle ownership, and expectations to change vehicle ownership. We use a dataset (N=3141) based on a custom-designed travel survey administered in Fall 2018 in the state of California. The proposed model, in addition to accounting for parameter heterogeneity through latent segmentation, allows for an insightful behavioral interpretation of the correlations among the latent unobserved components. Our results point to more nuanced relationships between the three variables of interest and the external factors associated with them than what most other studies in the literature have revealed so far. More specifically, we see a less straightforward relationship between age and ridehailing usage frequency, for which other studies have generally pointed to a negative relationship. Our results reveal two latent clusters of approximately similar average age who show drastically different RH usage frequency. Furthermore, although we see evidence of a negative association between vehicle availability and RH usage frequency, our latent class framework again reveals two clusters with approximately similar vehicle availability but different ridehailing usage, pointing to the influence of other factors such as attitudes and the built environment in differentiating their ridehailing usage. With respect to the relationship between ridehailing usage and expectations to change vehicle ownership, our results show that, of the two clusters with similar vehicle availability and age, the one with higher ridehailing usage is less likely to expect an increase in household vehicle ownership within the next three years. This result shows some promise for the future impact of ridehailing services in containing increases in car ownership.

The following section contains an extract from Dr. Ali Etezady's PhD dissertation which is currently in the process of peer review for journal publication. Please use the following citation to cite the PhD Dissertation:

> *Etezady, SeyedmohammadAli. Transportation in an Era of Disruption: How Generational Differences And New Transportation Technologies Are Influencing Travel Behavior. PhD Dissertation, Georgia Institute of Technology, 2021.*

Introduction and Background

Ridehailing (RH) services have been a growing topic of research in the transportation and economics literature over the past several years, with a large body of this literature motivated by a need to better understand the adoption and usage in addition to the mobility and economic impacts of these services. With respect to RH adoption and usage, the literature often agrees that younger, higher educated, and urban travelers are more likely to adopt and use these services (Alemi, Circella, Handy, and Mokhtarian, 2018; Clewlow and Mishra, 2017; Rayle, Dai, Chan, Cervero, and Shaheen, 2016; Young and Farber, 2019), while consensus is yet to form over the mobility impacts of these services. Among the several mobility impacts of RH services, the interaction of RH and vehicle ownership (VO) has been a topic of growing interest among researchers and practitioners, with studies often drawing opposing conclusions on the nature of this relationship. While some studies have reinforced the initial claims that RH services can decrease VO rates among households (Hampshire, Simek, Fabusuyi, Di, and Chen, 2017; Sabouri, Brewer, and Ewing, 2020; Ward, Michalek, Azevedo, Samaras, and Ferreira, 2019), others have cautioned or pointed out the opposite (Gong, Greenwood, and Song, 2017; Schaller, 2018). Although the direction of causality in the relationship between RH usage and VO levels may prove elusive or complex, it is important to model these two variables together so as to factor the joint nature of these decisions and the shared unobserved variability between them into the modeling process.

Evidence for the nature of the relationship between RH usage and VO levels may also coincide with that of generational differences in attitudes and choices, with early research showing that Millennials tends to have a lower rate of licensure, VO, and vehicle miles traveled (Delbosc and Currie, 2013; Hopkins, 2016; Kuhnimhof et al., 2012). Similarly, the Millennial generation is reported to be strong consumers of the sharing economy (Anderson and Rainie, 2010; Ranzini et al., 2017), a trend that encourages lower ownership rates and higher consumption of shared resources, giving rise to the expectation that the sharing economy may have a disparate role in the VO decisions of different generations.

The literature, moreover, is already showing evidence that such aforementioned trends may not be enduring, as several studies hint at the Millennial generation growing out of their unique trends of higher sharing economy consumption (Hudson, 2015; Rebell, 2015), and lower VO rates and car dependence (Etezady, Shaw, Mokhtarian, and Circella, 2020; Lavieri, Garikapati, Bhat, and Pendyala, 2017). A question of further interest, therefore, is how expectations to change VO levels interact with current VO decisions and sharing economy consumption, and whether, and to what degree, such expectations are subject to heterogeneity in the population.

Accordingly, the main goal of this study is to jointly investigate the RH usage frequency, VO levels, and expectations to change VO levels (within the next three years) while accounting for heterogeneity with respect to lifestyle and age. We argue that belonging to a certain generation alone does not determine the importance of various factors to these kinds of decisions; although generation is clearly relevant, individuals of any age can have attitudes or other characteristics that predispose them in one direction or another. Accordingly, it is appropriate to use an analysis method that does not deterministically assign individuals to one category or another, but rather specifies a probabilistic model for belonging to various categories, based on a number of observed traits including attitudes as well as age *per se.*

To achieve this goal, we use a custom designed travel survey administered in Fall 2018 in California that contains a rich array of variables facilitating our analysis. We propose a joint (trivariate) latent class (JLC) modeling methodology which not only readily allows for the joint modeling of multiple variables of different types, but, in contrast to more conventional trivariate models, provides insight into the correlations between the unobserved (latent) factors of the univariate models. The unique dataset and methodology of this study, therefore, can further help shed light on the factors influencing RH usage frequency, VO, and expectations to change VO, and how these decisions tend to interact within different latent population groups.

Literature review

The literature on each of the topics included in this study is fairly extensive, and in the case of VO and VO dynamics, dates back several decades. The intent of this section, subsequently, is not to provide an in-depth and extensive review of the literature in each area, but to briefly summarize the knowledge in each field and discuss the more relevant studies in more depth.

Ridehailing usage frequency

The growing body of literature on RH adoption, especially those studies conducted in the US and Canada, report the younger, well-educated, and urbanite travelers as more likely to be among RH users (Tirachini, 2019). The studies on RH usage frequency, however, are comparatively fewer, with results that sometimes point to different conclusions. Alemi, Circella, Mokhtarian, and Handy (2019) estimated ordered probit models of RH usage frequency, and found sociodemographics to be rather weak predictors of usage frequency. Their results point to long-distance travel, attitudes toward car ownership, and willingness to pay to reduce travel time to be strongly associated with RH usage. Some other studies, however, point to age and income as also being among the significant predictors of RH usage frequency (Sikder, 2019; Tirachini and del Río, 2019), with the younger or more affluent tending to be more frequent RH users. On the other hand, evidence from New York and Los Angeles, U.S., points to lower-income neighborhoods as producing more frequent users of ridehailing (Atkinson-Palombo, Varone, and Garrick, 2019; Brown, 2018). There is, therefore, a clear need for further investigation of RH usage frequency (and of its relationships with the other dependent variables of interest that are the object of investigation in this study).

Vehicle ownership and availability

VO has been an important area of research in the transportation field for the past few decades, a topic with important implications for public health (Giles-Corti et al., 2016), job accessibility (Gao, Mokhtarian, and Johnston, 2008), travel demand modeling (Cervero, 2006), and air quality (Kitamura, Pas, Lula, Lawton, and Benson, 1996). This variable has been studied in different forms: many studies directly model the number of vehicles owned by a household (Bhat and Pulugurta, 1998), while some study a measure of household vehicle availability such as the number of household vehicles per licensed driver, or a vehicle deficiency measure such as having fewer vehicles than drivers (Blumenberg, Brown, and Schouten, 2018).

Considering the nature of the VO variable, the literature offers various modeling frameworks for its study, including linear regression, count, ordinal, or multinomial logit (probit) models. The explanatory variables used with these models often include sociodemographics and built environment characteristics. Those living in higher income households with higher numbers of workers and licensed drivers tend to own more cars (Bhat, 1998; Potoglou and Kanaroglou, 2008), and households living in more urban areas tend to own fewer cars than their rural counterparts (Bento, Cropper, Mobarak, and Vinha, 2005; J. M. Dargay, 2002). Several studies, in addition, have implemented various versions of the aforementioned modeling techniques to account for heterogeneity in the data. Anowar, Yasmin, Eluru, and Miranda-Moreno (2014), for instance, used a latent class modeling framework to study vehicle ownership in Quebec, Canada, and identified two latent segments of transit independent and transit friendly travelers, with each segment showing distinct modeling coefficients. Kim and Mokhtarian (2018), using a similar framework, identified two latent segments of auto-oriented and urbanites, and reported built environment factors as more influential in VO decisions of the latter class than in those of the former class. In both studies, accounting for heterogeneity in modeling VO resulted in a superior model fit.

Intentions/decisions to change vehicle ownership levels

The dynamics of VO is another important area of transportation research, since change in a household's level of VO has implications for their overall mobility and mode choice. The availability of more large-scale panel datasets has engendered more studies on this topic, with research showing that household life-cycle, current status of VO, life events, and residential relocation all contribute to change in household VO (Clark, Lyons, and Chatterjee, 2016). J. M. Dargay and Vythoulkas (1999), using data from annual Family Expenditure Surveys in the UK reported that VO increases as the head of household grows older until 50 years old, and then decreases. In another study, J. Dargay and Hanly (2007) used the British Household Panel survey and reported the current VO levels to be strongly associated with the future VO levels, and that the probability of a decline in VO is higher in young (18-24 years old) and old (over 65 years old) households. Clark, Chatterjee, and Melia (2016) highlighted the influence of different life events on VO, reporting that changes such as entering the work force are associated with an increase in VO, while having a child showed an association with both an increase of VO from one to two, and also a decrease of VO from two to one. Yamamoto (2008), using French and Japanese datasets, reported on the influence of residential relocation in addition to life events on VO, concluding that relocation of younger households is associated with a decrease in VO.

While the studies above investigate *decisions* to change vehicle ownership levels, a number of other studies use self-reported *expectations/intentions* to change vehicle ownership. These studies are generally motivated either by a lack of available panel data, or the phenomenon under study whose impact is yet to come to pass. In any case, investigating people's intentions or expectations with regard to their vehicle ownership change can provide valuable behavioral insights. Examples of these studies include Luke (2018), who studied the factors influencing car ownership intentions among a sample of South African students; Kim, Mokhtarian, and Circella (2020) who studied the expectation to change vehicle ownership in an AV future among a sample of Georgians in the U.S.; or Sigurdardottir, Kaplan, and Møller (2014) who studied the intentions and motivations underlying the vehicle ownership time-frame decision and obtaining driving licensure.

Interaction of ridehailing usage and vehicle ownership

The interaction of RH and VO has been another topic of great interest in the literature. The direction of causality between these two variables can often be hard to elucidate; in other words, while for some a low level of VO may prompt a higher usage of RH, for others having access to RH services may prompt a decision to decrease VO levels. Most studies in the literature, however, often sidestep the possible bidirectional nature of this relationship, and use modeling techniques that tend to accommodate only one direction. For instance, Conway et al. (2018) used the U.S. 2017 National Household Travel Survey (NHTS) and applied a logistic regression model to estimate predictors of RH adoption, with results pointing to a negative impact of VO on RH adoption. Sabouri et al. (2020) used the same dataset and estimated both a multilevel Poisson and a random forest model to study the predictors of VO, and pointed to a negative impact of RH on VO. Dias et al. (2017) used the 2014-2015 Puget Sound Regional Travel Survey and estimated bivariate ordered probit models of RH and carsharing usage. Their results point to the built environment-mediated influence of VO on RH usage, with a clear negative relationship existing in low density neighborhoods. Tirachini and del R?o (2019), using a 2017 intercept survey in Santiago de Chile, estimated a generalized ordered logit model of RH usage, but did not find a statistically significant impact of VO levels on RH usage. On the other hand, however, Gong et al. (2017) used a dataset of new vehicle registrations in China, and investigated how the timing of Uber entry to the market impacted vehicle purchases (representing the opposite direction of causality, namely that RH influences VO). Their findings point to a significant positive impact of Uber entry on vehicle purchases. Schaller (2018), moreover, by studying VO data through the U.S. census and synthesizing results from other research, provided arguments against the negative relationship between RH usage and VO and auto usage.

Dependent variables

RH usage frequency

The survey recorded respondents' answers to their RH usage frequency by providing the following options: "I am not familiar with [this service]", " it's familiar but I've never used it", "I used it in the past, but not anymore", "I use it less than once a month", "I use it 1-3 times a month", "I use it 1-2 times a week", and "I use it 3 or more times a week". As mentioned, we excluded those who reported they were not familiar with RH services from our analysis. Furthermore, the shares of those reporting using RH "1-2 times a week" and "3 or more times a week" were very small at 3.8% and 1.3%, respectively, and we subsequently decided to merge these levels with the "1-3 times a month" level to avoid estimation issues (untenable coefficients) and called this new merged level "regular users". Similarly, those who use RH less than once a month were categorized as "infrequent users", and those who reported they are not current users were categorized as “not a user”. Table 32. shows more details on the RH usage variable used in this study.

Table 32. Distribution of the RH usage variable of this study (N=3141)

Variable used in the model	Underlying levels	N Underlying items (%)	N Variable used in the model (%)
Not a user	It’s familiar but I’ve never used it.	1342 (42.7%)	1512 (54.5%)
	I used it in the past, but not anymore.	370 (11.8%)	
Infrequent user	I use it less than once a month.	861 (27.4%)	861 (27.4%)
Regular user	I use it 1-3 times a month.	407 (13.0%)	568 (18.1%)
	I use it 1-2 times a week.	120 (3.8%)	
	I use it 3 or more times a week.	41 (1.3%)	

Vehicle availability

We decided to use a measure of “vehicle availability” in our modeling as opposed to a simple vehicle ownership variable, since vehicle availability is a more useful measure of a household’s mobility status (CambridgeSystematics, 1997), and can be more insightful in our context where its relationship with RH usage is of interest. We, therefore, defined a binary measure of “household vehicle deficiency” using the number of licensed drivers in a household vs. the number of vehicles owned by it. A household owning fewer vehicles than its number of licensed drivers is coded as “1” or “vehicle deficient”, and “0” otherwise. The share of vehicle deficient households in our dataset is 17.6%.

Intentions to change vehicle ownership

The survey used in this analysis also collected data on what respondents expected will happen to their household’s car ownership over the next three years. The options available included: “increase the number of cars”, “decrease the number of cars”, “keep the same total but replace one or more cars”, “No change”, and “I do not know”. Although we could have used the variable as is in a categorical format, the desire to focus on level, in addition to the added model parameters in return for small additional interpretability, prompted a recoding of this variable. Table 33. shows the distribution of this variable in our model.

Table 33. Distribution of the intentions to change VO levels in this study (N=3136)

Variable used in the model	Underlying categories	N Underlying categories (%)	N Variable used in the model (%)
Decrease intention	Decrease the number of cars	196 (6.2%)	196 (6.2%)
No/unclear intention	Keep the same total but replace one or more cars	1000 (31.8%)	2542 (80.9%)
	No change	1206 (38.4%)	
	I do not know	336 (10.7%)	
Increase intention	Increase the number of cars	398 (12.7%)	398 (12.7%)

Results

In discussing the results below, we first present the membership model portion of the analysis, and then focus on the outcome models. We divided the dataset into training and test sets (approximately 80%, 20% of the sample, respectively) to be able to check for improvements in model prediction accuracy as well. In deciding the number of latent clusters associated with each dependent variable, we firstly estimated separate univariate LC regression models for each variable, and identified a suitable number of latent clusters based on each model's information criteria (IC) (Magidson and Vermunt, 2004) and interpretation. We subsequently started from the identified number of clusters in the previous step and varied the number per each LC variable and looked for improvement in the joint model's IC, prediction accuracy, and overall interpretability, in addition to checking for violation of the CI assumption.

We used attitudinal factors (in addition to age, in the case of RH usage frequency) as the model covariates (Z) to be able to define the LCs as "lifestyle segments", and left the other sociodemographics and travel behavior variables to the outcome portion of the model.

Membership model

Figure 26 shows a more detailed schematic of the membership model of this study. We tested different covariate (Z) specifications and retained only statistically significant effects in the final model. Furthermore, the directions of effect between the LC variables were determined largely based on empirical grounds. It is relevant to note that our modeling structure does not assume a causal relationship between the dependent variables themselves, but establishes a correlation among them through their associated LC variables. Establishing directions of causality among the LC variables themselves, however, is a less straightforward matter, given their more abstract definition. Although assuming a bidirectional correlation among the LC variables would have been a more straightforward assumption, we could not establish such formulation mathematically in our model as defined previously. We, therefore, empirically tested different causal structures among the LC variables, and chose the one resulting in the best model fit. The results showed that the specification where memberships in the LCs associated with ridehailing and vehicle availability influenced membership in the LC associated with expectations to change VO had a superior model fit.

In discussing the results in this section, we only present the descriptive statistics of the LCs in addition to the parameters of their association, and include the detailed table of membership model parameters in the Appendix.

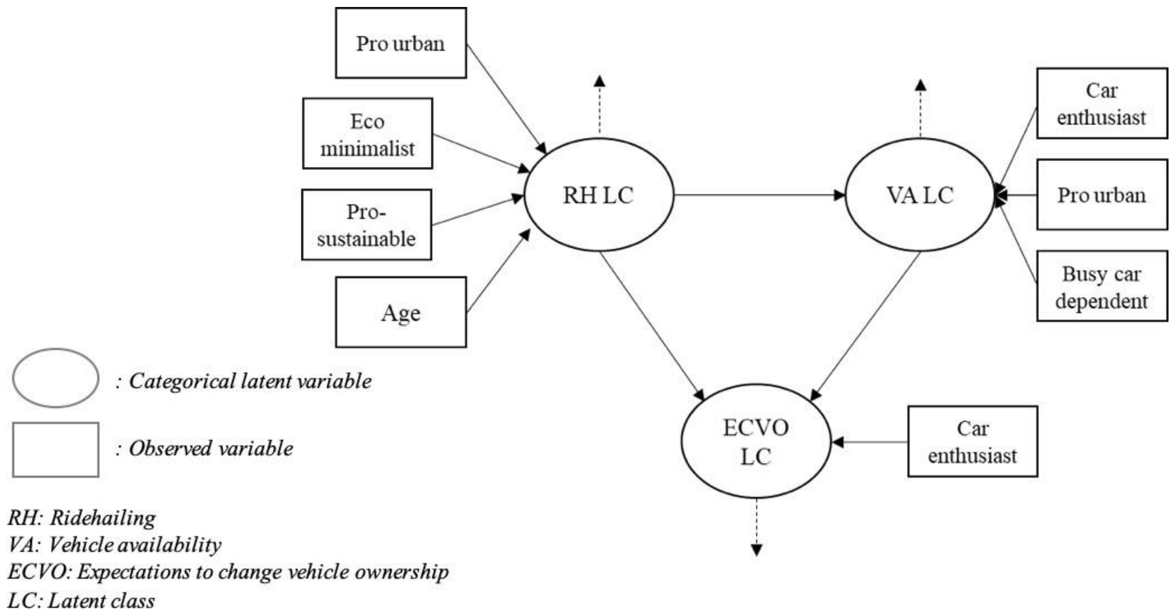


Figure 26. The schematic of the membership sub-model of this study

Table 34. shows a summary of the descriptive statistics of the membership model. In each vertical section, presenting the respective profiles of the LCs associated with each of the three outcome variables, the bolded rows highlight the values of the statistically significant variables directly involved in the class membership modeling for each associated LC variable. We should note that given the structure of the membership model of this study, the covariates that are involved in modeling the RH LC variable also indirectly influence the VA LC and ECVO LC variables formation, as do covariates involved in modeling the VA LC variable which also similarly exert an indirect influence on the ECVO LC variable. As such, we find the averages of some covariates in Table 34. to be noticeably different across the latent clusters of the VA and ECVO LC variables while their direct statistical influence appears to be insignificant.

Table 34. Summary of descriptive statistics of the Joint latent class membership sub-model ($N_{Training\ set}$=2412)

Model variables	Descriptive statistics Variable means/share per Class						
	RH usage frequency LC			Vehicle deficient household LC		Expectations to change vehicle ownership LC	
	Younger Eco-friendly (31.4%)	**Younger Non-eco-friendly (29.0%)**	**Older Car Enthusiast (39.6%)**	**Car Enthusiast & Dependent (58.5%)**	**Non-car Dependent Lower Income (41.5%)**	**Non-eco-friendly Car Enthusiast (29.6%)**	**Eco-friendly Stable in Life (70.4%)**
Outcome variables							
RH usage frequency *(ordinal)*							
Not a user	**0.124**	**0.728**	**0.740**	0.556	0.524	0.537	0.545
Infrequent user	**0.325**	**0.250**	**0.258**	0.290	0.258	0.267	0.281
Regular user	**0.552**	**0.022**	**0.002**	0.154	0.218	0.197	0.174
Vehicle deficient HH *(binary)*	0.203	0.223	0.131	**0.013**	**0.416**	0.296	0.132
Intentions to change HH's VO *(categorical)*							
Intention to decrease	0.049	0.036	0.073	0.064	0.042	**0.022**	**0.069**
Undecided or keep the same	0.812	0.695	0.922	0.879	0.741	**0.581**	**0.923**
Intention to increase	0.139	0.269	0.005	0.058	0.216	**0.398**	**0.009**
Model covariates							
Age	**40.96**	**41.63**	**59.33**	50.64	45.30	41.45	51.35
FS Pro-sustainable	**0.298**	**-0.209**	**-0.111**	-0.081	0.087	-0.051	0.006
FS Eco-minimalist	**0.107**	**-0.247**	**0.083**	-0.002	-0.011	-0.139	0.051
FS Pro-urban	**0.141**	**-0.362**	**0.116**	**-0.160**	**0.191**	-0.176	0.053
FS Car enthusiast	-0.161	0.016	0.112	**0.288**	**-0.409**	**0.096**	**-0.042**
FS Busy car dependent	-0.043	0.055	-0.015	**0.178**	**-0.259**	-0.038	0.011
Inactive covariates							
FS Life adrift	0.171	0.198	-0.254	-0.100	0.167	0.206	-0.071
HH income							
Low income HH (<$50K)	0.311	0.314	0.286	0.270	0.346	0.322	0.293
High income HH (>$100K)	0.409	0.338	0.374	0.403	0.334	0.356	0.382
Graduate degree or higher	0.221	0.198	0.259	0.241	0.213	0.205	0.240
Urban dweller	0.403	0.331	0.296	0.297	0.400	0.352	0.334

Latent classes associated with ridehailing usage frequency

The RH usage frequency LC variable denominates three clusters. Cluster 1, or the Younger Eco-friendly, comprises 31% of the sample. RH regular users form the majority of this cluster, while the non-users' share is the smallest at 12.4%. The respondents in this cluster have an average age of approximately 41 years old, making them the youngest of the three clusters (although by a small margin compared to the second cluster). With respect to the other active covariates, this cluster defines itself as the most pro-sustainable, eco-minimalist, and pro-urban of all the RH clusters. This cluster, in addition, is the least car enthusiast, and compatible with their average age, expresses a lower sense of life stability compared to the older Cluster 3. Moreover, the share of those living in vehicle deficient households, at 20.3%, is fairly similar to that of Cluster 2, but higher than Cluster 3, and the share of those who express an intention to increase their VO, at 13.9%, is considerably lower than Cluster 2, yet substantially higher than Cluster 3. With respect to income, this cluster has the highest share of high incomes, while its share of low incomes is similar to that of Cluster 2 and higher than that of Cluster 3. Moreover, the share of the highly educated in this cluster is higher than for the similarly aged Cluster 2, but lower than for the older Cluster 3. Finally, the share of those in this cluster living in urban areas, at 40.3%, is the highest of all the clusters.

Cluster 2, or the Younger Non-eco-friendly, comprise a slightly smaller share of the sample, at 29%. It largely includes those who are not users of RH (72.8%), with the share of infrequent and regular users at 25.0% and 2.2%, respectively. The average age of the respondents in Cluster 1 is approximately 41.6 years old, and they are on average the least pro-sustainable, eco-minimalist, and pro-urban of those in the sample. Their attitude toward car ownership is more positive than that of the approximately similarly aged Younger Eco-friendly, but less so than that of the older respondents of Cluster 3. With respect to inactive covariates (including the other dependent variables), we observe that this cluster has a slightly higher share of vehicle deficient households than do the Younger Eco-friendly. In terms of expectations to change VO in the next three years, we see that this cluster contains the largest share (at 26.9%) of those who express an intention of increasing, and the smallest share (3.6%) of those who express an expectation of decreasing. Furthermore, this cluster, on average, and consistent with their younger average age, are more life adrift than the older Cluster 3, but are fairly on par with the similarly aged Younger Eco-friendlies. In terms of income and education, the respondents in this cluster are comparatively lower income and lower educated than those of the other two clusters. Finally, with respect to the built environment, we see that the share of those living in urban areas in this cluster, at 33.1%, is in between those of the (similarly aged Cluster 2) and (older) Cluster 3.

Finally, Cluster 3, or the Older Car enthusiast, contains 40% of the sample. In this group we see, on average, older respondents whose share of regular RH users is close to zero. Their attitudes on sustainability, eco-minimalism, and urban living are in between those of Clusters 1 and 2, while they characterize themselves as the most car enthusiast and life stable among the clusters. The share of those who report an increase intention toward VO is close to zero, while the share of those with a decrease intention, albeit still relatively small, is the largest of all the clusters. In terms of income, the respondents in this cluster have the lowest share of low incomes, while their share of high incomes is in between those of Clusters 2 and 3. Furthermore, this cluster has the highest share of the highly educated, in addition to the lowest share of urban dwellers.

Latent classes associated with vehicle availability

The vehicle availability LC variable designates two clusters. Cluster 1, the Car enthusiast & Dependent cluster, involves about 58% of the sample. Its share of vehicle deficient households is quite small at approximately 1.3%, with attitudes against urban living and for car ownership considerably stronger than in the second cluster. Furthermore, this cluster is comparatively less pro sustainable but more life stable, and the share of those reporting an intention to increase their household's VO levels is substantially lower than the other cluster's at 5.8%. In terms of socioeconomic status, this cluster is relatively higher income, with it having a lower share of low-income households (27.0%) and a higher share of high-income households (40.3%). Finally, the share of those living in urban areas, at 29.7%, is comparatively lower than in the other cluster.

Cluster 2, or the Non-car Dependent Lower Income cluster, contains the remaining 42% of cases. A substantial portion of the respondents in this cluster live in vehicle deficient households, and they are comparatively more pro-urban and less car enthusiast than those in Cluster 1. Furthermore, the share of those who express that their household intends to increase its VO levels is comparatively higher at 21.6%, while the share of those expressing a decrease intent, at 4.2%, is relatively lower than that of Cluster 1. Finally, and as mentioned above, this cluster is comparatively lower income and lower educated, with a higher share of its respondents living in urban areas.

Latent classes associated with expectations of changing vehicle ownership

Finally, for the intentions to change vehicle ownership (in the next three years) variable, we identify two latent clusters. The Eco-friendly Stable in Life cluster, containing 30% of the sample, contains a relatively larger share of those with an intention to increase their household's VO (at 39.8%) compared to that of Cluster 2 (the Non-eco-friendly Car Enthusiast cluster) at less than 1%. Furthermore, the share of those expressing an intention to decrease, at 2.2%, is also comparatively smaller than that of Cluster 2, where 6.9% express such an intention. This cluster, furthermore, contains a larger share of vehicle deficient households than Cluster 2 does (29.6% vs. 13.2%, respectively), and on average has respondents that are more Car enthusiastic. The respondents in this cluster are also relatively less pro-sustainable, eco-minimalist, and pro-urban than the other cluster. Moreover, this cluster is a relatively lower income and lower educated group, with a slightly higher share of it living in urban areas.

The associations between the latent class variables

Table 35. shows a summary of the parameters of the LC variables' association model. Considering that the dependent variables here are categorical LC variables, the coefficients are associated with an MNL model (with effect coding). For ease of presentation and discussion, we only include the parameters directly related to the LC associations here, and leave the detailed

presentation of the results (such as constant terms and observed covariates' coefficients) to the Appendix.

Table 35. Summary of the (MNL) membership model parameters of the associations between the latent class variables (N=2412)

Explanatory variable	Clusters	Dependent variables: Vehicle deficient household LC — Car Enthusiast & Dependent	Vehicle deficient household LC — Non-car Dependent Lower Income	Expectations to change VO LC — Non-eco-friendly Car Enthusiast	Expectations to change VO LC — Eco-friendly Stable in Life
		Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)	Coef. (S.E.)
Ridehailing usage frequency LC	Younger Eco-friendly	-0.0010 (0.106)	0.0010 (0.106)	0.499** (0.248)	-0.499** (0.248)
	Younger Non-eco-friendly	-0.357* (0.214)	0.357* (0.214)	1.431*** (0.382)	-1.431*** (0.382)
	Older Car enthusiast	0.358** (0.171)	-0.358** (0.171)	-1.930*** (0.501)	1.930*** (0.501)
Vehicle deficient household LC	Car Enthusiast & Dependent	–	–	-0.710** (0.302)	0.710** (0.302)
	Non-car Dependent Lower Income	–	–	0.710** (0.302)	-0.710** (0.302)

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.

As Table 35. demonstrates, being a member of "RH: Younger Non-eco-friendly" cluster increases the propensity to belong to the "VA: Non-car Dependent Lower Income" cluster, while this relationship, although positive in sign, is statistically and practically zero for the "RH: Younger Eco-friendlies". This positive association in the former case is as expected, since this cluster contains a higher share of vehicle deficient households than the others, and some of its other characteristics such as income level and ECVO align with this cluster. On the other hand, we see that belonging to the "RH: Older Car enthusiast" cluster positively and significantly increases the propensity to belong to the "VA: Car Enthusiast & Dependent" cluster.

Moreover, being a "RH: Younger Non-eco-friendly" or "RH: Younger Eco-friendly" member increases the propensity of belonging to the "ECVO: Non-eco-friendly Car Enthusiast" cluster. Comparing the coefficient sizes of the two RH clusters, however, we see that (all else equal) the "RH: Younger Eco-friendlies" are less likely to belong to the "ECVO: Non-eco-friendly Car Enthusiast" cluster than the "RH: Younger Non-eco-friendlies". The "RH: Older Car enthusiasts", on the other hand, are more likely to belong with the "ECVO: Eco-friendly Stable in Life" cluster.

Finally, we see that, also as expected, being a member of "VA: Non-car Dependent Lower Income" cluster increases the likelihood of belonging to the "ECVO: Non-eco-friendly Car Enthusiast" cluster, implying that those with lower existing vehicle availability tend to have a higher intention to increase their household's VO.

Outcome models

In this section, we first discuss each of the outcome models of this study in turn, and then present the accuracy of the model with respect to the prediction of each dependent variable on the designated test set. As mentioned, the explanatory variables used in the outcome models include sociodemographics, built environment, and travel behavior variables.

Ordered logit model of ridehailing usage frequency

Table 36. shows the parameters of the ordered logit model of RH usage frequency. Among the sociodemographic variables, we largely see intuitive results. Those living in low-income households are less likely to be among the more frequent users of RH, while having a higher level of education is positively associated with a higher RH usage level.

The built environment, moreover, shows a logical relationship with RH usage frequency, with those living in urban areas more likely to be among the more frequent ridehailers. This relationship, however, is statistically weak in the “RH: Younger Non-eco-friendly” cluster, and further points to the difference between the “RH: Younger Eco-friendly” and “RH: Younger Non-eco-friendly” clusters.

With respect to other travel behaviors and opinions, we see that those with a more positive opinion about transit meeting their needs are also more likely to be among the more frequent ridehailers, although this positive impact is much weaker among the “RH: Younger Non-eco-friendlies”. This result implies that RH may be drawing from the same pool of travelers as transit, although we cannot necessarily infer the complementary/competitive nature of this relationship from this model. Finally, carsharing adopters across all three clusters are significantly more likely to use RH services on a regular basis, likewise pointing to the similar pool of travelers that both RH and carsharing have in common.

Table 36. Ordered logit outcome model of ridehailing usage frequency ($N_{training\ set}$=2412)

Explanatory variables	RH Clusters		
	Younger Eco-friendly	Younger Non-eco-friendly	Older Car enthusiast
	Coef. (Robust S.E.)	Coef. (Robust S.E.)	Coef. (Robust S.E.)
Low income HH	-1.110*** (0.230)	-4.387*** (0.887)	-1.101*** (0.302)
Holding a graduate degree or higher	0.713* (0.396)	0.588* (0.334)	0.713*** (0.23)
Urban dweller[1]	0.955*** (0.242)	0.183 (0.349)	0.455* (0.273)
Transit meets my needs[2]	0.238** (0.114)	0.026 (0.138)	0.260** (0.105)
Carsharing adopter	1.598* (0.934)	5.856*** (1.152)	1.639*** (0.624)
Thresholds			
Threshold 1 (non-user | infrequent user)	0.062 (0.19)	-4.308*** (1.029)	-4.732** (1.932)
Threshold 2 (infrequent user | frequent user)	0.357** (0.157)	1.694*** (0.475)	1.492 (0.921)

Model statistics:
Npar=31, LL_{EL}*=-2653.15,* LL_{MS}*=-2406.42*
LL_{β}*=-2112.36*
$\rho^2_{EL,\ adj.}$*=0.193,* $\rho^2_{MS,adj.}$*=0.109*

Model statistics for equivalent univariate model:
Npar=31
LL_{β}*=-2117.01*
$\rho^2_{EL,\ adj.}$*=0.193,* $\rho^2_{MS,adj.}$*=0.107*

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.
[1] Defined based on the geocoded home addresses of the respondents and the typology presented by Salon (2015).
[2] Single item measured on a 5-level Likert type scale from strongly disagree to strongly agree.

Binary logit model of household vehicle deficiency

Table 37. presents the binary logit model of household vehicle deficiency. Income is negatively associated with living in a vehicle deficient household, although this effect is statistically insignificant for the “VA: Car Enthusiast & Dependent” cluster. This result may imply that even if a household has lower income, if attitudinal traits favor auto-oriented lifestyles, income does not appear to be a significant deterrent to owning as many vehicles as there are licensed drivers. This may be as much a matter of lifestyle-generated ‘necessity’ as of preference, however. Furthermore, we see that the number of children in the household under 15 years old is statistically significant for the “VA: Non-car Dependent” cluster, indicating that a higher number of children decreases the likelihood of a household having an insufficient number of vehicles (possibly due to a higher demand for activities and personal travel).

A higher number of employed people in the household, moreover, is negatively associated with household vehicle deficiency status in the “VA: Car Enthusiast & Dependent” cluster, while this impact is practically and statistically insignificant in the "VA: Non-car Dependent Lower Income" cluster.

With respect to the impact of race, we see that White households in both clusters, when compared to the other races, are less likely to be among those with an insufficient number of vehicles (even after controlling for income, employment, and number of children), suggesting a racial inequality in vehicle availability among non-White households.

Finally, we see that built environment has a statistically significant relationship with vehicle deficient status in the "VA: Non-car Dependent Lower Income" cluster, where households living in urban areas are more likely to be among those with fewer vehicles than licensed drivers. This result is as expected, since urban life tends to help promote less reliance on car ownership, given the higher density and better transit services in urban areas than in suburban or rural areas.

Table 37. Binary logit outcome model of belonging to a vehicle deficient household ($N_{Training\ set}$=2412)

Explanatory variables	Vehicle deficient household clusters: Car Enthusiast & Dependent	Vehicle deficient household clusters: Non-car Dependent Lower Income
	Coef.[1] (Robust S.E.)	Coef.[1] (Robust S.E.)
High income HH	-0.661 (6.713)	-0.253** (0.111)
No. children in the HH under 15 years old	0.998 (0.626)	-0.135*** (0.045)
No. of employed in the HH	-4.819*** (1.685)	0.069 (0.062)
White	-1.097** (0.554)	-0.215 ** (0.104)
Urban dweller[2]	-0.721 (0.778)	0.278*** (0.084)
Constant	-0.714 (0.477)	-0.067 (0.195)
Model statistics: *Npar=18* LL_{EL}=-1671.87, LL_{MS}=-1138.87, LL_{β}=-1040.36 $\rho^2_{EL,adj.}$=0.367, $\rho^2_{MS,adj.}$=0.071	*Model statistics for equivalent univariate model:* *Npar=17* LL_{β}=-1037.61 $\rho^2_{EL,\ adj.}$=0.369, $\rho^2_{MS,adj.}$=0.074	

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.

[1]Since effect coding is used in the modeling process, the coefficient associated with the base level of the binary dependent variable (i.e., belonging to a vehicle-sufficient household) is no longer 0, but equal to the opposite sign of the reported coefficients here. For brevity, we have refrained from presenting those coefficients here.

[2] Defined based on the geocoded home addresses of the respondents and the typology presented by Salon (2015).

MNL model of expectations to change vehicle ownership

Table 38. shows the MNL model parameters of the expectations to change household's VO (in the next three years). Consistent with the literature, the group of explanatory variables used in this model include the household's current level of VO, its built environment, (expected) changes in life stage, and other variables including the impact of using carsharing services. With respect to the impact of the current number of household vehicles, we see that, in both clusters, a higher number is positively associated with an intention to decrease and negatively associated with an intention to increase (although this impact is statistically insignificant in the first cluster).

Furthermore, households in urban areas who belong to the "ECVO: Non-eco-friendly Car Enthusiast" cluster are more likely to express an intention to increase their VO levels, while this effect is reversed in the "ECVO: Eco-friendly Stable in Life" cluster (although it is statistically insignificant there). Considering that the "ECVO: Non-eco-friendly Car Enthusiast" cluster is comparatively less pro-urban than the other cluster, this result can possibly point to the higher intention of the urban dwellers in this cluster to move out and subsequently require a higher number of vehicles for personal travel.

In terms of expected changes in life stage, we see a statistically significant effect of finishing studies in the "ECVO: Eco-friendly Stable in Life" cluster, while interestingly this effect is statistically insignificant in the first cluster. Those who expect to graduate soon in the "ECVO: Eco-friendly Stable in Life" cluster are less likely to express an intention to decrease their household VO and more likely to express an intention to increase.

With respect to the impact of using other shared mobility services, we generally see statistically weak effects. However, those in the "ECVO: Non-eco-friendly Car Enthusiast" cluster who are among the adopters of carsharing services are more likely to have an intention to decrease their VO than their non-carsharing counterparts.

Table 38. MNL outcome model of expectations to change vehicle ownership (ECVO) ($N_{Training\ set}$=2412)

Explanatory variables	**Dependent variable level**	**ECVO cluster**	
		Non-eco-friendly Car Enthusiast	Eco-friendly Stable in Life
		Coef.[1] (Robust S.E.)	Coef.[1] (Robust S.E.)
HH current no. of vehicles	Decrease	0.217 (0.912)	0.945*** (0.232)
	Undecided or keep the same	-0.054 (0.487)	0.270 (0.222)
	Increase	-0.164 (0.430)	-1.214*** (0.442)

Explanatory variables	Dependent variable level	ECVO cluster: Non-eco-friendly Car Enthusiast	ECVO cluster: Eco-friendly Stable in Life
		Coef.[1] (Robust S.E.)	Coef.[1] (Robust S.E.)
Urban dweller[2]	Decrease	-1.641^{*} (1.007)	0.419 (0.437)
	Undecided or keep the same	0.826^{*} (0.52)	-0.005 (0.428)
	Increase	0.815^{*} (0.511)	-0.414 (0.829)
End studies in the next 3 years	Decrease	0.700 (1.102)	-3.021^{***} (0.518)
	Undecided or keep the same	-0.720 (0.587)	-2.061^{***} (0.425)
	Increase	0.021 (0.56)	5.082^{***} (0.787)
Carsharing adopter	Decrease	3.125^{*} (1.921)	-1.748 (2.657)
	Undecided or keep the same	-2.476 (2.01)	-0.479 (1.535)
	Increase	-0.650 (0.479)	2.226 (1.400)
Constant	Decrease	-3.114 (2.018)	-0.264 (0.390)
	Undecided or keep the same	1.734^{*} (1.038)	4.072^{***} (0.337)
	Increase	1.381 (1.055)	-3.808^{***} (0.667)

Model statistics:
Npar=25
LL_{EL}=-2649.85, LL_{MS}=-1395.83, LL_{β}=-1247.25
$\rho^2_{EL,adj.}$=0.520, $\rho^2_{MS,adj.}$=0.089

Model statistics for equivalent univariate model:
Npar=24
LL_{β}=-1277.24
$\rho^2_{EL,\ adj.}$=0.509, $\rho^2_{MS,adj.}$=0.067

***, **, * denote a statistical significance of less than 0.01, 0.05, 0.10, respectively.
[1] Effect coding has been used in the modeling process here.
[2] Defined based on the geocoded home addresses of the respondents and the typology presented by Salon (2015).

Prediction accuracy of the model

Although the JLC model provides improved interpretation of and a deeper insight into the relationship between our outcome variables and how the external variables affect them, it is also important to compare how it performs with respect to the prediction of the outcome variables. Table 39. presents a comparison of the prediction accuracy (defined as the share of correctly predicted cases) of the JLC model of this chapter with the equivalent univariate models. As points of comparison, we trained and tested equivalent (same explanatory variables and number of classes) univariate latent class regression models for each outcome variable, in addition to traditional (ordinal, binary, and multinomial logit) models and their respective market share models.

Overall, we see very small improvements in the prediction accuracy of the outcome variables as a result of using the JLC framework. For RH usage frequency, JLC performs similarly to its univariate counterpart. This improvement increases to 0.2 and 5.5 percentage points when using the univariate ordinal logit model and univariate market share model as the base, respectively.

With respect to the household vehicle deficiency status, we see that the JLC outperforms the univariate LC model by 0.6 percentage points, and further outperforms the univariate binary logit and market share models by 0.9 and 1.7 percentage points, respectively.

Regarding the expectations to change household's VO, the JLC model performs similarly as the univariate LC and traditional models, while outperforming the market share model by 0.2 percentage points.

Table 39. Summary of the comparison of the prediction accuracy of the JLC model against univariate models on the test dataset (N_{Test}=695)

	Prediction accuracy[1]			
Outcome variable	Joint latent class model	Univariate latent class model	Univariate traditional model	Univariate market share model
Ridehailing usage frequency	0.601	0.601	0.599	0.546
Household vehicle deficiency status	0.851	0.845	0.842	0.834
Expectations to change household's vehicle ownership	0.764	0.764	0.764	0.762
JLC model's log-likelihood = -4373.10 No. of parameters=74				

[1] Prediction accuracy is defined as the number of correctly predicted cases divided by the total number of predicted cases.

Discussion

The results of the RH frequency LC point to several interesting findings. Although literature often paints the younger generation as generally more pro-RH and pro-urban while less pro-car, our analysis presents two (roughly equally-sized) clusters who are of similar average (younger) age, but showing distinctly different behavior and attitudes. The first RH cluster in our analysis, i.e., the "RH: Younger Eco-friendly" cluster, is predominantly RH dependent, as a majority in it use RH services on a regular basis, a characteristic in stark contrast with the "RH: Younger Non-eco-friendly" cluster, where only 2% are among the regular users. Therefore, in contrast with the results of some other studies such as Sikder (2019) and Tirachini and del Río (2019), we see a less straightforward relationship between age and RH usage, a relationship where being younger is not necessarily associated with a higher RH usage. On the other hand, we find a similar relationship between income and RH usage frequency as compared to the literature: the membership model of our analysis points to the "RH: Younger Eco-friendlies" as having, on average, higher incomes than their counterparts, and the outcome model also consistently shows that being lower income diminishes the propensity for higher RH usage across the three RH clusters.

With respect to the relationship between RH usage and household vehicle availability LC variables, our results draw a more detailed conclusion compared to the other studies. Our younger clusters who use RH more frequently than the older cluster also contain a higher share of vehicle deficient households, a result further corroborated by the positive coefficients that associate the two younger clusters with the "VA: Non-car Dependent Lower Income" cluster. However, these two younger clusters with similar shares of vehicle deficiency show significantly different levels of RH usage frequency, indicating that factors other than vehicle availability (such as built environment and attitudes) are associated with their difference in RH usage.

Furthermore, the relationship between vehicle availability and expectations to change VO LC variables shows a positive association between the "VA: Non-car Dependent Lower Income" and "ECVO: Non-eco-friendly Car Enthusiast" clusters, indicating that belonging to the "VA: Non-car Dependent Lower Income" cluster increases the likelihood of being associated with the "ECVO: Non-eco-friendly Car Enthusiast" cluster. Interpreting this relationship with respect to the distributions of their respective outcome variables shows that members of the VA cluster who are more likely to live in vehicle deficient households are also more likely to be among those in the ECVO cluster with a higher share of those expressing an expectation of VO increase in the future. This relationship, moreover, is more specifically corroborated in the ECVO outcome model where the MNL results show that a higher number of vehicles in the household is negatively associated with an increase intention, and positively associated with a decrease intention.

Finally, the relationship between the RH LC and the ECVO LC variables shows that the first two RH LC clusters (Younger Eco-friendly and Younger Non-eco-friendly) are both significantly and positively associated with the "ECVO: Non-eco-friendly Car Enthusiast" cluster, while the "RH: Older Car enthusiast" cluster is positively associated with the "ECVO: Eco-friendly Stable in Life" cluster. Comparing the coefficients associated with the two younger clusters, however, reveals that the "RH: Younger Non-eco-friendlies" are considerably more likely to belong to the "ECVO: Non-eco-friendly Car Enthusiast" cluster. In other words, although both clusters are of similar average age and contain approximately similar shares of vehicle deficient households, those in the cluster with a higher RH usage are less likely to belong to the "ECVO: Non-eco-friendly Car Enthusiast" cluster. This result is also in line with the distribution of the expectations to change VO within the RH LC, where a smaller share of those in the "RH: Younger Eco-friendly" cluster report a VO increase intention than among the "RH: Younger Non-eco-friendlies". This conclusion, therefore, hints at the future impact of RH services, where its users, as they grow older and more stable in life, might be less likely to want to own more vehicles.

Summary and conclusion

In this chapter, we aimed to jointly study ridehailing usage frequency, household vehicle availability, and expectations to change household's vehicle ownership while also accounting for unobserved heterogeneity in the data. To accomplish this goal, we proposed a joint (trivariate) latent class modeling framework that not only can simultaneously model multiple variables of different types, but also accounts for unobserved heterogeneity in the data through the probabilistically defined categorical latent variables (classes). We further discussed how, as opposed to the traditional trivariate models where the correlation between the latent error terms of the models provide little additional insight into the data, this approach allows for the specification and interpretation of the association between the latent variables.

Our results further confirm the impact of income and education on RH usage frequency as reported in the literature, with those living in higher income households and having a higher education level tending to use these services more often. This study, however, provides more detailed insights with respect to the impact of age on RH usage compared to the previous studies. Our RH LC model identifies two clusters of similar age and reported life-stability level, with one having a significantly higher RH usage level. We further discussed the different characteristics that differentiate these clusters, and cautioned against homogeneously describing the younger generation as the more frequent users of RH services.

We, moreover, discussed the relationship between RH usage and vehicle availability, pointing out that, again, this relationship can be more nuanced than what is already discussed in the literature. Although the cluster with lower household vehicle availability tends to be positively associated with the two higher RH usage clusters (although weakly in the Younger Eco-friendly case), we see substantially different RH usage levels but similar shares of vehicle deficient households between the two RH clusters. This result, therefore, points out that the relationship between RH usage and vehicle availability is not the same across all segments of the population.

With respect to the interaction of latent clusters associated with RH usage and future intentions to change VO levels, we concluded that, controlling for age (and life stability) and vehicle availability levels, those in the RH LC cluster with a higher usage of RH services are less likely to belong to the Non-eco-Friendly car enthusiast cluster than those in the cluster with a low usage of RH. This result can further bolster the promise of a decreased car dependency in the future as a result of the availability of RH services.

This study entails a number of limitations that need to be mentioned. Firstly, the geography of our dataset, which covers only the state of California, can be limiting in terms of generalizability of the results. Future studies, therefore, should focus on different geographies to better investigate the interaction of RH usage and vehicle ownership. Furthermore, we use self-reported intentions when it comes to future changes in VO level of a household, rather than actual revealed changes. Although this application may be less insightful, we still believe that expressed intentions can be elucidating when it comes to the joint study of vehicle ownership and RH usage.

Latent Market Segments for the Adoption of Fully Automated Vehicles in California

Automobile manufacturers are pushing the rapid development of automated vehicles (AVs) despite a limited understanding of consumer demand and potential impacts on travel behavior. An effective policy response depends on an improved understanding of who will be interested in (early) adoption of AVs, what the users' preferred business models (private vs. shared) will be, and how the eventual adoption of shared automated vehicle (SAV) services will likely impact personal/household vehicle ownership levels. This study addresses these topics through a market segmentation analysis using latent-class modeling of data from a custom-designed transportation survey of California residents. I use sociodemographics, general attitudes, and current AV familiarity to define the segments. The analysis uncovered three latent classes: (1) AV Early Adopters who are enthusiastic about the fully automated AV scenarios presented (private ownership and shared services) and are ready to adopt shared AVs instead of owning other personal/household vehicles, (2) AV Curious who are less enthusiastic about AVs than the prior class and more likely to maintain their current vehicle ownership in the future even when using shared AV services, and (3) AV Hesitant who are resistant to using either private or shared AVs and would not be interested in reducing their vehicle ownership levels if they had access to SAV services. The characteristics of the three classes provide a basis for actionable recommendations for both private companies and transportation policy makers.

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Introduction

As the possibility of fully automated vehicles (AVs) comes closer to reality researchers can play an important role in the development of a policy response by examining how this new technology will be accepted by consumers and how it will impact travel behavior. Recent research into AVs has shown that AV deployment and adoption have many potential positive as well as negative effects. The positive effects range from (eventual) reduced traffic congestion and pollutant emissions, higher roadway throughput, increased mobility, to a reduction of safer roadway costs with the inverse of these as the potential negatives (Litman 2014). Beyond basic underlying acceptance of the new technology, it will be important to understand the rate of adoption and the adoption patterns among various segments of the population when this technology becomes available on the market. Anticipating the preferred ownership model and the potential impacts that AV adoption might have on household vehicle ownership is also imperative, particularly because it currently appears that shared automated vehicle (SAV) fleets that operate like transportation network companies (TNCs) will be deployed before private ownership becomes available. As the TNC deployment of AVs is driven by the development cycle of the technology and not necessarily underlying consumer preference, my thesis investigates consumer response to both shared and privately-owned AVs. Developing an understanding of the potential for the speed and magnitude of adoption during the transition period between the current transportation status quo (with no/extremely limited AVs) to a transportation future dominated by AVs is important for addressing issues such as road safety or congestion that may arise during the transition, thereby delaying the realization of the potential benefits. Two studies on this topic suggested that until the AV market reaches a saturation point of 30% the benefits of AVs will not be actualized (Ye and Yamamoto 2018, Nishimura, Fujita et al. 2019).

While it is easy to get tunnel vision on all the benefits of AVs, it is important to take a step back and consider the potential negative effects of AVs. AVs have the potential to further cement us into our current land-use and development preference of single-passenger vehicle focused infrastructure by making travel in AVs so easy people would not even consider alternative modes or designs. This would likely also negatively impact public transportation as AVs could siphon off passengers which would put further financial stress on these public services. It is important to have a robust public transportation system as it provides critical services to its users and when used at sufficient levels is more environmentally sustainable. It is important researchers, developers, and policymakers acknowledge the negative effects of AVs so they can find ways to mitigate the negative effects directly in the product design or indirectly via broader policies to ensure AVs are deployed equitably and sustainably.

Businesses are driving the development of AV-related technology at such an accelerated pace that the research community must conduct forward-looking research to try and anticipate the implications of this technological surge, and policy makers need to get ready to regulate the many aspects associated with this disruptive technology. It is estimated that an additional $80 billion in revenue for AV manufacturers captured by 2030 with the sales of automated vehicles and automated features (Jiang, Petrovic et al. 2015). With this significant future revenue stream available, there is so much interest from manufacturers and technology companies in bringing it to the market as soon as possible AVs and its supporting technology.

One of the critical requirements for AVs to produce many of their positive outcomes is achieving widespread acceptance of shared use over private ownership (Sperling 2018). One of the societal benefits of the shared ownership model of AVs is the potential for the associated car shedding, i.e., reducing the number of cars a person/household owns (Lavieri, Garikapati et al. 2017). While car shedding may reduce the revenue of AV manufacturers, in recent years we have seen them enter the shared vehicle market, which would provide the means for them to recapture this revenue. This would generate a reduced need for parking as well as other implications for land use and land consumption in cities thus prompting a potentially more efficient use of the existing resources. Whatever the business model behind the deployment of AVs, a person's willingness to reduce car ownership is an indicator of a pertinent shift in travel behavior that can lead to realizing the benefits of AVs. That is one of the topics I planned to investigate in my thesis.

Framing AVs in this manner lays the foundation for the study to seek answers to the following questions:

- Who will compose the different segments of the early AV adoption market?
- What ownership model would be preferred, i.e., private vs. shared. By whom and why?

While research in this field is inherently explorative given the lack of individuals' exposure to the topic, as well as the degree of misinformation in some media (Charness, Yoon et al. 2018) and the speculative nature of predicting future behavior, it is still important to conduct this research as it can help inform other research, policy makers, and business in the development of the AV field into a thriving and beneficial component of future transportation systems.

The following maps out the structure of the remaining sections. First, in the next section we summarize a review of the literature to present the current body of work related to the topic of this thesis, which will cover topics such as AV adoption, its benefits and costs, and related studies that highlight the gaps this research will address. Next, Section 3 presents a detailed account of the data collection efforts conducted for this research. Then the analytical methods utilized in the research are presented to provide a thorough accounting of the underlying thought processes for the major components of the data analysis, which is centered on the application of the latent class analysis (LCA) but also includes a factor analysis of individual attitudes. The following section delves into the conclusions that can be drawn from the analysis with an emphasis on practical policy implications that address current concerns among transportation planners and policy makers. This is then followed by a brief discussion on the limitations of this research and how future research efforts on this topic could address them while continually pushing the body of knowledge in the field forward.

Methods and Analysis

The modeling methodology used to analyze the data is latent class analysis. This was selected as it provided a robust method to probabilistically segment the data. The conceptual model in

Figure 27 was used to identify the groups of users with specific AV-related adoption propensity and study their associated expectations regarding changes in their household vehicle ownership.

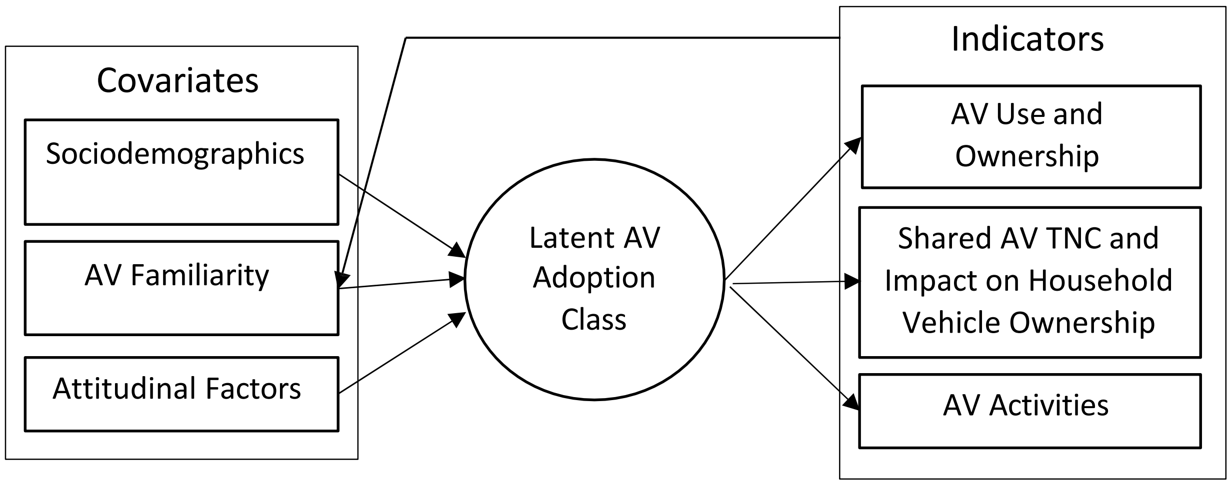

Figure 27. Conceptual model for latent class analysis

The active covariates of Sociodemographics, AV Familiarity, and Attitudinal Factors were selected to define the latent classes which then are used to estimate the likelihood of key AV-related activities across the indicators of AV Use and Ownership, AV TNC and Impact on Vehicle Ownership, and AV Activities. AV Familiarity plays a unique role as it can be an exogenous variable, but it can also be an endogenous variable as a person's environment may have a level of AV activity that encourages one to gain familiarity with it. In this case, the indicators would affect the level of AV Familiarity. While it is important to capture this in the conceptual model this interaction was not included in the model as the indicators as measured in the survey were measuring hypothetical future scenarios so it could not be the case of them influencing the AV Familiarity as they are not currently widely deployed on the streets.

Two quality of fit measures were used to aid in the assessment of an LCA model, Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC), to balance the model's specificity and sensitivity. They consist of a log-likelihood function (i.e., a goodness of fit term) and a penalty function to control overfitting.

While there is no single best IC for all scenarios the literature suggests that AIC is preferred when good future prediction is the emphasis while BIC is preferred when emphasizing a parsimonious model (Nylund, Asparouhov et al. 2007, Tihomir Asparouhov 2015, Dziak, Coffman et al. 2020). Is a variation of AIC and is another IC that I used as it more heavily penalizes the additional parameters in the models compared to AIC at a rate of 3 versus 2, respectively? This is beneficial in finding an optimum solution that favors parsimony in the model specification, i.e., not ballooning the number of parameters to artificially improve the AIC score. The penalty weights for the three ICs are present in Table 40.

Table 40. Summary of information criterion penalty weights

Information Criterion	Penalty Weight
AIC	$A_n = 2$
AIC3	$A_n = 3$
BIC	$A_n = \ln(n)$

Another factor to consider is that each IC tends to a different type of error, with AIC more likely to overfit while BIC is most likely to underfit (Dziak, Coffman et al. 2020). When considering the different emphasis, penalty weight, and likely error of each IC is best to run all of ICs to get a holistic picture of the quality of the model as the strengths and weaknesses of the ICs to offset each other resulting in the best attempt deriving the most valid assessment.

Interpretability was a subjective process where each estimated model's results were assessed based on how clear of a result it provided. The goal was to have classes of clear and differentiated characteristics. It was also important to have the results make sense in the real world as there is potential for results to be counter to observations due to forced unrealistic parameters on the model, i.e., too many or too few classes.

To determine the specific variables among these categories and the number of classes, an iterative process of increasing complexity was used to estimate the model which was assessed for quality of fit and interpretability. The initial round included only the indicator variables related to AV Use and Ownership and AV TNC and Impact on Household Vehicle Ownership were used to provide an estimate of the number of classes to use in later rounds with the results being between 3 and 4. It was limited at this point to establish a baseline on a simplified model. Round 2 added sociodemographic variables of Household Income, Age, Neighborhood Type, Gender, Employment Status, and Education Level as covariates. The result of this estimation indicated that the additional indicators would be needed to add in the interpretability of the results and thus align with the conceptual model. Round 3 went back to a simplified indicator-only model to reestablish the ideal number of classes since all future models would include the full complement of variables. The results indicated that the additional classes should be considered so the following rounds 3-7 classes were estimated. Round 4 reintroduced the sociodemographic variables as covariates: while the results had a high quality of fit, the interpretability was difficult due to the limited number of characteristics available to define the classes. The 7 class results were poor and future rounds did not include an estimation of a 7-class model. Round 5 had the inclusion of a new indicator of expected changes in the level of car ownership in the next 3 years as it was directly related to the other variables. This additional was not impactful as the results followed in lock step with the other covariates and were therefore dropped because interoperability of the results was unaffected. The level of familiarity with AVs was added to the covariates as it made logical sense that a class of current familiarity would impact future expected behaviors. After estimating the results from these 4 levels of classes, an error was noticed in the level of responses for the AV familiarity. It had 5 categories and not the expected 4. This was an error introduced during the data cleaning process and was easy to recode to the correct value for the 2 cases that had the miscoded 5th categorical response. Round 6 was conducted at this point. It was determined that 3 classes would be the final solution as it provides interpretable results and the BIC supported this conclusion. Also, Round 7 was an intermediate step that involved reviewing the covariates and recoding where appropriate. The Age variable was the only variable that needed additional recoding. One category had only 53 responses compared to the others which were 5 to 18 times higher. It was decided to combine the low response category of 18-20 years old with the adjacent category of 21-37 years old to make an 18-37 year-old category. This also had the benefit of creating age categories that were more comparable in size. The 18-20 years old bin included only 3 years because of the artificial boundaries of the data collection process not allowing respondents under 18 to respond. This did not significantly affect the model's statistical results but did greatly improve the interpretability. The two combined age groups closely mirror one another thus simplifying the results while not reducing the meaning. Round 8 was an attempt to make the results even more interpretable by including additional covariates to define the characteristics of the different classes more clearly. The new covariates were the attitudinal factors that were binned (Low, Medium, High) and standardized to allow for comparison while not introducing additional complexity to the interpretability that would come with a continuous variable.

The final vectors of variables used for the indicators and covariates are presented in Table 41. and Table 42.

Table 41. Summary of indicators

Variables	Question/Statement	Variable Type	Response Scale
AV Ownership – First to buy	I would be one of the first people to buy a self-driving vehicle.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
AV Ownership – Wait until widely accepted	I would eventually buy a self-driving vehicle, but only after these vehicles are commonly used.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
Use AV taxi service	I would use a driverless taxi alone or with others I know.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
Vehicle Ownership – Keep current vehicle ownership level, not use AV TNC services	I would keep the vehicles(s) that I/my household owns (if any) and not use a driverless taxi or shuttle.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
Vehicle Ownership – Keep current vehicle ownership level, use AV TNC services	I would keep the vehicles(s) I/my household owns (if any) and also use a driverless taxi or shuttle, when needed.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
Vehicle Ownership – Reduce current vehicle ownership level, use AV TNC services	I would get rid of one (or more) of my household vehicles and use a driverless taxi or shuttle.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
AV Activities – Increase travel while tired	I would more often travel even when I am tired, sleepy, or under the influence of alcohol/medications.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
AV Activities – Send empty AV for simple errands	I would send an empty self-driving car to do simple errands (e.g., pick up groceries, pick up clothes from dry cleaners).	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
AV Activities – Send empty AV to pick up/drop off kids	I would send an empty self-driving car to pick up/drop off my child.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
AV Activities – Travel more frequently for social/leisure activities	I would travel to social/leisure activities more often (e.g., dining at restaurants, shopping at malls).	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
AV Activities – Travel farther for social/leisure activities	I would go to more distant social/leisure activities (e.g., visiting friends, shopping).	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
AV Activities – More long-distance trips by AV, replacing other modes	I would make more long-distance trips by car because it would be less burdensome to travel in a self-driving car.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely
AV Activities – Work in AV	I would reduce my time at the regular workplace and work more in the self-driving car.	5-point Likert-type scale	1=Very Unlikely – 5=Very Likely

Table 42. Summary of covariates

Variables	Question/Statement	Variable Type	Response Scale
Neighborhood Type	Imputed via geolocation data	Categorical variable	1=Urban 2=Suburban 3=Rural
Gender – Female	What is your gender identity?	Recoded to dummy variable	1=Female 0=Not Female
Employment Status	Are you currently employed?	Recoded to dummy variable	1=Employed 0=Not Employed
Education Level	What is your educational background? Please check the highest level attained.	Recoded to dummy variable	1=Bachelor's Degree or higher 0=Below Bachelor's degree
Age	In what year were you born?	Recoded to categorical variable	1=18-37 2=38-53 3= 54-73 4=73+
Household Income Level	Please check the category that contains your approximate annual household income before taxes.	Categorical variable	1=<$25,000 2=$25,000 to $49,999 3=$50,000 to $74,999 4=$75,000 to $99,999 5=$100,000 to $149,000 6=$150,000 or more
Level of Familiarity with AVs	We are interested in your awareness of or familiarity with the concept of self-driving vehicles before you started taking this survey. Please check the response that best describes you.	Categorical variable	1=I have never heard of it 2=I have heard of it but am not familiar with it 3=I have heard of it and am somewhat familiar with it 4=I have heard of it and am very familiar with it
Attitudinal Factor – Pro-sustainability	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High
Attitudinal Factor – Pro-technology	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High
Attitudinal Factor – Pro-car enthusiast	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High

Variables	Question/Statement	Variable Type	Response Scale
Attitudinal Factor – Pro-suburbia	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High
Attitudinal Factor – Pro-car dependency	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High
Attitudinal Factor – Pro multitasking while commuting	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High -1 to 1
Attitudinal Factor – Anti-consumerism	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High
Attitudinal Factor – Life/Career Adrift	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High
Attitudinal Factor – Pro-car utilitarian	Factor score based on self-reported level of agreement with attitudinal statements.	Categorical variable	1=Low 2=Medium 3=High

Results

The composition of the sample is shown in Table 43 with a sample size of n=2,918. The final sample is in line with the expectations of our sampling method. Due to the limitations of a mailed survey, responding to all questions could not be mandatory. Education Level, Age, and Familiarity with AVs have a lower sample size than the other variables. Without the means to reliably impute the missing values, the cases with missing data for variables used in the model were listwise deleted from the dataset. The respondents' self-reported familiarity with AVs was rather high with 65.7% expressing at least some level of familiarity with the technology.

Table 43. Sample demographics (n=2,918)

Variable	n	%
Neighborhood Type		
Rural	651	22.3
Suburban	1343	46.0
Urban	924	31.7
Gender		
Female	1574	53.9
Male	1344	46.1
Transgender	0	0.0
Employment Status		
Employed	1844	63.2
Unemployed/Retired	1074	36.8
Education Level		
Some Grade School/High School	45	1.3
Completed High School	280	8.1
Some College/technical School	1485	43.1
Bachelor’s Degree	1000	29.0
Graduate Degree	500	14.5
Professional Degree	135	3.9
Age		
18-37 years old	861	29.5
38-53 years old	919	31.5
54-72 years old	894	30.6
73 years old or older	244	8.4
Income		
Less than $25,000	372	12.7
$25,000 to $49,999	545	18.7
$50,000 to $74,999	494	16.9
$75,000 to $99,999	440	15.1
$100,000 to $149,999	552	18.9
$150,000 or more	515	17.6
Familiarity with AVs		
I have never heard of it	134	4.6
I have heard of it but am not familiar with it	866	29.7
I have heard of it and am somewhat familiar with it	1422	48.7
I have heard of it and am very familiar with it	496	17.0

As discussed in the previous section, I tested various model specifications with two through five classes and used the criteria of the fit indices plus interpretability of the results to select the final model. Table 44 summarizes the fit indices (BIC, AIC, AIC3) for the two, three, four, and five class solutions.

Table 44. Fit indices for LCA solutions

Model	BIC_{LL}	AIC_{LL}	$AIC3_{LL}$
2-class	94500	93920	94017
3-class	90336	89487	89629
4-class	89117	87999	88186
5-class	89376	87988	88220

The indices suggested a solution of four classes as it is the local minimum for the BIC_{LL}, and $AIC3_{LL}$ fit indices. AIC_{LL} did not result in a minimum, which was expected as this fit index does not heavily penalize for the additional classes (and therefore additional parameters) as AIC3. The fit indices suggested a four-class solution, so it was further scrutinized for real-world interpretability. This solution did not pass this test even though the classes were statistically unique, but two of the classes were close enough that it made interpreting the results impractical. I then reviewed the five-class solution, but the classes continued to provide inconclusive interpretations. Then the three-class solution was reviewed which provided an interpretable result by not having classes that overlapped. The two-class model was examined but it reintroduced the issues of having ill-defined classes as it oversimplified the solution. Thus, the three-class solution was selected as the LCA model for the remainder of the analysis.

Class 1 has 949 members (32.51%), Class 2 has 1,259 members (43.15%), and Class 3 has 711 members (24.35%). Table 45 presents the membership probability for each covariate which is a measure of the likelihood of being in a particular class based on the observations of each variable. Then Table 46 presents the same data for the indicators.

Table 45. Membership model for 3 class solution – covariates

Covariate	Class 1 *AV Early Adopter* 32.50%	Cluster2 *AV Curious* 43.20%	Cluster3 *AV Hesitant* 24.40%
Neighborhood Type			
Urban	38.90%	41.20%	19.90%
Suburban	34.00%	43.90%	22.10%
Rural	20.30%	44.40%	35.30%
Gender			
Not Female	38.40%	42.00%	19.60%
Female	27.50%	44.10%	28.40%
Employment Status			
Not Employed	23.20%	45.40%	31.40%
Employed	37.90%	41.80%	20.30%
Education Level			
Up to some college/tech school	26.70%	43.00%	30.40%
Bachelor or Higher	37.10%	43.30%	19.60%
Age			
18-37 years old	45.40%	40.60%	14.00%
38-53 years old	33.20%	44.00%	22.80%
54-72 years old	23.60%	43.10%	33.30%
73 years old +	17.20%	49.00%	33.70%
Household Income			
Low (<$50k)	26.70%	45.70%	27.60%
Medium ($50k-100k)	31.40%	40.40%	28.20%
High (>$100k	38.50%	43.30%	18.20%
Familiarity with AVs			
I have never heard of it	25.90%	49.60%	24.50%
I have heard of it but am not familiar with it	24.50%	46.80%	28.60%
I have heard of it and am somewhat familiar with it	32.10%	44.30%	23.60%
I have heard of it and am very familiar with it	49.40%	31.70%	19.00%
Pro-Sustainable Policy			
Low	12.50%	38.70%	48.80%
Medium	31.50%	45.00%	23.60%
High	51.50%	40.40%	8.10%
Tech Enthusiast			
Low	13.30%	43.20%	43.50%
Medium	31.90%	45.30%	22.80%
High	52.60%	34.30%	13.10%
Car Enthusiast			
Low	38.60%	45.80%	15.60%
Medium	31.50%	42.70%	25.80%
High	30.10%	42.00%	27.90%

Covariate	Class 1 *AV Early Adopter* 32.50%	Cluster2 *AV Curious* 43.20%	Cluster3 *AV Hesitant* 24.40%
Pro-Suburbia			
Low	33.90%	40.90%	25.20%
Medium	31.30%	46.00%	22.70%
High	35.50%	34.60%	29.90%
Car Dependent			
Low	30.40%	42.50%	27.10%
Medium	32.20%	45.70%	22.20%
High	35.60%	36.30%	28.10%
Commute Multitasker			
Low	23.70%	46.70%	29.60%
Medium	30.80%	44.70%	24.60%
High	47.80%	33.60%	18.60%
Eco-minimalist			
Low	23.40%	44.40%	32.20%
Medium	32.60%	44.00%	23.40%
High	41.00%	38.20%	20.70%
Life/Career Adrift			
Low	21.30%	40.60%	38.10%
Medium	33.20%	43.30%	23.50%
High	40.70%	45.00%	14.30%
Car Utilitarian			
Low	27.10%	43.50%	29.40%
Medium	33.20%	44.50%	22.40%
High	35.10%	37.30%	27.60%

Table 46. Membership model for 3 class solution – indicators

Indicator	Class 1 *AV Early Adopter* 32.5%	Cluster2 *AV Curious* 43.2%	Cluster3 *AV Hesitant* 24.4%
AV Use and Ownership			
Be one of the first to buy an AV			
Very Unlikely	12.5%	45.9%	41.7%
Somewhat Unlikely	43.5%	54.0%	2.5%
Neither Unlikely nor Likely	51.8%	47.9%	0.3%
Somewhat Likely	83.6%	16.3%	0.1%
Very Likely	91.7%	8.4%	0.0%
Eventually buy an AV, only after commonly used			
Very Unlikely	2.9%	25.3%	71.8%
Somewhat Unlikely	11.6%	68.4%	20.0%
Neither Unlikely nor Likely	25.1%	68.4%	6.6%
Somewhat Likely	50.9%	47.2%	1.9%
Very Likely	78.9%	20.8%	0.3%
Willing to use an AV TNC service			
Very Unlikely	4.4%	32.8%	62.8%
Somewhat Unlikely	16.7%	75.0%	8.3%
Neither Unlikely nor Likely	33.2%	65.3%	1.5%
Somewhat Likely	65.3%	34.7%	0.1%
Very Likely	91.7%	8.3%	0.0%
Shared AV TNC and Impact on Household Vehicle Ownership			
Keep the same number of vehicles and not use an AV TNC service			
Very Unlikely	67.7%	29.0%	3.4%
Somewhat Unlikely	64.5%	34.8%	0.7%
Neither Unlikely nor Likely	44.8%	49.9%	5.3%
Somewhat Likely	38.9%	55.2%	5.9%
Very Likely	12.3%	38.8%	49.0%
Keep the same number of vehicles and use an AV TNC service			
Very Unlikely	5.1%	21.4%	73.5%
Somewhat Unlikely	14.4%	67.1%	18.4%
Neither Unlikely nor Likely	25.2%	65.0%	9.8%
Somewhat Likely	54.9%	43.2%	1.9%
Very Likely	70.2%	23.6%	6.3%
Reduce the number of vehicles and use an AV TNC service			
Very Unlikely	16.5%	41.4%	42.1%
Somewhat Unlikely	42.3%	53.1%	4.6%
Neither Unlikely nor Likely	40.6%	53.6%	5.8%
Somewhat Likely	70.8%	28.5%	0.7%
Very Likely	75.9%	18.1%	6.0%
AV Activities			
Use AVs to travel more when tired or under influence of alcohol			
Very Unlikely	3.2%	20.5%	76.3%
Somewhat Unlikely	8.8%	70.9%	20.3%

Indicator	Class 1 *AV Early Adopter* 32.5%	Cluster2 *AV Curious* 43.2%	Cluster3 *AV Hesitant* 24.4%
Neither Unlikely nor Likely	16.9%	73.4%	9.8%
Somewhat Likely	46.9%	50.3%	2.9%
Very Likely	78.4%	20.8%	0.8%
Use AVs to do simple errands			
Very Unlikely	5.6%	29.2%	65.2%
Somewhat Unlikely	22.4%	70.5%	7.1%
Neither Unlikely nor Likely	28.2%	67.3%	4.5%
Somewhat Likely	58.3%	40.4%	1.4%
Very Likely	85.5%	13.5%	1.0%

To aid in the analysis a visualization of the results is prepared in Figure 28 as a profile plot. A profile plot is a useful way to compare the different classes by plotting the class-specific mean magnitude of each indicator for each class rescaled to lie within 0 and 1, so when viewed against each other one can see the distinct profile for the various indicators of each class. The rescaling is “accomplished by subtracting the lowest observed value from the class-specific means and dividing the results by the range” (Vermunt and Magidson 2005). Consistent with the previous description of the three classes, the members of the AV Early Adopter class have a higher average willingness to adopt and use AVs for all activities. Interestingly, they express a stronger propensity towards both buying an AV and using AV TNC service. Interestingly, and somewhat differently from my previous expectation, this class tends to be more “pro-AVs” in general, regardless of the ownership and operational model that is deployed for AVs. This class represents the most interested and engaged AV adopters of all classes, so it has been labeled as “AV Early Adopter”.

The profile of the AV Curious class identifies those who are interested in AVs but are somewhat more hesitant than the members of the first group. They tend to be moderately interested in adopting AVs and use them for several purposes, but also more resistant to being the first one to buy an AV and/or jumping on the automated TNC model and reducing their household vehicle ownership. For this reason, the class is labeled as “AV Curious” to capture their mild interest in AVs but that it is not strongly held.

Members of the AV Hesitant class have little interest in AVs or AV TNC services as suggested by the near 0 values for their profile except for a near 1 value for “Keeping the same number of vehicles and not using AV TNC services”, a clear marker of their adversity to the vehicle automation and their strong preference to maintaining the current status quo. Accordingly, this group is labeled as “AV Hesitant”.

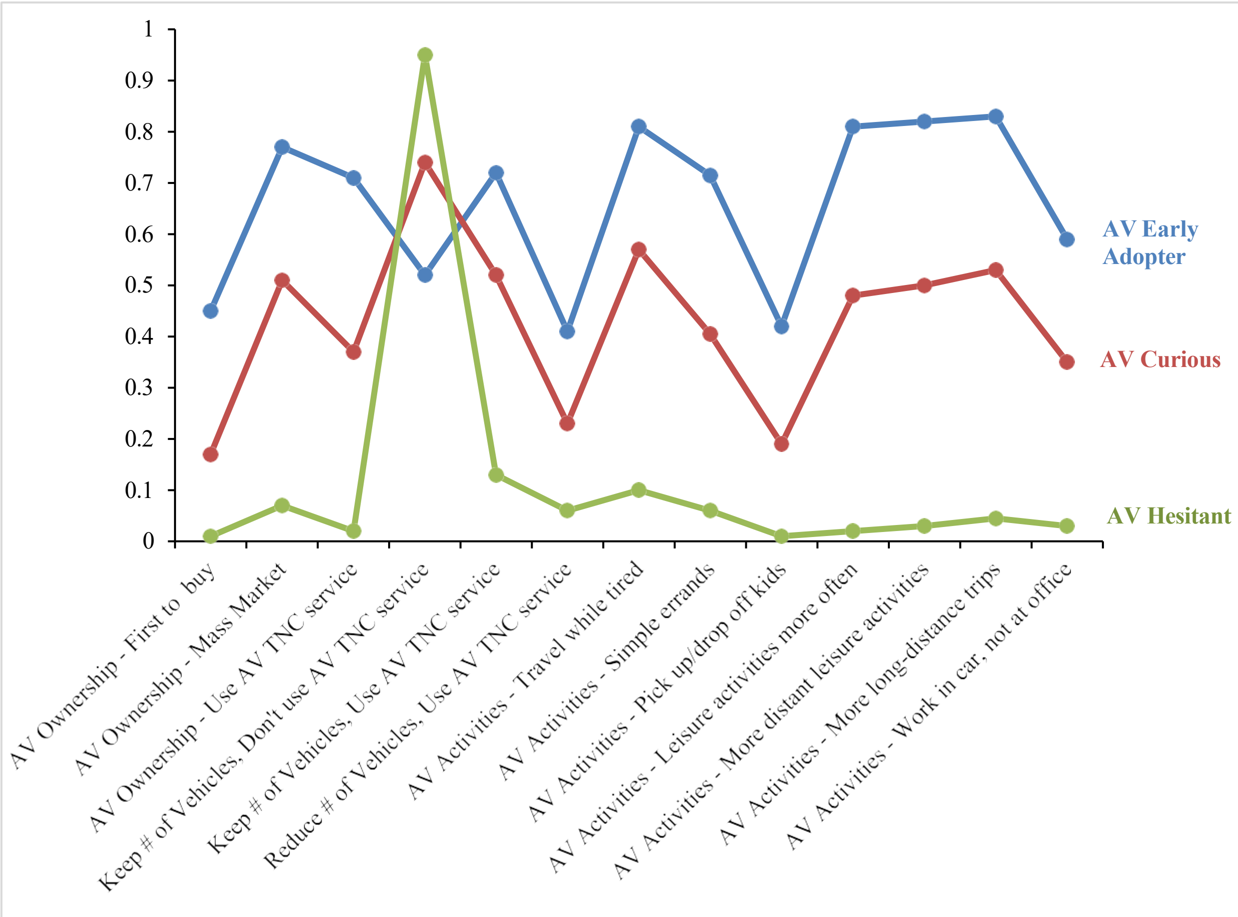

Figure 28. Profile plot for 3 class model

With the classes well defined, it is important to understand who is composing the class. Table 47 lists the membership percent of the sample for each of the sociodemographic characteristics. As AV Early Adopter class is the largest share (43.15) of the sample it closely follows the full sample and will therefore be used as the reference for the comparison of the other two classes. Looking at the neighborhood type, AV Hesitant skew more rural (.32) while AV Curious has the highest likelihood of being in an urban location (.38). AV Hesitant lean more heavily toward being female (.63) and the AV Curious class goes against the full sample and has a bias towards being not female, *i.e.,* males and other non-binary responses. Employment status for AV Early Adopters is in line with the full sample while AV Curious is more likely to be employed while AV Hesitant is more likely to be unemployed. The AV Curious class is more likely to be more highly educated while the AV Hesitant is more likely to be less highly educated. Regarding the age of the classes, AV Curious skews younger than AV Early Adopters, in contrast to the AV Hesitant who tend to be older individuals. The composition of the classes regarding their household income suggests that AV Curious people have higher household incomes compared to AV Hesitant which skews away from the high level towards medium and low levels of household income. Finally, for the self-reported level of familiarity with AVs before taking the survey AV Curious report a much higher level of being very familiar with AVs (.26) compared to the other classes, AV Early Adopters (.12) and AV Hesitant (.13).

Table 47. Distribution of covariates by class

	AV Early Adopter	AV Curious	AV Hesitant	Sample Share
Neighborhood Type				
Urban	30.2%	37.9%	25.9%	31.7%
Suburban	46.8%	48.1%	41.8%	46.0%
Rural	23.0%	14.0%	32.3%	22.3%
Gender				
Not Female	44.9%	54.4%	37.1%	46.1%
Female	55.1%	45.6%	62.9%	53.9%
Employment Status				
Not Employed	38.7%	26.3%	47.4%	36.8%
Employed	61.3%	73.7%	52.6%	63.2%
Education Level				
Up to some college/tech school	43.8%	36.1%	54.8%	44.0%
Bachelor or Higher	56.3%	63.9%	45.2%	56.1%
Age				
18-37 years old	27.8%	41.2%	17.0%	29.5%
38-53 years old	32.1%	32.2%	29.5%	31.5%
54-72 years old	30.7%	22.2%	41.9%	30.7%
73 years old +	9.5%	4.4%	11.6%	8.4%
Household Income				
Low (<$50,000)	33.3%	25.8%	35.6%	31.4%
Medium ($50,000-$100,000)	30.0%	30.9%	37.0%	32.0%
High (>$100,000)	36.7%	43.3%	27.4%	36.6%
Familiarity with AVs				
I have never heard of it	5.3%	3.7%	4.6%	4.6%
I have heard of it but am not familiar with it	32.2%	22.4%	34.9%	29.7%
I have heard of it and am somewhat familiar with it	50.1%	48.1%	47.3%	48.8%
I have heard of it and am very familiar with it	12.5%	25.8%	13.2%	17.0%

The attitudinal factors covariates are also important in understanding the composition of classes. As with the sociodemographic covariates, the AV Adopter closely follows the full sample share so it will again be used as the reference point for the analysis of the other two classes. See Table 48. for the full set of results. The AV Curious class has a much higher proportion of people who score high on Pro-Sustainable Policy (.31) than the expected (.18) while AV Hesitant skews the other direction with .30 scoring in the Low category compared to the expected .14. The same pattern is found in Tech Enthusiast with AV Curious have a higher proportion in the High category (.27) while AV Hesitant lean more to the Low category (.27). The attitudes toward being a Car Enthusiast are consistent across the classes with the only notable variance being that the AV Hesitant have a lower share in the Low category and a corresponding shift upwards in the Medium category. The factors for Pro-Suburbia, being a Car Dependent, or being a Car Utilitarian do not suggest anything across the different classes as the differences between them are minimal. The AV Curious class has a notable skew toward the High category for Commute Multitasker (.24) from the expected (.16). AV Hesitant are less likely to be in the High and Medium category for Eco-Minimalist and more likely to be in the Low category (.15) compared to the full sample (.15). The differences are the opposite for the AV Curious, with a lower share in the Low category (.11) and a higher share in the High category (.20) for Eco-Minimalist attitudinal factor. For having the attitude that their Life/Career is Adrift AV Curious people feel this more strongly (.20) than AV Hesitant (.10) which have a higher share in the Low category (.25) than expected (.16). This is likely due to AV Curious people skewing younger than the AV Hesitant and it is reasonable to assume that one's life might not be fully defined and fulfilling compared to when one is older.

Table 48. Attitudinal factor covariates percent of sample

	AV Early Adopter	AV Curious	AV Hesitant	Sample Share
Neighborhood Type				
Urban	30.2%	**37.9%**	25.9%	31.7%
Suburban	46.8%	**48.1%**	41.8%	46.0%
Rural	23.0%	14.0%	**32.3%**	22.3%
Gender				
Not Female	44.9%	54.4%	37.1%	46.1%
Female	55.1%	45.6%	**62.9%**	53.9%
Employment Status				
Not Employed	38.7%	26.3%	**47.4%**	36.8%
Employed	61.3%	73.7%	52.6%	63.2%
Education Level				
Up to some college/tech school	43.8%	36.1%	**54.8%**	44.0%
Bachelor or Higher	56.3%	63.9%	45.2%	56.1%
Age				
18-37 years old	27.8%	**41.2%**	17.0%	29.5%
38-53 years old	32.1%	32.2%	29.5%	31.5%
54-72 years old	30.7%	22.2%	41.9%	30.7%
73 years old +	9.5%	**4.4%**	11.6%	8.4%
Household Income				
Low (<$50,000)	33.3%	25.8%	35.6%	31.4%
Medium ($50,000-$100,000)	30.0%	30.9%	37.0%	32.0%
High (>$100,000)	36.7%	**43.3%**	27.4%	36.6%
Familiarity with AVs				
I have never heard of it	5.3%	3.7%	4.6%	4.6%
I have heard of it but am not familiar with it	32.2%	22.4%	34.9%	29.7%
I have heard of it and am somewhat familiar with it	50.1%	48.1%	47.3%	48.8%
I have heard of it and am very familiar with it	12.5%	**25.8%**	13.2%	17.0%
Neighborhood Type				
Urban	30.2%	**37.9%**	25.9%	31.7%
Suburban	46.8%	**48.1%**	41.8%	46.0%

	AV Early Adopter	AV Curious	AV Hesitant	Sample Share
Rural	23.0%	14.0%	**32.3%**	22.3%
Gender				
Not Female	44.9%	54.4%	37.1%	46.1%
Female	55.1%	45.6%	**62.9%**	53.9%

The sociodemographic makeup and attitudinal factors of the classes suggest the following generalization of the classes. The AV Curious class is composed of a highly urban and suburban population that is employed, younger, highly educated, has a Medium ($50,000-$100,000) to High household income (>$100,000), and is somewhat to very familiar with AVs. This class leans more towards being highly Pro-sustainable Policy, Tech Enthusiast, and Eco-minimalist. The attitudes indicate that they see the potential benefits of the technology but given their current stage in life, e.g., too young, they are hesitant to commit to new technology. Conversely, their enthusiasm for AVs may be hampered by the potential for AVs to be net negative on the environment and society. AV Hesitant is the opposite of the AV Curious with a shift towards being rural, more likely to be unemployed, less highly educated, older, and less likely making a High (>$100k) household income. They are less interested in Pro-Sustainable Policy and do not see themselves as being a Tech Enthusiast (two factors that are the main selling points for the technology) which aligns with not expressing interest in AVs. Also, they reported higher levels of being highly car dependent and seeing a car as a utilitarian device that again reinforces the suggestion from the model that these people see their vehicles as a crucial element in their lives and are hesitant to switch to new, disruptive technology. The AV Early Adopter fits between these two classes but tends to be closer to the AV Curious. AV Early Adopters covers a wide swath of the populace but are predominantly suburban, middle-aged people without strongly leaning attitudes. This is an interesting result as it hints that there might be something else driving this desire that is not captured in the model.

Table 49 shows the beta parameters for the indicators in the 3-class model, which is a “measure of the influence on that predictor” (Vermunt and Magidson 2005). This is a useful way to see the relative loading of each indicator between the three classes. The AV Early Adopters has very strong positive loading on indicators that suggest an early adoption of AV and AV services, “Be one of the first to buy an AV”, “Eventually buy an AV, only after commonly used” and “Willing to use an AV TNC service” had parameters of 1.8227, 1.6729, and 2.1196, respectively. AV Early Adopters also exhibits a strong negative loading for “Keeping the same number of vehicles and not use and AV TNC service” (-1.02361) while having a positive parameter for the related indicator of “Keeping the same number of vehicles and use and AV TNC service” (1.2569). This suggests that they are responding to the AV TNC use and not the vehicle ownership levels and therefore continues to build the picture of this class as being very interested in AV use. There was a weaker loading of the “Reduce the number of vehicles and use an AV TNC service” (.8985), which is likely attributed to the reluctance to reduce vehicle ownership more so than the reluctance to use AVs. The remaining indicators, which all related to the potential for use of AVs for different tasks, all loaded strongly.

AV Curious follows a similar pattern as AV Early Adopters but loads weaker on all the indicators which suggest they are interested in AVs but not nearly as enthusiastically as the first class. The three indicators for AV ownership and use, “Be one of the first to buy and AV” (0.7952), “Eventually but an AV, only after commonly used” (0.3102), and “Willing to use an AV TNC service” (0.6583), are all positive which suggests that this group would be interested in these behaviors but not with the same magnitude of the first class. The indicators related to changes in the vehicle ownership associated with the adoption of automated TNC services suggest that this class would be interested in using AV TNC services as the two indicators for AV TNC services were loading positively (“Keep the same number of vehicles and use an AV TNC service” (0.2433) and “Reduce the number of vehicles and use an AV TNC service” (0.2804)) while the one indicator for not using AV TNC service (“Keep the same number of vehicles and not use an AV TNC service”) was loading negatively (-0.3982). These loadings were again all in the same direction as Class 1 but with a much lower magnitude. The same trend continues with the AV activity indicators by being positively loading on the indicators but rather weakly.

The AV Hesitant is a very different class as it is the inverse of AV Early Adopters. The loadings for AV ownership and use are loading strongly negative, “Be one of the first to buy and AV” (-2.6179), “Eventually but an AV, only after commonly used” (-1.9831), and “Willing to use an AV TNC service” (-2.7779). This suggests a strong disinterest in owning or using AVs. This negative view of AV continues when looked at in relation to their vehicle ownership levels. The only indicator to load in the positive direction is “Keep the same number of vehicles and use an AV TNC service” (1.4242) as it is for the situation where no AV use is expected. Further supporting this clear class characteristic of having little interest in AVs are the indicators for AV activities, which all load very strongly and in a negative direction.

Table 49. Estimates of LCA parameters for indicators

	Class 1 AV Early Adopter	*Class 2 AV Curious*	*Class 3 AV Hesitant*	Wald	p-value
AV Use and Ownership					
Be one of the first to buy an AV	1.8227	0.7952	-2.6179	348.1849	<0.001***
Eventually buy an AV, only after commonly used	1.6729	0.3102	-1.9831	474.9077	<0.001***
Willing to use an AV TNC service	2.1196	0.6583	-2.7779	413.1809	<0.001***
Shared AV TNC and Impact on Household Vehicle Ownership					
Keep same number of vehicles and not use an AV TNC service	-1.0261	-0.3982	1.4242	254.047	<0.001***
Keep same number of vehicles and use an AV TNC service	1.2569	0.2433	-1.5003	405.5033	<0.001***
Reduce number of vehicles and use an AV TNC service	0.8985	0.2804	-1.1789	261.04	<0.001***
AV Activities					
Use AVs to travel more when tired or under influence of alcohol	1.7559	0.2009	-1.9568	427.271	<0.001***
Use AVs to do simple errands	1.6505	0.4848	-2.1353	358.324	<0.001***
Use AVs pick up/drop off kids	1.8226	0.9598	-2.7824	298.904	<0.001***
Use AVs to travel to leisure activities more often	3.5722	0.8406	-4.4128	462.8171	<0.001***
Use AVs to go to more distant leisure activities	3.8219	0.9017	-4.7236	385.7579	<0.001***
Use AVs to make more long-distance trips	3.1601	0.6522	-3.8123	317.6634	<0.001***
Use AVs to work in car and not at office	1.9161	0.8878	-2.8038	248.3397	<0.001***

Note: *** denotes statistical significance at p<0.001

Conclusions

By conducting a latent class analysis, I determined there were three classes of individuals related to their intentions towards the adoption and use of AVs for various activities. The three classes were defined as AV Early Adopter, AV Curious, and AV Hesitant. The AV Early Adopters were most interested in using and/or owning AVs and were middle-income, tech enthusiasts, and less enthusiastic for car ownership. The AV Curious group members were interested in AVs but were more interested in waiting until the technology matured, and using them to supplement their current vehicle ownership rather than replace them with a shared-AV service. The last segment was the AV Hesitant group which is more rural, older, and lower-income than the other segments. They were less likely to be concerned about environmental or sustainable policy and are enjoying their current vehicle use. This segment was the most reluctant to consider AV use.

The market segmentation suggested by the three-class model provides the groundwork for interesting applications across many cross-sections of the transportation field. The level of interest in AVs is high with the two classes that look at AVs positively, accounting for 75.66% of the market. The two classes that are interested in AVs, AV Early Adopters and AV Curious, seem more interested in TNC services in the early stage of deployment but when AVs are an established mass-market item they shift to a preference of private ownership. This is interesting as it shows that they want to try it before buying it while waiting for the technology to mature which is a prudent approach with such cutting-edge technology. This eventual switch to a preference for private ownership of an AV over their use as part of a TNC service is disconcerting as many of the benefits of lower cost, reduced emissions, and congestion is not realized unless AVs are shared, which is typically expected to be part of a TNC service. A recent study demonstrated via a naturalistic experiment that when AVs are used privately there is a "sizable increase in vehicle miles traveled and the number of trips" with "a substantial proportion of "zero-occupancy" vehicle-miles traveled" (Harb, Xiao et al. 2018). While some of these trips may be beneficial as they are new trips for under-traveled populations, e.g., the elderly, there is still a potential for the benefit to be overshadowed by an influx of less beneficial VMT. The complexity of the situation will require strong policy to encourage AVs to be deployed in a manner that puts shared AVs as a priority over privately-owned AVs, still allowing for private ownership but reducing its negative impacts.

As automobile manufacturers have typically not been overly concerned with the negative externalities of their products, they will be encouraged by these results as they suggest that even with relatively little experience and knowledge of AV, consumers are interested in them. Because of clear demand for AVs, manufacturers will race to deploy AV technology at as many levels of the transportation system as they find profitable. While this is good for the rapid deployment of the technology as companies seek market efficiency by being the leader in a market segment, it will in turn put additional pressure on policymakers to keep pace. The main objects of the policymakers should be to ensure the AVs are deployed safely, equitably, and sustainably. The specifics of how to achieve these goals are outside the scope of this research but this analysis can be used to inform elements of these policy objectives.

If policymakers decide AVs are in the public interest, they should consider the level of external motivation that these segments need to get them to adopt AVs. The AV Early Adopters are already embracing this technology in the limited forms it is currently available in. So little effort should be focused on this group as they do not need any additional incentive. The AV Curious would likely need some policies and initiatives targeted at them but this should not require a massive investment as a small nudge should be enough to get them over their initial skepticism and then they would likely embrace it. As to what their reluctance is grounding in would need additional research but is likely rooted in safety concerns and familiarity/ease of use of new technology. These concerns could be addressed through education campaigns (e.g., demonstrations, informational advertisements, or test drives) and the passive acquisition of experience and familiarity with AVs as the AV Early Adopters begin to normalize the use of AVs. The AV Hesitant group would need the largest and broadest set of policies to shift them into greater acceptance of AVs given their current disinterest in them which begins to illuminate the potential for inequitable AV adoption. The AV Hesitant were more likely to live in a rural neighborhood than the other classes therefore if left for the market to develop naturally these people may be the last to get the services deployed in their areas. While the case can be made from a TNC or automobile manufacturers that building AV services in rural areas are inefficient it should still be encouraged through policy initiatives. To support this, policymakers need to also run education and PR campaigns to inform AV Hesitant of the benefits of AVs to either create the demand for the services or encourage the willingness to use AVs when available. These education campaigns can utilize the attitudinal factors to describe the different classes to steer the messaging to ensure it speaks to the underlying values of each class which would aid the internalization of information that would elicit the desired travel behavior change. For example, a targeted campaign for AV Hesitant could utilize the messaging of its reliability and low cost while not explicitly mentioning the sustainability benefits or going into details on the technology.

Another important result from this study is the clear reluctance from all the classes to reducing their vehicle ownership levels even when presented with the potential for a robust AV TNC service that could replace a personal vehicle. Given California's well-documented love affair with the automobile (Marling 1989, Sachs 1992, Howe 1995, Falconer 2008) it will always be hard to break the cultural norm of personal car ownership even faced with the very real effects of anthropogenic climate change which have materialized more frequency with increasing intensity. As this data was collected in 2018 it does not consider the rise of the COVID-19 pandemic and the crippling effect it has had on shared service due to the requirement to avoid shared spaces and interacting with strangers. While the reluctance to reduce vehicle ownership level is good for the automobile manufacturers, it should be discouraged from a policy standpoint as it is a clear driver of greenhouse gas emissions, increasing congestion, negative health and safety impacts, and relinquishing an ever-increasing portion of public land to infrastructure to support this inefficient mode of transportation. It is hard for policymakers to change an established behavior (Zimbardo and Ebbesen 1970, Lunn 2012) and is even more of a challenge to change a widely accepted cultural behavior (Biglan 1995). This will be a process that will need long-term support both politically and financially as it is not likely behavior can be changed quickly. For lasting behavior change to be achieved according to the Precede-Proceed Model (Green and Kreuter 2005), policy needs to be applied across the three factors of behavior change which are predisposing factors (e.g., attitudes, preferences), enabling factors (e.g., social support, peer influence), and reinforcing factors (e.g., supporting programs and services) (Gielen, McDonald et al. 2008).

This segmentation of the market would also be useful for AV manufacturers and TNC service providers to help them understand the composition of the potential market for AVs and related services. While the three classes are not necessarily the most revelatory by themselves as they follow typical technology adoption types, the attitudinal factors and sociodemographics would be useful in establishing other predictive models for product development, inclusion in forecasting business scenarios, and eventually inform marketing campaigns.

Long-range planning by regional transportation agencies has the challenging task of modeling future scenarios of the impacts of AVs even though many key variables are still not fully understood thus relying on assumptions for adoption, technology development timelines, and impacts on travel behavior. Childress, Nichols et al. 2015 present a good example of this as they created four scenarios for AVs impacts on the Seattle, Washington transportation system in 2040 via the region's activity-based travel model. To achieve this given the uncertainty inherent to this type of modeling, models levels of adoption (30%) for 2 scenarios and full adoption (100%) for the remaining 2 scenarios (Childress, Nichols et al. 2015). While this was a good approach for initial impact assessments of AVs in 2015, now this type of planning, especially in California, should incorporate more precise assumptions as the body of knowledge in the field has expanded. The segmentation presented in this research could be incorporated into long-range planning models to better reflect the likely adoption characteristics of AV users. With the three classes exhibiting different attributes, such as neighborhood type, sociodemographics, and expected adoption preferences, they demonstrate that AV adoption will not be uniform across the general population and the models should reflect this. This would allow planners to anticipate locations where adoption may happen first and ensure infrastructure and policy are in place to encourage responsible adoption of AVs. They would also be able to identify areas or user segments that are not receiving or utilizing the benefits of AVs and work to preemptively address potentially equity concerns that may arise from the imbalance in deployment and adoption.

In the time since the data collection was conducted the COVID-19 pandemic has sent shockwaves through transportation systems, as well as all other aspects of life. Therefore, it would not be reasonable to assume COVID-19 has not impacted the results of this study in at least a few ways. The use of shared transportation has taken a serious setback as most TNC services have dropped that option which will likely slow down the adoption of future shared services, automated or human-driven. Relatedly, during the initial spring 2020 peak of COVID-19 it was observed that non-shared ridehailing active users (used in last 30 days) dropped by as much as 66% (Matson, McElroy et al. Pending Review for Publication - 2021). Conversely, the appeal of a service that does not need a person to drive the vehicle thus providing a trip that adheres to social distancing precautionary measures may have increased the appeal of AV services. As the world continues the arduous task of vaccination, all of this may be eventually moot, but it is unclear on how long the tail will be on this catastrophic event and how long, if ever, it will take to get back to "normal". So, it will be important to continue to follow transportation research related to the effects of COVID-19 to adapt the findings presented here to the "new normal" we all find ourselves in.

IV Conclusions and Policy Implications

This report summarizes the efforts and research carried out for California Panel Study of Emerging Transportation Trend (Phase 2). This research helps to increase the understanding of the impacts of emerging transportation technologies and trends in California. The significance of the research is particularly relevant at a time in which the rapid expansion of digital technology, the increased availability of locational data and smartphone apps, and the emergence of technology-enabled transportation and shared-mobility services are quickly transforming transportation, while traditional data collection efforts (e.g., National Household Travel Survey data) have limitations in investigating these topics.

Our studies conclude that there are attitudinal and behavioral differences in, i.e., *urban living*, *car ownership*, *environmentally-conscious lifestyles* across generations, but the differences may be converging as the younger generation enter later life stages. We observe that Millennials' attitudes differ from those of Generation X only by small, albeit statistically significant, amounts on average; and *are* closer to those of Generation X as they gain on a host of life-stage variables such as marital status, income, and education. At the same time, Millennials are found to adopt multimodality more often than Gen Xers, on average. However, substantial heterogeneity are identified among them and indicates that, perhaps contrary to expectations and the stereotype in the media, the majority of millennials are monomodal drivers. Findings from this study complements existing literature findings that Millennials' *behaviors* may be converging to those of Generation X as they enter later life stages. They have important implications for transportation planning and forecasting. Perhaps, those generational labels that are prevalent in social media should be challenged. Research and practices focusing on age, period and cohort effects might be more informative other than discrete groupings based on arbitrary year groups.

Our studies also reveal complex relationship between observed/latent characteristics and the current adoption of and future interest in new transportation technology including alternative fuel vehicles, automated vehicles and shared mobility. We tend to witness divergent consumer segments within each of the three markets, characterized by their socio-demographics, latent attitudes, built environment, related local/regional policy and the level of familiarity with new technologies, which together shape the uniqueness of their vehicle ownership, residential location choice, daily travel behavior, activity patterns and overall lifestyle.

By exploring the effects of socio-demographic characteristics, latent attitudes, and regional context of electric vehicle market on consumers' current vehicle fuel type choice and their future interest in purchasing or leasing an alternative fuel vehicle (AFV), our study suggests that people who are more pro-environment, tech-savvy and car-utilitarian are more likely to choose an AFV currently as well as in the future. Car-dependent people are also found to be more likely to adopt an AFV in the future than their counterparts. In term of EV local market, the higher the local hybrid electric vehicle density in the neighborhood, the more likely that residents adoption of an AFV. Thus, improving EV network could be significant in removing people's psychological barriers. Also, individual's current user experience in AFV has positive effect on their future interest in AFV, therefore, increasing people's knowledge and experience of EV, especially those that have not used AFV ever before, is critical strategy for market uptake. This study helps understand the market share of different type of vehicle technologies. Policymakers and other stakeholders can design efficient policy provisions and marketing efforts regarding heterogeneity taste among population segments.

By exploring the factors that affect the use of ridehailing services (Uber, Lyft) as well as adoption of shared (pooled) ridehailing (UberPOOL, Lyft Share), our study suggests that the high-income white individuals are more likely to be a frequent user of regular ridehailing, while better-educated, younger individuals who currently work or work and study are more likely to use shared ridehailing services. Residents of urban neighborhoods are found to be more likely to use ridehailing often than the residents of suburban and rural neighborhoods. High employment entropy of the neighborhood is associated with a higher frequency of using ridehailing and a higher propensity to adopt shared ridehailing services. The increased travel time and lack of privacy decreases the likelihood of adopting shared services.

By estimating how the built environment affects the decision to choose ridehailing for making non-work trips, the study suggests that mode share of ridehailing services is higher when destinations are within walkable distance of the home location and individuals living in vibrant and walkable neighborhoods replace other modes (possibly active modes) with ridehailing. Besides, previous studies may have overestimated the complementary or supplementary relationships between public transit and ridehailing by ignoring confounding effects. From planners' and policymakers' perspective, if the goal is to discourage ridehailing from replacing active modes, pricing should be employed to discourage short-distance ridehailing trips.

By investigating the latent patterns in the modal impacts of ridehailing services, our study identified three latent classes of ridehailers: substituters who substitute transit modes and taxi cabs with ridehailing (30% of the total shared ridehailing adopters, and 50% of the frequent users in our sample), personal car augmenters who complement personal car with ridehailing (49% of the total adopters), and multimodal augmenters who use public transit and active modes and their usage are not impacted by ridehailing (21% of the total adopters). Our study suggest that taxi and personal cars are most strongly hit due to ridehailing. Whether taxi or ridehailing is a "greener" or more efficient mode of transportation is up for argument, from dimensions such as congestion and VMT, but a lower use of personal cars may be counted as a positive impact of ridehailing services, since it can help reduce some urban maladies such as unwarranted parking spaces in urban areas. Also, our study indicates stronger RH substitution effect on transit rather than a bolstering impact.

By jointly studying ridehailing usage frequency, vehicle ownership, and expectations to change vehicle ownership, our study with a latent class framework reveals different latent clusters. There are three classes associated with ridehailing usage frequency. The "RH: Younger Eco-friendly" cluster (30% of the sample) is predominantly RH dependent, as a majority in it use RH services on a regular basis, a characteristic in stark contrast with the "RH: Younger Non-eco-friendly" cluster (29% of the sample), where only 2% are among the regular users. The third is "Older Car Enthusiast" cluster (40% of the sample) with a nearly zero share of regular RH users.

The study shows drastically different RH usage frequency despite of similar vehicle availability and age, and the one with higher ridehailing usage is less likely to expect an increase in household vehicle ownership within the next three years. With respect to the relationship between RH usage and household vehicle availability, younger clusters who use RH more frequently than the older cluster also contain a higher share of vehicle deficient households. Furthermore, the relationship between vehicle availability and expectations to change vehicle ownership shows that those who are more likely to live in vehicle deficient households are also more likely to express an expectation of vehicle ownership increase in the future.

By segmenting respondents based on socio-demographics, general attitudes, and current familiarity with automated vehicle (AV) into three classes, including AV Early adopters, AV Curious and AV Hesitant, our study reveals who will be interested in (early) adopting AVs, what the users' preferred business models (private vs. shared) will be, and how the eventual adoption of shared automated vehicle (SAV) services will likely impact personal/household vehicle ownership levels. If policymakers decide AVs are in the public interest, they should consider the level of external motivation that these segments need to get them to adopt AVs. The AV Early Adopters are already embracing this technology in the limited forms it is currently available in, so less incentives are needed for this group. The AV Curious would likely need some policies and initiatives targeted at them but this should not require a massive investment as a small nudge should be enough to get them over their initial skepticism and then they would likely embrace it. The AV Hesitant were more likely to live in a rural neighborhood than the other classes, therefore if left for the market to develop naturally, as these people may be the last to get the services deployed in their areas.

Understanding how new mobility services are changing individual lifestyles and the use of transportation is of strategic importance for the definition of policies that improve the efficiency and increase sustainability of transportation. Overall, this project has generated important and multi-dimensional insights into travel demand patterns, changes in travel behavior among various segments of the population, and the impact of emerging transportation technologies on travel demand and auto ownership. The increased insights gained through this process can help provide efficient, reliable, and accessible transportation solutions that better match travelers' needs and support sustainability, livability and the economic activities of California communities, also through the integration of transportation services and modes.

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VI Data Summary

Products of Research

This dataset consists of survey data collected in 2018, including information on the personal attitudes and preferences, lifestyles, adoption of social media and ICT, e-shopping patterns, residential location, living arrangements, recent major life events, commuting and other travel-related patterns, auto ownership, awareness, adoption and frequency of use of shared mobility (carsharing, bikesharing, ridehailing services such as UberX or Lyft Classic, pooled ridehailing services such as UberPOOL or Lyft Line), propensity to purchase vehicle and/or modify vehicle ownership, perceptions and propensity to adopt driverless vehicles, interest in mobility-as-a-service (MaaS), propensity towards shared or personal ownership and use models of driverless vehicles, and sociodemographic traits.

The data collection was completed with a mixed sampling method: (1) A paper survey was mailed out to a stratified random sample of 30,000 California residents, by adjusting the sampling rates to obtain sizable numbers of respondents in all six geographic regions; (2) A sample of 2,000 Californians was recruited through an online opinion company using quota sampling based on six geographic regions, three neighborhood types (urban, suburban, and rural), and selected socio-demographics (age, gender, race, ethnicity, presence of children, household annual income, student status and employment status); and (3) All respondents from 2015, the first wave of data collection (N=1,975), were re-contacted through the same online opinion panel company. In the end, these three channels generated a total of 4,071 complete responses. The online survey responses were downloaded from the survey provider website, while the paper surveys were collected from respondents and the contents were transcribed and coded. Eventually, surveys from both channels were combined into the same dataset. After data cleaning, a total of 3,767 responses are kept in the final dataset. The data is stripped of all identifiable information.

Data Format and Content

There are two data files (one .sav file from SPSS system, the other is .xlsx file from Microsoft Office), and .xlsx file for the codebook describing all variables in the database.

Database: Each row represents a single survey respondent with a unique ID number assigned, and each column corresponds to one variable.

Codebook: The codebook corresponds to the variables in the database. Each row represents a categorical variable, with its level and label. Continuous variables were omitted from this spreadsheet.

Data Access and Sharing

The final data of this project is subject to the UC Davis Institutional Review Board (IRB) guidelines on the treatment of human subject data and is available upon request from the principal investigator.

Reuse and Redistribution

The final data of this project is subject to the UC Davis Institutional Review Board (IRB) guidelines on the treatment of human subject data and is available upon request from the principal investigator. For all purposes allowed by the IRB guidelines, there are no restrictions to the use of the data. Data can be reused and redistributed with credit to this report and the authors of the research.

Appendix

This appendix discusses the data cleaning process. To ensure the quality of the analysis based on the data collected, the survey responses went through a thorough cleaning process. The goal was to identify problematic cases and make sure the data was consistently coded prior to running the analysis. There were two main actions taken during this process. First identifying cases of such questionable quality that they needed to drop them from the study and second, finding obvious errors to appropriately recode. Please note that this research is based on the dataset as of July 19, 2019, as it had to be locked in to complete the analysis while other team members continued to clean the data for their analysis.

Review of Cases to Remove from Dataset

To identify the potential cases to be reviewed for quality control, a multi-step process was used. The first step was to run a series of logic-based tests on the responses to create flags for potential issues. These tasks included but were not limited to the following:

1) **Error in sampling:** If people responded but lived outside the area of study (California) they were flagged to be dropped without further review once their address was confirmed.
2) **Failing the trap questions:** These were questions that request the respondent to provide a specific response and were flagged if not answered with the requested value.
3) **Flat lining Section A of the survey:** Section A consists of 35 Likert-type scale attitudinal statements which has the potential for a respondent to provide a single response for nearly the entire section. While this has the potential to be a valid response, the survey was designed to have statements on the same topic, but each phrased positively and negatively so a person would need to provide a different response (unless it was the middle response) to be consistent within the section.
4) **Speeding:** During the testing and design of the survey, it was determined that it would be suspect for a respondent to finish the survey in less than 14 minutes given the length of the survey and the time needed to complete it. These respondents were flagged for review.
5) **Inconsistent responses:** Using the screener for the online opinion panel and asking for related data across the survey, we were able to establish many checks to determine inconsistencies of responses which included:
    - Household composition not totaling to the provided household size.
    - Provided commute information but state they are retired/do not work and not a student.
    - Provided telecommuting patterns but state they are retired/do not work and not a student.
    - Stated they work and are retired, which are incompatible statements.
    - Home zip code was asked twice and thus should be the same.

6) **Questionable or poor quality of survey responses** which included:
   - Open response questions provided an opportunity to assess the level of engagement with the survey and gibberish or nonsensical responses were flagged.
   - If stated commute to work was over 150 miles, it was flagged.
   - Travel patterns for leisure and commuting were reviewed to identify any that stood out as being unlikely for using a large number of modes or a frequency of use that was unreasonable.
   - Cases that claimed more than 365 long distanced travel trips in a year were flagged.
   - Weekly vehicle miles traveled was an open response and an extremely high value case was flagged.

Once these checks were completed the total number of issues were tallied for each respondent to determine which were the most problematic. Not solely relying on mechanical checks, the most problematic cases were then manually reviewed in detail on a case-by-case basis to avoid dropping any valid cases that were just outside an expected or typical response. This process was labor intensive given the number of cases that needed to be reviewed and the amount of data each person provided. However, it was imperative for the researchers to ensure the data was reliable. To prevent an individual researcher imparting his own implicit biases on the dataset, all final decisions were reviewed and finalized by the entire research team to ensure there was consensus on the rationale, thus limiting any biases given the size and diversity of the research team. This process resulted in the identification of 349 cases that were dropped from the dataset.

Recoding

The next step in the data cleaning was a thorough review of each individual case and variable to make any necessary recodes to the provided responses. After dropping the clearly bad cases, the remaining cases were reviewed for issues on individual questions or key piece of missing information. If a response was clearly an error, such as a typo, and if the actual response could be determined, the response would be recoded as the intended response. For example, if someone said his commute was 100 miles but the distance between his home and office was 10 miles the response for commute distance would be recoded to 10 miles. The other key part of recoding was to establish and implement a system for the missing responses in the survey. Three different types of missing data were coded as described in Table 50..

Table 50. Missing response coding

Missing Response Value	Definition
-77777	Question was not displayed or should have been skipped due to the logic in the survey
-88888	Skipped a displayed question
-99999	Invalid response provided

It is worth noting that the “skipped a displayed question” (-88888) and the “invalid response” (-99999) occurred predominately in the non-online surveys since the online survey platform requires a question to be answered and validated to progress. These values were selected to provide a layer of security in our analysis to clearly highlight missing values to avoid accidently inclusion in the analysis. The extreme negative value would be apparent in the output thus preventing any remaining in the analysis without proper removal.