Final Project Report

Heterogeneous Preferences for Activities While Traveling in Autonomous Vehicles: Relationships With Travel Contexts and Attitudes

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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16. Abstract

Although the literature on autonomous vehicles (AVs) has been growing with a focus on adoption, expected changes in travel behavior, and travel demand and land use in the future, few studies have analyzed envisioned activities in AVs, which will affect all those outcomes at the micro level. To address this gap, this study examines preferred activities in autonomous vehicles (AVs), and especially their heterogeneity. In doing so, it uses a rich survey dataset (N=3,376), collected in four regions of the southern United States from June 2019 to March 2020 and weighted to be representative of the study population on key sociodemographic features. A latent-class cluster analysis (LCCA) enables us to identify a few distinctive combinations of preferred in-vehicle activities, separately for one group of respondents with respect to hypothetical alone trips (N=1,995) and for another group with respect to family trips (N=1,381). The alone-trip model uncovers *Active use of time* (37.6%), *Passive use of time* (19.9%), *Alert* (23.8%), and *No-ride* (18.7%) classes. Similarly, the family-trip model reveals *Active use of time* (35.3%), *Relax and interact* (18.8%), *Alert and interact* (32.1%), and *No-ride* (13.9%) classes. As for underlying factors affecting individuals' class membership, travel contexts, attitudes (e.g., tech-savviness, trust in AV technology, appreciation of varied benefits of AVs), and employment status (for alone-trip model only) account for the heterogeneity in preferences for in-vehicle activities and willingness to ride in AVs. With respect to the latter, we further examine their links to expected changes in travel behavior when AVs become available. In sum, this study investigates a wide range of in-vehicle activities (including the option of not to ride in an AV), identifies groups of activities preferred together, and explains respondents' choices with respect to various attitudes and travel contexts.

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EXECUTIVE SUMMARY

Although the literature on autonomous vehicles (AVs) has been growing with a focus on adoption, expected changes in travel behavior, and travel demand and land use in the future, few studies have analyzed envisioned activities in AVs, which will affect all those outcomes at the micro level. To address this gap, this study examines preferred activities in autonomous vehicles (AVs), and especially their heterogeneity. In doing so, it uses a rich survey dataset (N=3,376), collected in four regions of the southern United States from June 2019 to March 2020 and weighted to be representative of the study population on key sociodemographic features. A latent-class cluster analysis (LCCA) enables us to identify a few distinctive combinations of preferred in-vehicle activities, separately for one group of respondents with respect to hypothetical alone trips (N=1,995) and for another group with respect to family trips (N=1,381). The alone-trip model uncovers *Active use of time* (37.6%), *Passive use of time* (19.9%), *Alert* (23.8%), and *No-ride* (18.7%) classes. Similarly, the family-trip model reveals *Active use of time* (35.3%), *Relax and interact* (18.8%), *Alert and interact* (32.1%), and *No-ride* (13.9%) classes. As for underlying factors affecting individuals' class membership, travel contexts, attitudes (e.g., tech-savviness, trust in AV technology, appreciation of varied benefits of AVs), and employment status (for alone-trip model only) account for the heterogeneity in preferences for in-vehicle activities and willingness to ride in AVs. With respect to the latter, we further examine their links to expected changes in travel behavior when AVs become available. In sum, this study investigates a wide range of in-vehicle activities (including the option of not to ride in an AV), identifies groups of activities preferred together, and explains respondents' choices with respect to various attitudes and travel contexts.

INTRODUCTION

Autonomous vehicles (AVs) refer to those vehicles that effectively manage key operation and safety functions without (constant) input or feedback from passengers. In the United States, its initial hype, spiked by pilot programs in selected cities, appears to have subsided, mostly after recent high-profile accidents that occurred in part because of roadway situations that designers did not anticipate, and now the industry proceeds in a much more careful manner. Still, proponents believe that AVs will greatly benefit society: providing, e.g., support of mobility-limited populations including seniors and those with disabilities, improved safety to all road users via fewer crashes, damages, and casualties, and reduced environmental impacts and maximized use of limited roadway capacity. In this context, improving automation technology is a crucial component that determines the mass adoption of AVs in society. However, perhaps more importantly, even with an enhanced level of safety and performance, whether and to what extent people perceive and derive utility from AVs, more so than they do from the existing means of travel, will affect the timing, nature, and implications for various other components of daily life of such adoption.

On the consumer demand side, transportation scholars and professionals have focused on AV's potential for reduced disutility from travel (and even net positive utility (Salomon & Mokhtarian, 1998)) from sources such as productive or meaningful use of in-vehicle travel time (Ettema & Verschuren, 2007; Molin et al., 2020; Wardman et al., 2020) and release from manual driving (Singleton, 2019). However, to date, the travel behavior literature lacks systematic investigation into the envisioned use of time in AVs, its links to potential use cases for AVs, and implications for travel demand in an AV era. Various studies examine adoption and expected use cases of AVs, but many of them did not consider in-vehicle time use, whose omission leads to unreliable, even unrealistic, results with limited value for planning and policy.

To address this research gap, this study presents analyses of preferred in-vehicle activities on hypothetical AV trips and factors accounting for their preferences, both passenger characteristics and travel contexts. With a rich survey dataset (N=3,376), collected from four regions in the U.S. South from June 2019 to March 2020 (i.e., before the COVID-19 pandemic), we employ a latent-class cluster analysis (LCCA) that enables us to uncover groups of individuals with heterogeneous preferences for in-vehicle activities (Choi & Mokhtarian, 2020). For each group, we examine its member profile, which helps identify underlying reasons for heterogeneous preferences and the members' expected use cases for AVs, which provides useful insights into effective policy responses for a future with AVs.

This report is organized as follows. Section 2 presents a summary of recent relevant studies, and Section 3 provides details of the main dataset and analytical method. Next, Section 4 presents main results and interpretations, and Section 5 concludes with implications, contributions, and future research directions. Two appendices provide additional technical details.

LITERATURE REVIEW

Conceptual Framework

Studies report smaller values of travel time savings (VOTTS) for (hypothetical) trips on AVs, compared to those taken by other means of travel (Kolarova et al., 2019; Zhong et al., 2020). Such findings are attributed either to productive/meaningful use of in-vehicle time (Correia et al., 2019; Gao et al., 2019) or to reductions in physical/mental burden inflicted by manual driving (Singleton, 2019). However, we have few empirical analyses estimating the extent to which each of these two sources contributes to reductions in VOTTS. This lack of knowledge on their relative contributions prevents us from making accurate predictions regarding the magnitude, scope, and nature of changes in travel demand and land use patterns, which AV would bring about. For instance, suppose that travelers benefit from riding an AV *primarily* by being able to relax in a car instead of having to manually drive it. Then, AVs might not change activity-travel patterns as fundamentally as they would otherwise do in the case in which travelers use their AV travel time productively or meaningfully (more so than they can do now while driving cars manually), and in response, rearrange their daily routines more flexibly across in-vehicle and out-of-vehicle times.

As a first step to investigate the complex links from in-vehicle activity engagement at a micro scale to AV impacts at the macro scale, we develop a multi-step process by which individual travelers' in-vehicle time use could bring about changes in travel demand and land use patterns at the aggregate level. The links in **Error! Reference source not found.**, from A to E, represent specific c hoices, behaviors, or outcomes, which are affected by the preceding factor(s) (i.e., bubbles) and affect the following one(s).

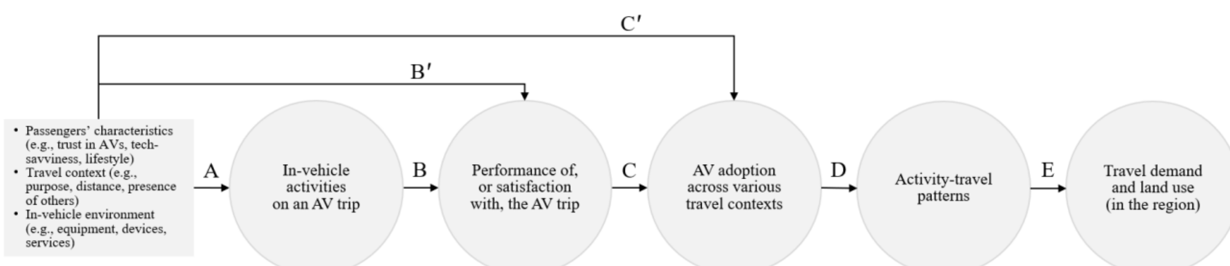


Figure 1. A multi-step process whereby time use in AVs leads to changes in travel demand and land use

A. AV riders could engage in certain activities while being released from manual driving, and the nature, intensity, or combination of those activities could be a function of travelers' characteristics, the travel context, and the in-vehicle environment (e.g., physical, social, or ICT-related).
B. Such "new" forms of in-vehicle time use may increase utility (i.e., decrease disutility) derived from AV trips, compared to the case in which the same trips are made by manual driving.
C. According to behavioral theories (e.g., the law of effect (Thorndike, 1927)), if individuals find a certain choice better-performing (e.g., more satisfying or less stressful), they will choose that experience more often than other alternatives in a similar situation in the future.

D. When such a more satisfying experience is repeated, it could be incorporated into one's daily routine, which could eventually reshape activity-travel patterns of individuals and their households (Mokhtarian, 2018; Pudāne et al., 2019).
E. When many households in a region adjust their activity-travel patterns in various ways, the effects of AV adoption at the household level will be aggregated to the effects in the region.

We find a relatively rich and continuously growing body of a literature on the links in the later part of the process (Soteropoulos et al., 2019); however, those links in the early part of the process are less examined. For instance, recent studies on VOTTS for AV trips (Kolarova et al., 2019; Zhong et al., 2020) report estimates on the extent to which AVs are expected to perform better than existing travel means (e.g., as envisioned by survey respondents), but many of those studies did not consider the role of in-vehicle activities. That is, they examine a single link B', instead of separately treating links A and B. In a similar vein, studies (Asmussen et al., 2020; Guo et al., 2021) report data collection and analyses on AV adoption; however, they do so at a *low* resolution (e.g., without any travel contexts at all) or with only limited trip attributes (e.g., travel time and costs on regular commutes). That is, when it comes to AV adoption, these studies employ a somewhat simplified conceptualization of a *single* link C' for multi-link relationships from links A through C.

Regarding the passengers' choice of (envisioned) in-vehicle activities inside AVs (i.e., Link A in **Error! Reference source not found.**), studies provide useful insights by exploring the type, nature, a nd implication of diverse in-vehicle activities. However, these studies are limited in that their collected data omit critical pieces of relevant information, they don't employ rigorous modeling, and most importantly, they lack a sound conceptualization regarding in-vehicle time use. Table 1 presents a summary of the research designs and identified/analyzed in-vehicle activities in selected studies.

Patterns of Preferred Activities in AVs

Studies on activities in AVs can be classified by whether data collection is via surveys or driving simulators. In a study with a survey administered to a German-speaking population (Pfleging et al., 2016), researchers asked for expected non-driving-related activities or tasks during an imaginary AV ride. Among the most popular choices are listening to music, radio, or audio books, talking to passengers, looking out of the window, and texting. By contrast, least preferred activities include smoking, knitting, playing (musical) instrument, and fitness, which appear either undesirable or highly specific (so that only a small portion in the population would consider them). Overall, activities selected for AVs are quite like those that respondents performed at the moment as a passenger in non-AVs, with a few activities slightly more popular in an AV environment (e.g., making calls and performing office tasks).

In another study, researchers deployed a survey in Seoul, South Korea (Lee et al., 2021), and in doing so, they designed a stated-preference (SP) choice experiment, in which respondents were to choose between a human-driven vehicle and an AV for a trip with a preset distance with varying time and monetary costs. In an immediately following question, the survey also asked respondents to select two most preferred in-vehicle activities in AVs (out of six) for the trip in the preceding question. Among three traveler groups, identified via latent-class choice models, "AV-oriented" are those who prefer AV rides the most. Even for them, as the distance increases, preferred activities switch from productive to leisure activities: e.g., from business-related to sleep/rest and lunch. Interestingly, as the trip gets longer, these individuals tend not to choose using ICT devices and services, likely because they consider such activities to be a way to pass the time, but not necessarily a means of deriving utility from performing specifically desired tasks.

To determine the extent to which in-vehicle activities contribute to the adoption of AVs, researchers in Hungary added an in-vehicle activity, randomly selected from a set of six, to a choice experiment (Hamadneh & Esztergár-Kiss, 2022). Among six preset activities, "Using social media and gaming" presents the largest marginal effects on the choice of AVs, followed by "Talking" and "Reading", both of which could be performed in person/with physical materials or digitally. By contrast, "Eating and drinking" has the smallest positive marginal effects on probabilities, and "Writing" even has negative effects. Although informative, the findings are rather general in that respondents were asked to imagine performing a single "assigned" activity on a trip with unspecified purpose, time of day, or location.

Another study by the same researchers (Hamadneh & Esztergár-Kiss, 2021) looks at factors affecting the choices of performing in-vehicle activities and carrying devices and tools onboard for these activities. In doing so, its researchers started by collecting trip attributes for the most frequent trip and asked about onboard activities and devices and tools for the trip. The study includes 14 activities in total: four (reading, writing, talking, and listening) were split into two, either related to the trip purpose or not, and the remaining six were not. Respondents would engage in reading, writing, and talking more in shared AVs than they did with existing travel means. While rich in detail, the study's analytical approach provides relatively limited insights: i.e., the engagement in current and future activities was analyzed one activity at a time via a series of unrelated bivariate test statistics.

A U.S.-based time-use study (Teodorovicz et al., 2022) focuses on non-driving-related activities by knowledge workers on their commute trips as the driver. Its survey collected the current time use while driving and expected time use inside fully automated vehicles. Overall, these workers selected work-related activities less often than non-work-related alternatives (e.g., 21.4% reading emails for work in the morning, vs. 38.9% listening to music/radio in the afternoon). In addition, in AVs they expected to conduct more of the types of activities that would take their attention away from vehicle operation and surroundings. In a similar vein, these driving commuters anticipated less time on listening to music/radio in AVs, suggesting a latent demand for activities that they would actively engage in when there are fewer constraints.

A study with survey responses from Austin, TX (Dannemiller et al., 2021) looked at envisioned activities while riding AVs (i.e., "travel based activities"), together with intention for additional local/long-distance trips in AVs (i.e., "activity-based travel"). The survey asked respondents to choose the three most preferred activities among 11 preset options, and the study labeled eight among them as "chill" travel-based activities, which would allow travelers to relax and refresh by engaging in low-key fun activities. Examples in the study include read, talk on /use the phone, watch movies, play games, eat/drink, interact with other passengers, sleep, and enjoy the scenery. In their sample (N=970), 28.7% selected only chill activities, and 58.7% chose these activities along with work/study or "Watch the road, even though I would not be driving", treated as a proxy measure for unease about riding in AVs.

Driving simulators are intended to stimulate participants' imagination for the physical, digital, and social environment inside AVs by having them experience physical vehicle-like structures. In a study about information and services provided via the user interface in the passenger vehicle, Korean researchers started by classifying information and services into three groups, depending on their direct relevance to vehicle operation: primary (e.g., speedometer), secondary (e.g., blind spot sensor), and tertiary (e.g., entertainment and communication). Next, they invited participants (N=156) to a driving simulator and had them report preferences for 29 types of information and services under manual and automated driving scenarios. As expected, in the manual driving scenario, participants more preferred safety-enhancing secondary information and services, and in the automated driving scenario, they highly rated communication services in the tertiary category.

In a two-paper study with a driving simulator (Tang, Sun, & Cao, 2020; Sun, Cao, & Tang, 2021), participants reported preferred activities in AVs, which differed between two scenarios: riding alone and riding with their family/friend. In the simulator (converted from an actual passenger vehicle), a researcher sat in its second row and asked the participants to envision activities in the AV while the simulator was in operation (i.e., a 360° screen surrounding the simulator projected preprogrammed changing scenes on highways and urban streets). Overall, these participants wanted to monitor vehicle operation (even if they were not supposed to drive manually), and entertainment and relaxation were mentioned more than work and communication. In addition, in the riding alone scenario, "monitoring the driving" and "making audio/video calls" were reported more often, and "sleeping/resting", "working/studying", and "online shopping" were selected much less compared to the other scenario in which participants rode with family/friend. All told, these participants appeared to be *less* concerned about AVs when riding with others.

In brief, our review of recent relevant studies identifies some critical gaps in our knowledge about the envisioned use of in-vehicle travel time in AVs, which we attempt to address in this study. First, not all studies allowed respondents to consider a wide range of in-vehicle activities or clarify the nature of their selected activities (e.g., purpose and intensity). Such incomplete approaches limit the understanding of the true nature of their envisioned in-vehicle time use and implications for out-of-vehicle activity patterns. Second, many studies reported summary statistics and only a few employed regression analyses. Note that regression enables separate estimation of unique associations between the selection of each activity and relevant factors. Third, even studies in the latter group tend to model each activity separately from the others, placing a few challenges. A single-activity model is based on an unrealistic assumption (i.e., people perform multiple activities on a trip, instead of choosing one); it does not always permit identifying the purpose and implications of activities (e.g., Is "Read" for work, leisure, or passing time?); and it masks potential heterogeneity in the preferences for bundles of multiple activities. Last but importantly, information about the travel context (e.g., purpose, distance, and presence of a travel companion) is minimal; however, even the same individual would choose markedly different activities depending on the context. Thus, analyses based on limited trip attributes produce results that are abstract and not readily applicable to planning and policy.

Table 1. Studies on Time-Use in Autonomous Vehicles

Studies	Study area; data collection period	Sampling frame & recruitment	Sample size	Travel behavior of interest	Factors behind the choice	In-vehicle activities	Analytical methods
Data collected via surveys							
Pfleging et al., 2016	Germany; December 2015	German-speaking population; recruited via e-mail, Facebook, faculty mailing lists, & learning platforms	300	Activity today as a driver, usual frequencies of performing activities while traveling as a passenger (in a car or public transit), and expected activities in AVs	N/A	23 activities presented in a 6-point Likert scale (from never to very frequently)	Summary statistics
Lee et al., 2021	South Korea; May 2019	Outsourced to a market research firm with its own opinion panel (R's should be a driver at least for a year)	511	Whether to choose a human-driven vehicle or AV in given scenarios	Distance, travel time, and travel cost in choice model); sex, age, income, and vehicle type in membership model	Six (R's select 1st/2nd most preferred activities)	Latent-class choice model with in-vehicle activities as inactive covariates for a post-estimation analysis
Hamadneh & Esztergar-Kiss, 2022	Budapest, Hungary; March-April, 2020	Social media platform; email	525	Choice among three options: riding AV alone, sharing AV with an unknown passenger, and riding public transit	Trip cost, trip time, and available in-vehicle activities (as trip attributes); education, sex, car ownership, income, age, and work/ study status (as personal characteristics)	Out of six predefined activities, one is given randomly as a part of the choice experiment	Mixed logit
Hamadneh & Esztergar-Kiss, 2021	Budapest, Hungary; Feb 9-Apri 25, 2020	*Not specified*	276	Whether to perform in-vehicle activities (binary) & whether to carry and use ICT devices or non-ICT items for multitasking (binary)	Trip purpose, travel means, travel time, education, work/ study status, age, household income, gender	14 (four activities considered twice depending on whether they are related to trip purposes, in addition to six activities not linked to the trip purpose)	Bivariate statistical tests
Teodorovicz et al., 2022	U.S.; not specified	Online platform, Lucid, in which its partner companies recruit participants	400	Secondary (i.e., non-driving-related) activities while commuting	Morning (outbound) vs. afternoon/evening (inbound)	30 were provided initially (17 work-related and 13 non-work-related), and	Summary statistics; tables, charts; chi-square tests

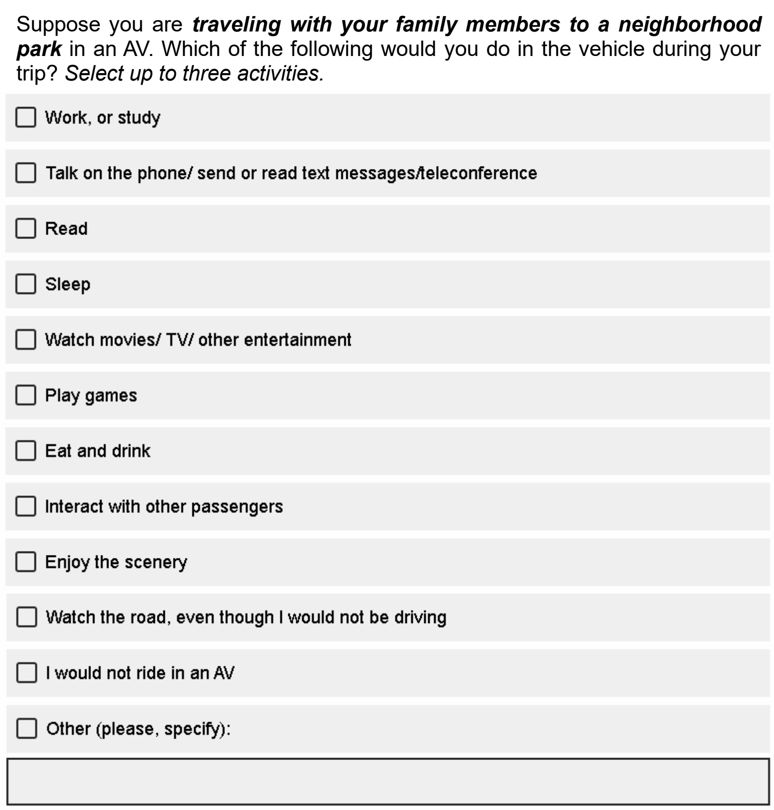
Studies	Study area; data collection period	Sampling frame & recruitment	Sample size	Travel behavior of interest	Factors behind the choice	In-vehicle activities	Analytical methods
		($13/completed case); full-time "knowledge workers" who commuted by driving at least once in the past week with a minimum annual income $40k+/year		by driving to/from work on a representative day in the past week, and expected ones in a hypothetical AV in the future		later classified into 10 (5 for work and 5 for non-work) based on the involvement of major sensory input	
Dannemiller et al. 2023	Austin, TX; June-September 2019	Random address-based sampling, social media advertisement, and local professional networks	970	Envisioned activities in AVs (binary) and intention for additional local/ long-distance trips with AVs (ordered on a five-point Likert scale)	Attitudes, gender, age, employment status, education, household income, household composition, neighborhood type, trip purpose, and companion	Initially asked for the top three choices among 12 preset activities, regrouped into seven categories	Generalized heterogeneous data model (GHDM)
Data collected with driving simulators							
Lee, Park, & Ju, 2020	A city in Korea; not specified	Koreans living in the city	156	Preference for each of 29 information activities, under three categories (depending on the extent to which each piece of information is directly related to vehicle operation)	Manual vs. automated driving mode; age; sex	29 preset information activities, some of them related to travel-based multitasking	Summary stats (bar chart) and repeated measures analysis of variance (repeated measures ANOVA)
Tang, Cao, & Sun, 2020	Ningbo, China; not specified	Via a social media advertisement	30 (16 alone, and 14 together with a friend/family member)	Activities in a driving simulator, both envisioned to be performed and actually performed	Travel alone and with a friend or family member; on highways and urban streets	23 activities (self-reported by participants) and five categories (identified from video recordings)	Summary statistics
Sun, Cao, & Tang, 2021	Ningbo, China; not specified	Local drivers with at least one year of experience and currently driving three or more times a week	44	Activities in a driving simulator, both envisioned to be performed and actually performed	drive to work and for a leisure activity; on highways and urban streets	23 activities (self-reported by participants) and five categories (identified from video recordings)	Summary statistics

Note: in-vehicle activities were either specified as options in the survey or asked in an open-ended question and post-processed by the researcher.

DATA AND METHODS

In this study, we analyze data collected via a comprehensive multi-region transportation survey administered online by researchers at four universities in the U.S. (N=3,376). The survey obtained information on a variety of variables including individual attitudes, current travel patterns, use of new mobility services, propensity towards the adoption of autonomous vehicles, and sociodemographic attributes. Participants were recruited via postal and email invitations (whose addresses were purchased from a market research firm) and social media advertisements at four metropolitan areas in the southern U.S.: Atlanta, Georgia (GA); Phoenix, Arizona (AZ); Austin, Texas (TX); and Tampa, Florida (FL). The data were collected from June to October 2019 for all regions except Florida, where cases were collected until March 2020. Thus, the data can be considered pre-COVID-19 pandemic.

In the survey each respondent was randomly presented one among five hypothetical AV travel contexts and asked to select up to three in-vehicle activities (see Figure 2). The five contexts are: travel alone to the store, alone to work/school, alone long distance, with family members to a neighborhood park, and with family members long distance (see Table 2). Also, the question assumed that fully "hands-off" AVs (i.e., at Level 5 (*Automated Vehicles for Safety | NHTSA*, n.d.)) would be adopted widely in society with human-driven vehicles still present on streets. In addition to the eleven activities including "other (please specify)", the respondents are given "*I would not ride in an AV*" as an exclusive option (i.e., when the option was selected, all the other options were automatically de-selected). Also note that "interact with other passengers" was not given for the three contexts of traveling alone.


Suppose you are ***traveling with your family members to a neighborhood park*** in an AV. Which of the following would you do in the vehicle during your trip? *Select up to three activities.*

- ☐ Work, or study
- ☐ Talk on the phone/ send or read text messages/teleconference
- ☐ Read
- ☐ Sleep
- ☐ Watch movies/ TV/ other entertainment
- ☐ Play games
- ☐ Eat and drink
- ☐ Interact with other passengers
- ☐ Enjoy the scenery
- ☐ Watch the road, even though I would not be driving
- ☐ I would not ride in an AV
- ☐ Other (please, specify):

Figure 2. One version of the survey question on preferred activities in an AV
Note: In this version, travel context was "traveling with family members to a neighborhood park".

A few data preparation steps were performed to create the working dataset for analyses. The first step was to conduct exploratory factor analysis (EFA) (Rummel, 1970) to empirically uncover attitudinal constructs (i.e., factors) utilizing the answers to attitudinal statements, asked on a 5-point Likert scale from "strongly disagree” to “strongly agree”. The factors used in this study, statements with high loadings on the factors, and some details about the conducted EFA are presented in Appendix A. The second step was to reclassify (where possible) the “other (please specify)” responses (constituting less than 1% of the total) to one or more of the prespecified activities based on the text inputs specifying the activities. A few cases with invalid text inputs that prevented reclassification were excluded from the dataset. The third step was to impute missing values in key sociodemographic variables that were used for sample weighting[1]. The fourth step was to remove cases with missing values for any of the indicators and candidates for active covariates. The last step was to calculate sample weights so that the sample represents the study population (i.e., adults aged 18 or over) of the four regions to the extent feasible. Iterative proportional fitting (IPF) was utilized to obtain sample weights using the American Community Survey (ACS) 2019 5-year estimates as the population shares for age, sex, race, ethnicity, educational attainment, household income, and employment status (see Figure 3). Sample weights were calculated separately for each region and then trimmed using the threshold of median plus six times interquartile range (IQR). Next, the trimmed weights were adjusted such that the sum of weights for each region became proportional to the adult population based on the ACS 2019 5-year estimates for each region (see Appendix B for more details). *Trimmed* sample weights are used (instead of *untrimmed* sample weights) to obtain summary statistics and conduct statistical analyses in the following sections.

[1] A random-forest-based non-parametric imputation method was implemented in R (ver. 4.2.1) with “missForest” function in “missForest” package (ver. 1.5). Inputs are region, whether the respondent holds a driver’s license, number of licensed drivers in the household, number of motorized vehicles in the household, housing type, housing tenure, employment status, age, sex, place of birth (inside or outside of the U.S.), race/ethnicity, educational attainments, household size, and household income.

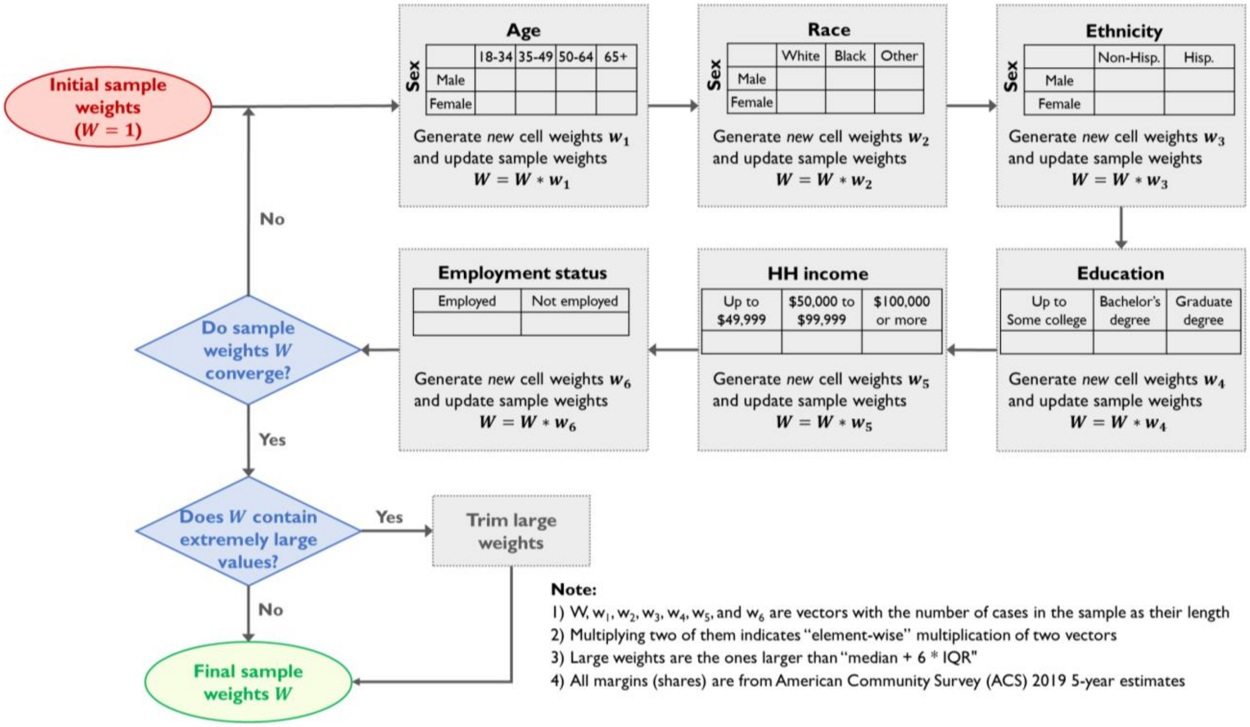


Figure 3. Flow chart of the weighting process (adapted from Wang et al. (2023))

We employ LCCA to identify groups of individuals with heterogeneous preferences for in-vehicle activities (see Figure 4). LCCA consists of two sub-models: a measurement model and a membership model. In this study, the former helps identify distinctive patterns (i.e., latent classes) of individuals choosing in-vehicle activities, and it does so by taking binary variables (i.e., whether given activities were selected or not) as indicators. We determine the optimal number of latent classes by estimating LCCA with varying numbers of classes and considering goodness-of-fit, interpretability, and class sizes. The membership model determines the statistical association of each unique pattern of activity selection with a wide set of individual characteristics as well as travel contexts (i.e., covariates), which affect the probabilities of individuals belonging to one class or another. Some of the covariates not found statistically significant are used as "inactive" covariates, which provide useful insights into the profile of each class.

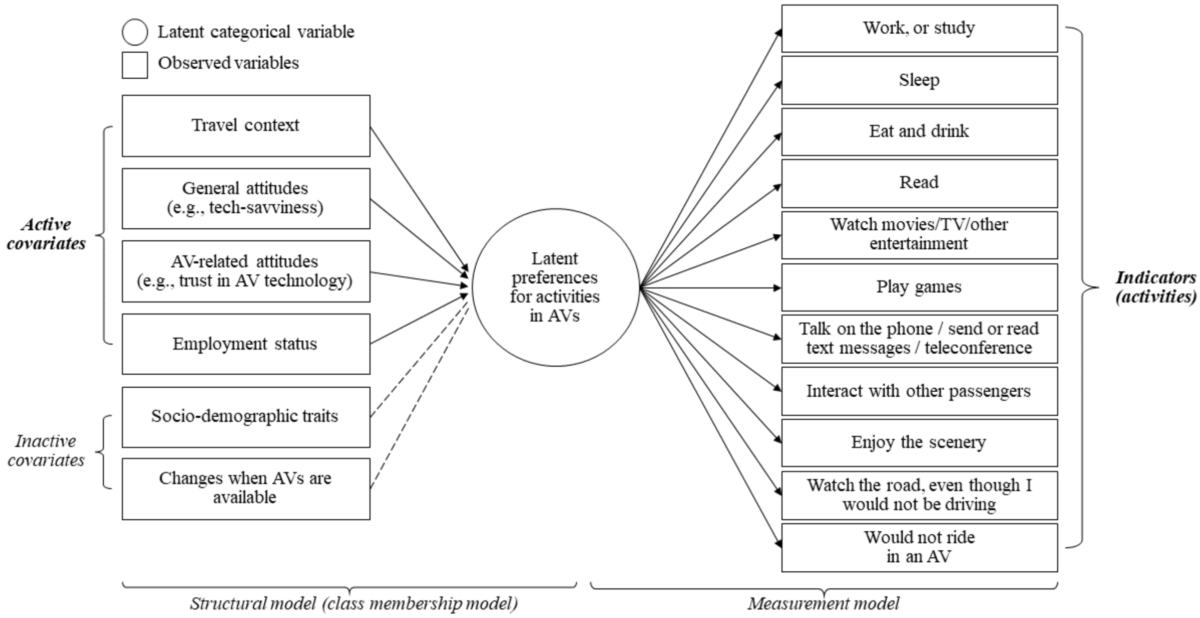


Figure 4. Structure of LCCA (adapted from Lee et al. (2022))

RESULTS

Preferred In-Vehicle Activities by Travel Context

Table 2 presents the (trimmed-weighted) distributions of preferred in-vehicle activities by travel context. The activities are ordered such that the lower the activity number is, the more likely the activity could free up time for other activities out of the vehicle. For example, *work/study* (Activity 1), *sleep* (Activity 2), and *eat/drink* (Activity 3) are rather active/productive use of in-vehicle time, which would likely otherwise consume some out-of-vehicle time. In contrast, *interact with passengers* (Activity 8)*, enjoy the scenery* (Activity 9)*,* and *watch the road* (Activity 10) are more of passing time in nature (even though *watch the road* also entails staying alert to take over when necessary). The last option in Table 2 is *I would not ride in an AV* (Activity 11), an exclusive option and *not* a specific activity.

The share of respondents who selected not to ride in an AV is smaller for those in family-travel contexts (13.9%) than for those in alone-travel contexts (18.7%). Especially, the share is distinctively low for those who were given the context of long-distance travel with family members (11.8%). This suggests that the perceived benefits from not manually operating vehicles are large and/or people feel more comfortable riding in an AV when other (close) passengers are present, both of which appear to be more prominent with longer travel time.

Overall, respondents prefer passing time or engaging in light activities not requiring full immersion (Activities 7-10). This can be partially attributable to the fact that Activities 1-6 (except sleeping) may generate or exacerbate carsickness and are more prone to be interfered with when vehicles accelerate, decelerate, and make turns. For alone-travel contexts, the three most popular activity choices are *talk on the phone / send or read text messages / teleconference* (Activity 7, 46.7%); *watch the road* (Activity 10, 38.0%) and *enjoy the scenery* (Activity 9, 29.9%), which allow riders to relax but take over immediately if necessary. On the other hand, for family-travel contexts, *interact with other passengers* (Activity 8, 41.9%) takes the first place, followed by the top-three choices for the alone-travel contexts (in reverse order): *enjoy the scenery* (36.8%), *watch the road* (34.0%), and *talk on the phone / send or read text messages / teleconference* (32.7%).

Table 2. Distribution of preferred in-vehicle activities

Travel Context	N	Weighted N	Activity (% chosen, weighted)										
			1	2	3	4	5	6	7	8	9	10	11
Alone to the store	657	657.4	16.9	12.1	16.8	20.0	13.4	8.2	47.2	-	28.2	46.9	19.2
Alone to work/school	695	728.6	28.5	16.2	16.9	20.9	13.4	6.8	47.3	-	28.5	39.8	19.0
Alone long distance	643	604.8	25.4	21.1	17.8	25.7	23.6	11.1	45.4	-	33.5	26.1	17.9
Alone combined	**1995**	**1990.7**	**23.7**	**16.3**	**17.2**	**22.1**	**16.5**	**8.6**	**46.7**	**-**	**29.9**	**38.0**	**18.7**
With family to a neighborhood park	705	671.2	11.7	11.3	14.3	14.1	15.1	8.9	37.7	45.1	38.3	35.3	16.1
With family long distance	676	714.1	14.6	30.1	16.1	22.2	26.9	7.4	28.0	38.8	35.3	32.7	11.8
With-family combined	**1381**	**1385.3**	**13.2**	**21.0**	**15.2**	**18.3**	**21.2**	**8.1**	**32.7**	**41.9**	**36.8**	**34.0**	**13.9**

Activity 1: Work, or study
Activity 2: Sleep
Activity 3: Eat and drink
Activity 4: Read
Activity 5: Watch movies / TV / other entertainment
Activity 6: Play games
Activity 7: Talk on the phone / send or read text messages / teleconference
Activity 8: Interact with other passengers
Activity 9: Enjoy the scenery
Activity 10: Watch the road, even though I would not be driving
Activity 11: I would not ride in an AV

As somewhat expected, respondents in alone-travel contexts tend to expect to *work, or study* (23.7%) while riding in an AV more than those in family-travel contexts (13.2%), which holds true even after excluding those in the "alone to work/school" travel context (21.0%, not shown in Table 2). One thing to note is that *work, or study* is selected by less than 30% of respondents even in the context of traveling alone to work/school (28.5%). This observation supports the argument that positive utilities of travel in AVs will arise more from "reduced stresses of driving or the ability to relax and mentally transition" (Singleton, 2019, p. 14) than from productive use of time. It is also loosely consistent with the approximately 25% share of non-transit commuters that Choi and Mokhtarian (2020) found to be work-oriented (with respect to attitudes toward work and travel time use).

For both alone-travel and family-travel contexts, respondents in a long-distance travel context are more likely to engage in Activities 1-5 (with the one exception that *work, or study* is selected more by those in the "alone to work/school" context). Especially, the tendency is stronger for *sleep* and *watch movies / TV / other entertainment*. For instance, only 11.3% and 15.1% of respondents in the "with-family-members to a neighborhood park" context chose those two activities, whereas 30.1% and 26.9% of those in the "with-family-members long-distance" context did so. The observed patterns make intuitive sense given that people would be more likely to want to "use" their time in AVs in certain ways when travel time is long, so that they can focus on the activities for a meaningful span of time without interruptions. It is also probable that people expect less stopand-go driving (that may induce carsickness and distractions) for long-distance trips.

Latent Classes Based on Preferences for In-Vehicle Activities

Acknowledging that traveling alone differs from traveling with family members with respect to the ability to *interact with other passengers* as well as the preferred ways of spending time in AVs, we estimated LCCA models separately for alone trips and family trips. Binary variables for Activities 1-11 (showing whether they are selected) are used as indicators, while the binary variable for *interact with other passengers* was not included in the alone-trip model. This section focuses on the summary statistics of indicator variables by class (i.e., the measurement model part of LCCA) for each model, and the following section (Section 4.3) delves into the class membership model part for each model, together with class-specific profiles.

Table 3 presents four unique patterns of selected activities (i.e., latent classes), identified separately for alone-trip and family-trip models. Classes names are mainly based on the preferred activities (shown in Table 3). The two models have one class in common: *No ride* containing respondents who decided not to use an AV in a given travel context (class shares of 18.7% and 13.9% in the alone-trip and family-trip models, respectively). Each model revealed a distinct set of three additional classes from respondents who did not pick *I would not ride in an AV*.

The three classes (other than *No ride*) in the alone-trip model are *Active use of time* (37.6%), *Alert* (23.8%), and *Passive use of time* (19.9%) in descending order of class share (see Table 3). Comparing the three classes, *Active use of time* members are most likely to expect to conduct activities that can save or free up time before/after the trip (Activities 1-3) and/or spend time leisurely on reading, watching videos, or playing games (Activity 4-6). Especially, the shares for *work/study* (45.6%), *sleep* (35.5%), and *watch movies / TV / other entertainment* (33.0%) are much larger than sample shares. Considering that such activities, in most cases, cannot be done while being cautious about surroundings and other road users, they have high trust in AV technology on average (see Table 5), which aligns with the fact that they do not *watch the road* (0.0%). On the other hand, *Passive use of time* members are least likely to select activities that *Active use of time* members prefer (Activities 1-6), but are most likely to select *enjoy the scenery* (100.0%) and many of them selected *watch the road* (71.3%). The *Alert* class is characterized by having all members selecting *watch the road* (100.0%) but not *enjoy the scenery* (0.0%).

The family-trip model discovered a slightly different set of classes: *Relax and interact* (33.5%), *Alert and interact* (29.1%), and *Solo and immerse* (23.5%) in descending order of class share. The activities that are much more popular in *Solo and immerse* (than in the sample) are *sleep* (63.3%), *watch movies / TV / other entertainment* (47.1%), and *work/study* (33.9%), all of which usually require time alone without interruptions and in-person interactions. In contrast, *interact with others* (22.7%) and *enjoy the scenery* (15.0%) are relatively less preferred in *Solo and immerse* (than in the sample). *Relax and interact* and *Alert and interact* members are similar in that they have high preferences for *interact with others* (58.6% and 58.0%) and *enjoy the scenery* (53.9% and 52.2%). However, *Relax and interact* members prefer to *read* (21.2%), *eat/drink* (30.6%), and *talk on the phone / send or read text messages / teleconference* as well while not *watching the road*, which can be considered as relaxing. One the other hand, *Alert and interact* members chose to *watch the road* (100.0%) instead of actively engaging in other activities (Activities 1-7), which is potentially associated with low trust in AV technology (see Table 5).

Table 3. Summary statistics of indicators by class

Travel Context		Alone trip (N = 1995; weighted N = 1990.7)					Family trip (N = 1381; weighted N = 1385.3)				
Class		Active use of time	Passive use of time	Alert	No ride	Sample	Solo and immerse	Relax and interact	Alert and interact	No ride	Sample
Class share (%)		37.6	19.9	23.8	18.7	100.0	23.5	33.5	29.1	13.9	100.0
Activity (% selected)	1	**45.6**	3.5	24.7	0.0	23.7	**33.9**	13.4	2.7	0.0	13.2
	2	**35.5**	1.0	11.5	0.0	16.3	**63.3**	16.7	1.8	0.0	21.0
	3	**23.9**	16.7	20.4	0.0	17.2	15.4	**21.2**	15.3	0.0	15.2
	4	**33.5**	18.5	24.4	0.0	22.1	17.5	**30.6**	13.4	0.0	18.3
	5	**33.0**	4.7	13.3	0.0	16.5	**47.1**	26.0	4.8	0.0	21.2
	6	**14.5**	3.6	10.1	0.0	8.6	**13.8**	13.0	1.7	0.0	8.1
	7	58.5	**60.2**	53.6	0.0	46.7	36.3	**44.7**	31.7	0.0	32.7
	8	-	-	-	-	-	22.7	**58.6**	58.0	0.0	41.9
	9	26.8	**100.0**	0.0	0.0	29.9	15.0	**53.9**	52.2	0.0	36.8
	10	0.0	71.3	**100.0**	0.0	38.0	20.7	0.0	**100.0**	0.0	34.0
	11	0.0	0.0	0.0	**100.0**	18.7	0.0	0.0	0.0	**100.0**	13.9

Note: **Bolded** numbers indicate the **row-wise largest values** for each of the two travel contexts (alone and family trips).

Activity 1: Work, or study
Activity 2: Sleep
Activity 3: Eat and drink
Activity 4: Read
Activity 5: Watch movies / TV / other entertainment
Activity 6: Play games
Activity 7: Talk on the phone / send or read text messages / teleconference
Activity 8: Interact with other passengers
Activity 9: Enjoy the scenery
Activity 10: Watch the road, even though I would not be driving
Activity 11: I would not ride in an AV

Personal Characteristics Associated with Each Latent Class

The membership model helps us better understand latent classes, by identifying factors associated with the probability of belonging to each class. With statistical significance (at the 5% level) of estimated coefficients and interpretability (with respect to class profiles and signs of estimated coefficients) as the two main criteria, we tested travel contexts and various individual characteristics as active covariates to obtain the final models. This section examines the estimated class membership models (Table 4) and compares the descriptive statistics of active and inactive covariates across classes, weighted by posterior class probabilities (Table 5).

Travel Contexts

Table 4 presents estimated coefficients of active covariates with *No ride* as the reference class. Travel contexts turned out to have statistically significant impacts on class membership (and, therefore, on expected time-use in AVs) in both models after controlling for individual characteristics (see Table 4).

When traveling alone, going to a store is associated more positively with belonging to *Alert* and more negatively with *Active use of time*, relative to traveling long distance. Short trip distances appear to discourage working or sleeping while bringing high levels of interactions with traffic signs, signals, and other road users, typically expected when traveling to a nearby store. Note that all three coefficients of “Alone to work/school” are not statistically significant in Table 4. However, when *Alert* is set as the reference class (instead of *No ride*), “Alone to work/school” is associated with *Active use of time* with a coefficient estimate of -0.862 = (-0.518) - 0.344 and a p-value of 0.002 (not shown in Table 4). That is, on an “Alone [trip] to work/school”, respondents are *less* likely to use in-vehicle time actively, but *more* likely to stay alert, compared to "traveling long distance alone". Consistent with these observations, around half (49.7%) of those respondents (randomly) presented with the "alone long distance" context belong to *Active use of time*, larger than the shares of the *Active use of time* class among those presented with the "alone to work/school" (37.0%) and "alone to the store" (27.2%) contexts (see Table 5). Interestingly, the order among the three travel contexts is reversed for *Alert* ("alone long distance": 14.6%, "alone to work/school": 23.6%, "alone to the store": 32.5%; see Table 5).

A similar pattern emerges for trips with family. The travel context "with family to a neighborhood park" is statistically significant and negatively associated with *Solo and immerse* (see Table 3). That is, respondents have a greater tendency to belong to *Solo and immerse* (e.g., sleep, work/study, and watch videos) when traveling long distance with the family, compared to going to a neighborhood park with the family.

Attitudes

A few attitudes are found to affect class membership as well. Four attitudinal variables are included as active covariates in the alone-trip model: tech-savviness, appreciation of varied benefits of AVs, trust in AV technology, and concern about information security and safety. One additional attitudinal construct, transit-as-reliable, is included in the family-trip model.

Comparing the classes in the alone-trip model, *Active use of time* members appreciate the varied benefits of AVs and trust AV technology the most, while being most tech-savvy and least concerned about AV-related information security and safety issues, on average (see Table 5). In contrast, *No ride* members have the exact opposite attitudes, explaining why they do not want to ride in an AV. This finding is very much consistent with the preferred activities of *Active use of time* members. For instance, one cannot sleep while riding in an AV without high trust in AV technology. In addition, appreciation of varied benefits of AVs may be linked to the willingness to engage in various activities (Activities 1-6) other than using the phone (Activity 7) or watching outside (Activity 9-10). Comparing the *Passive use of time* and *Alert* classes, the former group tends to trust AV technology more (which makes it less likely to *watch the road*), but is less tech-savvy and less appreciates the varied benefits of AVs (which may lead to lower participation in Activities 1-6) (see Table 5). These findings align well with the signs and magnitudes of the associated coefficients in Table 4.

Among the three AV-inclined classes in the family-trip model, members of both *Solo and immerse* and *Relax and interact* classes tend to be more positive toward AVs than *Alert and interact* members are, encouraging them to actively participate in activities (Activities 1-6) instead of *watching the road* (Activity 10) or *choosing not to use an AV*. However, the two classes have a few differences. One difference is that on average, *Solo and immerse* members have both higher trust in AV technology and greater concern about the information security and safety of AVs than *Relax and interact* members do (see Table 5). Another notable difference is that *Solo and immerse* members tend to be more tech-savvy, which makes intuitive sense considering that *working/studying* and *watching videos* (activities that *Solo and immerse* members prefer) are more likely to involve the use of electronic devices other than phones (e.g., laptops, tablet PCs), compared to *eating/drinking* and *reading* (activities that *Relax and interact* members prefer). It is also interesting that *Solo and immerse* members tend to regard transit as more reliable than *Relax and interact* members do. This observation is consistent with the finding in Choi and Mokhtarian

(2020) that workers who like working when commuting are more likely to switch to public transit with internet access. After all, the preference for working while traveling is linked to positive attitudes toward transit potentially due to the ability to work while using transit (although the family-trip model contains respondents in family-travel contexts excluding commuting).

No ride classes in both models share similar attitudinal characteristics, but *No ride* members in the family-trip model regard transit as more reliable than *Relax and interact* and *Alert and interact* members do (see Table 5). Given that the "transit as reliable" variable is associated not only with the pro-transit attitude but also with the quality of transit services available to respondents (see Appendix A for statements with high factor loadings), *No ride* members, on average, appear to be in more transit-friendly environments (at least partially by self-selection) than *Relax and interact* and *Alert and interact* members are. Thus, some respondents may have selected not to ride in an AV because they had access to quality transit services (and/or prefer using the services).

Other Characteristics

The sole sociodemographic variable included (but only in the alone-trip model) as an active covariate is employment status. In the alone-trip model, workers and students are more likely to belong to the *Active use of time* class and less likely to belong to the *Passive use of time* class, relative to the *No ride* class (see Table 4). In contrast, being a worker or student does not have a statistically significant association with class membership in the family-trip model, after controlling for travel contexts and attitudes. Still, note that this does not indicate a complete absence of the relationship, given that the *Solo and immerse* and *Relax and interact* classes have slightly larger worker shares (64-65%) than other classes (58%) and *Solo and immerse* has an especially large student share (25.1%) compared to other classes (8-16%) (see Table 5).

Multiple factors (e.g., the presence of "alone to work/school" travel context only in the alone-trip model) may have contributed to the difference between the two models. However, it can be conjectured that some of the workers/students who selected working, sleeping, or watching videos (and belong to *Active use of time*) when traveling alone would have wanted to enjoy the scenery and interact with family members (and therefore belong to *Relax and interact*) when traveling with family (instead of selecting themselves into the *Solo and immerse* class with similar activity preferences to those of the *Active use of time* class). This idea is supported by a small class share of *Solo and immerse* (23.5%) compared to *Active use of time* (37.6%), as well as similarly high shares of workers (64-65%) in *Solo and immerse* and *Relax and interact* (see Table 5).

Characterizing classes in the alone-trip model with other sociodemographic variables in Table 5, *Active use of time* members are more often younger, male, highly educated given their young ages (Bachelor's degree or higher), and with high household income ($100k+/year). *Passive use of time* members are more often older and with low household income (less than $50k+/year). *Alert* members are more often female and with high household income, while *No ride* members are more often less educated (up to some college or technical school) and with low household income (less than $50k+/year). In the family-trip model, *Solo and immerse* members are similar to *Active use of time* members with respect to sociodemographic variables. *Relax and interact* members are characterized by high educational attainments and household income, whereas *Alert and interact* members are characterized otherwise. *No ride* members are more often older, female, less educated, and with low household income.

The familiarity with and willingness to purchase AVs of individual classes align well with their AV-specific attitudes. *Active use of time* members tend to be familiar with AVs and more apt to think of buying an AV (as an early adopter or when AVs are in common use) compared to other classes in the alone-trip model. *Passive use of time* and *No ride* members are more often unfamiliar with AVs (than other classes are), and the latter are much more likely *never* to purchase an AV (92.6%, compared to 40.2% for the former). In the family-trip model, *Solo and immerse* and *Relax and interact* members are more familiar with AVs and expect to buy an AV more than those in the other classes (especially *No ride*).

Table 4. Class membership model (base class: *No ride*)

	Alone trip (N = 1995; weighted N = 1990.7)			Family trip (N = 1381; weighted N = 1385.3)		
Class	Active use of time	Passive use of time	Alert	Solo and immerse	Relax and interact	Alert and interact
Intercept	1.299 ***	1.477 ***	0.764 *	1.977 ***	1.985 ***	1.634 ***
AV travel context (Reference: traveling long distance, respectively alone or with family)						
Alone to the store	-0.757 *	0.181	0.824 *	-	-	-
Alone to work/school	-0.518	-0.057	0.344	-	-	-
With family to a neighborhood park	-	-	-	-2.234 *	-0.570	-0.210
General attitude						
Tech-savviness	0.351 ***	0.163	0.336 ***	0.827 ***	0.237	0.141
Transit as reliable	-	-	-	0.038	-0.339 .	-0.336 *
AV attitude						
Appreciation of varied benefits of AVs	1.220 ***	0.943 ***	1.215 ***	1.103 ***	1.349 ***	1.069 ***
Trust in AV technology	0.984 ***	0.624 ***	0.359 *	0.991 ***	0.813 ***	0.225
Concern about info security and safety	-0.319 **	-0.157	-0.177 .	-0.062	-0.270 *	-0.041
Employment status						
Worker or student	0.808 **	-0.794 **	-0.071	-	-	-
Class share	37.6%	19.9%	23.8%	23.5%	33.5%	29.1%
Number of cases[2]	1995			1381		
Log-likelihood	-8361.285			-6573.067		
AIC	16850.571			13276.134		
BIC	17208.868			13616.121		
Entropy	0.961			0.846		

Note:
1) Significance level: "." (10%), "*" (5%), "**" (1%), and "***" (0.1%)
2) Mplus 8.1 was used to estimate the model, in which sample weights are rescaled such that they sum up to the number of cases. In other words, sample weights sum up to 1990.7 (alone trips) and 1385.3 (with-family-members trips), but they are rescaled to make the sums equal 1995 (alone trips) and 1381 (with-family-members trips).

Table 5. Summary statistics of covariates by class

	Alone trip (N = 1995; weighted N = 1990.7)					Family trip (N = 1381; weighted N = 1385.3)				
Class	Active use of time	Passive use of time	Alert	No ride	Sample	Solo and immerse	Relax and interact	Alert and interact	No ride	Sample
Class share	37.6%	19.9%	23.8%	18.7%	100.0%	23.5%	33.5%	29.1%	13.9%	100.0%
AV travel context[2]										
Alone to the store	27.2%	21.1%	**32.5%**	19.2%	-	-	-	-	-	-
Alone to work/school	**37.0%**	20.4%	23.7%	19.0%	-	-	-	-	-	-
Alone long distance	**49.7%**	17.9%	14.6%	17.9%	-	-	-	-	-	-
With family to a neighborhood park	-	-	-	-	-	12.0%	**37.5%**	34.3%	16.1%	-
With family long-distance	-	-	-	-	-	**34.3%**	29.8%	24.2%	11.8%	-
General attitude										
Tech-savviness	**0.41** (1.28)	-0.21 (1.39)	0.14 (1.21)	-0.56 (1.16)	0.04 (1.32)	**0.63** (1.14)	0.01 (1.24)	-0.35 (1.19)	-0.61 (1.29)	-0.03 (1.28)
Transit as reliable	**0.10** (1.34)	0.08 (1.19)	-0.01 (1.31)	-0.03 (1.28)	0.04 (1.29)	**0.53** (1.39)	-0.01 (1.28)	-0.08 (1.07)	0.22 (1.41)	0.13 (1.29)
AV-related attitude										
Appreciation of varied benefits of AVs	**0.42** (0.97)	-0.02 (0.95)	0.21 (1.01)	-1.20 (0.95)	-0.02 (1.14)	0.27 (0.97)	**0.35** (0.95)	-0.01 (0.95)	-1.03 (0.86)	0.04 (1.05)
Trust in AV technology	**0.48** (1.08)	-0.05 (0.98)	-0.19 (1.00)	-0.95 (0.83)	-0.05 (1.12)	**0.55** (1.04)	0.37 (1.04)	-0.35 (0.99)	-0.73 (0.85)	0.05 (1.10)
Concern about info security and safety	-0.19 (1.41)	0.13 (1.29)	0.10 (1.37)	**0.42** (1.55)	0.06 (1.42)	0.11 (1.48)	-0.17 (1.44)	**0.44** (1.33)	0.42 (1.77)	0.16 (1.49)
Employment status[3]										
Worker	**73.3%**	48.3%	61.8%	55.8%	62.3%	**65.0%**	63.9%	58.0%	58.5%	61.7%
Student	**22.8%**	7.7%	19.6%	14.3%	17.4%	**25.1%**	16.4%	13.6%	8.4%	16.5%
Neither	15.1%	**49.8%**	29.1%	36.6%	29.3%	24.6%	29.7%	37.9%	**40.3%**	32.4%
Age										
18 - 34	**37.4%**	13.8%	28.8%	23.3%	28.0%	**43.7%**	28.6%	23.6%	17.7%	29.2%
35 - 49	**31.3%**	24.4%	26.9%	27.1%	28.1%	28.1%	26.2%	**29.9%**	11.5%	25.7%
50 - 64	22.6%	**34.0%**	24.0%	26.4%	25.9%	21.0%	27.1%	20.9%	**27.9%**	24.0%
65+	8.7%	**27.8%**	20.3%	23.2%	18.0%	7.2%	18.1%	25.7%	**42.8%**	21.2%
Sex										
Male	**57.6%**	43.3%	38.8%	43.5%	47.6%	**62.3%**	45.3%	41.1%	31.2%	46.1%
Female	42.4%	56.7%	**61.2%**	56.5%	52.4%	37.7%	54.7%	58.9%	**68.8%**	53.9%
Education										
Up to high school	**18.7%**	15.2%	17.9%	17.5%	17.6%	17.1%	12.5%	15.3%	**20.2%**	15.5%
Some college or technical school	39.7%	48.3%	48.2%	**56.9%**	46.7%	44.7%	50.6%	**57.3%**	47.0%	50.7%
Bachelor's or higher	**41.6%**	36.6%	33.9%	25.7%	35.8%	**38.1%**	36.8%	27.4%	32.8%	33.9%
Household income										
Up to $49,999	28.3%	**44.4%**	35.7%	40.4%	35.5%	40.7%	33.8%	35.5%	**52.3%**	38.5%
$50,000 to $99,999	**35.6%**	33.1%	28.9%	33.8%	33.2%	24.0%	29.5%	**34.9%**	26.8%	29.4%
$100,000 or more	**36.1%**	22.5%	35.4%	25.8%	31.3%	35.3%	**36.7%**	29.5%	20.9%	32.1%
Familiarity with AVs										
Not familiar	48.1%	**60.0%**	49.4%	58.7%	52.8%	44.0%	45.9%	50.7%	**63.4%**	49.3%
Somewhat familiar	32.1%	27.5%	**38.9%**	32.5%	32.9%	36.4%	**40.5%**	39.1%	27.6%	37.3%
Very familiar	**19.8%**	12.5%	11.7%	8.8%	14.4%	**19.6%**	13.7%	10.2%	9.0%	13.4%
When to buy an AV										
Early	**4.5%**	2.2%	2.2%	0.0%	2.7%	**6.3%**	5.4%	0.7%	0.0%	3.5%
When in common use	**74.2%**	56.3%	72.8%	3.8%	57.2%	**70.3%**	67.6%	60.5%	5.1%	57.5%
Never	18.7%	40.2%	24.7%	**92.6%**	38.2%	20.2%	23.7%	37.5%	**94.1%**	36.7%
No response	2.5%	1.3%	0.3%	**3.6%**	2.0%	3.2%	**3.3%**	1.2%	0.8%	2.3%

	Alone trip (N = 1995; weighted N = 1990.7)					Family trip (N = 1381; weighted N = 1385.3)				
Class	Active use of time	Passive use of time	Alert	No ride	Sample	Solo and immerse	Relax and interact	Alert and interact	No ride	Sample
Class share	37.6%	19.9%	23.8%	18.7%	100.0%	23.5%	33.5%	29.1%	13.9%	100.0%

Note:
1) Numbers shown in the table are shares, means, or standard deviations (in parentheses) as appropriate, **bolded** ones indicating **the highest value for each row for a given model**.
2) Shares for each AV travel context sum to 100.0% row-wise. Shares for the other categorical variables, except for employment status, add to 100.0% column-wise.
3) Employment statuses do not sum to 100.0% (column-wise) because being a student and worker at the same time is possible.

Expected Behavioral Changes When AVs Are Available

This subsection investigates whether and in which ways those in different latent classes change their travel behavior and location choices when AVs are available, and in doing so, it focuses on class-specific statistics on relevant variables, not included in the LCCA (Table 6). These variables are respondents' answers to statements regarding potential changes with access to an AV (by owning, leasing, or using automated ride-hailing services). For brevity, the shares of those who selected "somewhat likely" or "very likely" are presented in Table 6.

Overall, with access to an AV, respondents expect to modify their travel behavior more than to change home or workplaces. To be specific, the shares of those who would tolerate congestion better (40%) and travel farther for social/recreational activities (39-41%) are much higher than the shares of those who would change home (16-19%) or workplaces (16%) (see Table 6). A few additional oft-selected changes include traveling and doing more activities after dark (37-38%), making more long-distance trips (39-40%), and traveling more in peak hours (37-38%).

Table 6 clearly illustrates the correlations of class membership with the extent to which members of each class are potentially likely to change their travel behavior with AVs. *Active use of time* members are the most likely to make most changes listed in Table 6, followed by *Alert*, *Passive use of time*, and *No ride* members. In fact, the order of these classes coincides with their order in terms of the appreciation of varied AV benefits (see Table 5). In the meantime, preferred activities in AVs appears to be at work: e.g., working/studying, sleeping, and watching videos (which *Active use of time* members prefer) would reduce VOTTS more than staying alert or passing time would do.

The classes in the family-trip model present a somewhat different pattern. *Solo and immerse* and *Relax and interact* have similarly high shares of those who agree with the statements, followed by *Alert and interact* and *No ride*. Between *Solo and immerse* and *Relax and interact*, the former group is slightly more inclined to think of long-term, big changes (e.g., move to a better location or home: by 4.3 percentage points) while the latter group is moderately more likely to consider short term, small changes to be plausible (e.g., tolerate congestion better: by 4.9 percentage points). These subtle differences may suggest that a more intense use of in-vehicle time facilitates (or even motivates) riders to choose their home and workplace from a wider range of options, including those previously considered beyond geographic reach.

Table 6. Potential changes with AV access (% choosing “somewhat likely” or “very likely”)

	Alone trip (N = 1995; weighted N = 1990.7)					Family trip (N = 1381; weighted N = 1385.3)				
Class	Active use of time	Passive use of time	Alert	No ride	Sample	Solo and immerse	Relax and interact	Alert and interact	No ride	Sample
Statement										
Make additional trips that I do not make now	**37.9%**	19.0%	32.5%	2.8%	26.3%	32.6%	**34.1%**	19.7%	7.2%	25.8%
Travel farther to go shopping or eat out	**46.8%**	27.8%	40.2%	5.0%	33.6%	40.6%	**43.4%**	24.9%	10.7%	32.8%
Travel farther to go to social/recreational activities	**53.6%**	37.3%	43.5%	4.9%	38.8%	51.6%	**51.8%**	32.9%	10.7%	40.6%
Travel and do more activities after dark	**50.3%**	40.3%	44.1%	5.2%	38.4%	44.7%	**46.8%**	33.1%	10.6%	37.2%
Tolerate congestion better (no need to drive)	**57.3%**	37.4%	43.7%	5.2%	40.4%	46.4%	**51.3%**	34.6%	13.3%	40.0%
Travel more in peak hours (due to in-vehicle activities)	**53.4%**	30.5%	41.1%	4.0%	36.7%	**49.9%**	48.9%	32.8%	4.0%	38.2%
Make more long-distance road trips	**57.4%**	36.0%	42.5%	4.8%	39.7%	**50.6%**	48.1%	32.1%	8.7%	38.5%
Change workplace to a location with better/more jobs	**25.6%**	11.5%	12.9%	3.4%	15.6%	**22.9%**	20.2%	10.5%	6.4%	16.1%
Move to a better location or home	**28.0%**	13.5%	10.8%	3.8%	16.5%	**28.9%**	24.6%	13.1%	4.2%	19.4%

Note: Numbers shown are shares (percentage values), and **bolded ones** indicate **the highest value for each row in the same travel context** (i.e., alone or with-family-members).

DISCUSSION AND CONCLUSIONS

This study finds that using phones, interacting with other passengers, enjoying the scenery, and watching the road are more popularly envisioned activities in AVs than working/studying and sleeping. This finding is consistent with the literature suggesting that the primary value of AVs would come from the reduced burden of driving or the capability of taking rest, and less from the productive use of in-vehicle time (Singleton, 2019). In addition, travel contexts and attitudes are among the key factors accounting for the selection of activities in AVs. In the meantime, heterogeneous preferences for in-vehicle activities are linked to expected changes in travel behavior and location choice when AVs become widely available.

This study advances our knowledge regarding expected changes in travel behavior due to AVs in valuable ways. First, we measured preferences for in-vehicle activities (as well as the unwillingness to ride in an AV) in great detail by having respondents choose up to three from a wide range of activities, which may or may not free up time use out of the vehicle. Second, we employed LCCA, separately for each of two sets of travel contexts. Our chosen analytical approach uncovered a few distinct, heterogeneous patterns of activity combination, which enabled us to determine the nature of those combinations, especially whether and to what extent they are oriented towards productive use of in-vehicle travel time. Last but importantly, with a post-estimation analysis, we examined unique ways in which members of each class expect to change travel behavior and location choice in the future with AVs, consistent with their envisioned in-vehicle activities.

While adding valuable insights to the current knowledge regarding travel behavior in a future with AVs, this study also provides a key implication for future travel demand modeling. Specifically, it confirms that it would be desirable not to assume the same utility of using AVs (and willingness to ride in an AV) across all travel contexts and individuals, given the revealed heterogeneity. For example, instead of assuming the same VOTTS across all individuals when simulating travel patterns with AVs, we might want to make more realistic assumptions regarding the share of people with relatively low VOTTS when using AVs (e.g., *Active use of time*, *Solo and immerse*, *Relax and interact*), and share of people with no willingness to ride in an AV, for each travel context. One noteworthy point is that class shares are dependent on the distribution of travel contexts. Although this study developed sample weights to closely replicate the adult population in the study areas, each survey respondent only received one of the five travel contexts (randomly assigned). Therefore, it would be desirable to refer to the class shares for each travel context and class-specific profiles (in Table 4) to adjust class shares as appropriate when applying the results in this study. Such modeling and simulation efforts would benefit from further research on how people want to split their time in AVs for multiple activities and how the in-vehicle activity patterns would differ in travel contexts not considered in this study (e.g., commuting with family members, ridesharing with strangers).

One topic that requires further investigation is the underlying motivations and constraints associated with the choices of what activities to select and whether to ride in an AV. In this study, we observed the attitudes and travel contexts linked to the choices. However, directly asking the associated motivations and constraints is beneficial in a few ways. First, it would help better explain a few observations in this study (e.g., why the profiles of *No ride* in the two models slightly differ with respect to some sociodemographic characteristics, why employment status has statistically significant impacts on class membership only in the alone-trip model). Second, the information on key motivations/constraints would give us an idea of how we could encourage/discourage specific in-vehicle activities or the use of AVs, and to what extent if possible. For instance, suppose that working/studying, sleeping, and watching videos help people tolerate long-distance travel the best (compared to other activities), potentially leading to reduced carbon emissions by shifting long-distance mode shares from airplanes to cars. The effectiveness of encouraging such activities with policies and vehicle design would be limited if many of those who do not expect to engage in such activities report that their main constraints are serious carsickness and a problem with sleeping in a moving vehicle. Lastly, an improved understanding of key motivations/constraints would help us design a set of survey questions on the choices of travel modes and in-vehicle activities under various scenarios (e.g., by time, distance, presence of other passengers). We can use the answers to reveal the key factors affecting the utility of using AVs, which leads to estimation of VOTTS in AVs under various scenarios and, thus, to better modeling of travel behavior with respect to mode choice, AV adoption, and vehicle miles traveled.

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APPENDIX A: STATEMENTS WITH HIGH FACTOR LOADINGS

Attitude/preference[1]		Statement[2] (factor loading)
General[3]	Tech-savviness	I like to be among the first people to have the latest technology. (0.560) Learning how to use new technologies is often frustrating for me. (-0.484)
	Transit as reliable	Public transit is a reliable means of transportation for my daily travel needs. (0.659) Most of the time, I have no reasonable alternatives to driving. (-0.489)
AV-related[4]	Appreciation of varied benefits of AVs	AVs would save me time and money for parking by dropping me off and parking themselves. (0.830) AVs would make it easy to share vehicles within my household because they can pick-up/drop-off household members on their own. (0.751) I would send an AV to pick-up groceries/laundry/food orders by itself. (0.546) I would make more long-distance trips when AVs are available because I wouldn't have to drive. (0.472) AVs would help me avoid impaired driving (e.g., under the effects of medication or alcohol). (0.404) AVs would make traveling by car less stressful for me. (0.337) I want the ability to take control of the AV at any time during the ride. (0.306)
	Trust in AV technology	I would feel comfortable having an AV pick-up/drop-off children without adult supervision. (0.730) AVs would make me feel safer on the street as a pedestrian or as a cyclist. (0.688) I would feel comfortable sleeping while traveling in an AV. (0.670) AVs would make traveling by car less stressful for me. (0.526) I want the ability to take control of the AV at any time during the ride. (-0.392) I would make more long-distance trips when AVs are available because I wouldn't have to drive. (0.338) I am concerned about the potential failure of AV sensors, equipment, technology, or programs. (-0.302)
	Concern about info security and safety	I am concerned that my travel logs and personal information stored in AVs could be leaked. (0.528) AVs will eliminate my joy of driving. (0.446) I am concerned about the potential failure of AV sensors, equipment, technology, or programs. (0.378)

Note:
1) Factor solutions were obtained from exploratory factor analysis conducted in R (ver. 4.2.1) with *factanal* function, using *oblimin* rotation. Bartlett factor scores were calculated from the factor solutions.
2) Statements with a factor loading at least 0.3 in magnitude.
3) Factor analysis was conducted with the answers to 28 statements designed to measure attitudes toward various topics in general.
4) Factor analysis was conducted with the answers to 13 statements designed to measure attitudes toward AVs.
5) Each factor analysis was conducted after removing cases with more than two missing values from the dataset and imputing missing values of cases with one or two missing values using a random-forest-based non-parametric imputation method (implemented with "missForest" function in "missForest" package (ver. 1.5)).

APPENDIX B: SAMPLE WEIGHTING RESULTS

Variable		Total (N=3376)											
		Phoenix, AZ			Atlanta, GA			Tampa, FL			Austin, TX		
		Population	Sample		Population	Sample		Population	Sample		Population	Sample	
			Unweighted (N=1026)	Weighted (N=967.1)		Unweighted (N=1003)	Weighted (N=1164.7)		Unweighted (N=255)	Weighted (N=766.6)		Unweighted (N=1092)	Weighted (N=477.6)
Sex	Male	48.9%	49.6%	47.3%	47.4%	41.7%	46.0%	47.9%	42.0%	46.9%	49.8%	33.7%	49.0%
	Female	51.1%	50.4%	52.7%	52.6%	58.3%	54.0%	52.1%	58.0%	53.1%	50.2%	66.3%	51.0%
Age	18-34	31.5%	10.0%	28.9%	31.1%	15.1%	27.7%	25.9%	19.2%	24.5%	35.4%	68.4%	36.0%
	35-49	25.7%	18.2%	26.7%	28.7%	27.0%	29.2%	23.3%	26.7%	23.7%	29.2%	12.8%	28.4%
	50-64	23.2%	34.2%	24.1%	24.8%	32.3%	26.7%	25.7%	31.8%	26.2%	21.7%	10.4%	21.7%
	65+	19.6%	37.5%	20.3%	15.3%	25.6%	16.5%	25.2%	22.4%	25.6%	13.7%	8.3%	13.9%
Race	White only	79.5%	89.9%	80.6%	52.2%	74.6%	55.2%	80.7%	82.7%	81.0%	77.3%	68.0%	78.1%
	Black only	5.4%	2.1%	5.6%	35.8%	18.0%	32.9%	10.9%	8.2%	10.5%	7.3%	3.1%	6.3%
	Other	15.1%	8.0%	13.8%	12.0%	7.4%	11.9%	8.4%	9.0%	8.5%	15.4%	28.8%	15.7%
Ethnicity	Hispanic	73.1%	90.8%	75.8%	90.6%	96.1%	91.1%	82.8%	89.8%	84.3%	70.8%	73.6%	70.8%
	Not Hispanic	26.9%	9.2%	24.2%	9.4%	3.9%	8.9%	17.2%	10.2%	15.7%	29.2%	26.4%	29.2%
Education	Up to some college	70.1%	38.6%	68.9%	62.5%	25.7%	60.1%	72.1%	49.8%	71.6%	59.2%	49.0%	58.5%
	Bachelor's degree	19.4%	36.5%	20.1%	23.7%	38.8%	25.1%	18.3%	36.9%	18.6%	26.8%	34.2%	27.2%
	Graduate degree	10.6%	25.0%	11.0%	13.7%	35.5%	14.7%	9.6%	13.3%	9.8%	14.0%	16.8%	14.3%
Annual household income	Up to $49,999	38.4%	21.1%	36.7%	35.7%	17.3%	32.7%	45.8%	28.6%	46.1%	31.5%	41.0%	31.9%
	$50,000-$99,999	31.5%	38.5%	32.5%	30.9%	31.2%	32.3%	30.4%	38.4%	29.8%	30.6%	29.9%	31.1%
	$100,000+	30.1%	40.4%	30.8%	33.4%	51.4%	35.1%	23.7%	32.9%	24.1%	37.9%	29.0%	37.0%
Employ-ment	Employed	60.9%	56.5%	61.7%	64.5%	71.1%	65.0%	55.7%	71.0%	54.9%	67.7%	61.0%	67.1%
	Not employed	39.1%	43.5%	38.3%	35.5%	28.9%	35.0%	44.3%	29.0%	45.1%	32.3%	39.0%	32.9%

Note:
1) Universe: (1) 18 and over (sex, age, race, ethnicity, and education), (2) all households (annual household income), and (3) 16 and over (employment status).
2) Phoenix: 1 county (Maricopa)
3) Atlanta: 15 counties (Fulton, Gwinnett, DeKalb, Cobb, Clayton, Cherokee, Henry, Forsyth, Paulding, Coweta, Douglas, Fayette, Newton, Rockdale, and Spalding)
4) Tampa: 5 counties (Citrus, Hernando, Hillsborough, Pasco, and Pinellas)
5) Austin: 5 counties (Bastrop, Caldwell, Hays, Travis, and Williamson)