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Identifying latent mode-use propensity segments in an all-AV era

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ABSTRACT

This study offers an early glimpse of how individuals perceive the advantages/disadvantages of AVs, their mode-use intentions, and potential market segments with respect to mode use, should AVs eventually become the only way to travel by car. To do so, we implemented a statewide survey of Georgia residents (N = 2890) and using that data, we applied factor analyses to two blocks of AV-related statements. The first block measured 12 perceptions of AVs, and yielded two psychological constructs: *AV pros* (advantages/ benefits) and *AV overuse cons* (negative outcomes specifically associated with the excessive use of AVs). The second block of statements measured respondents' inclinations between AV and non-AV options for 12 hypothetical transportation "needs", and factor analysis identified four mode-use propensity constructs: *AV(-inclined) over walk/bike*, *AV over flight*, *zero-occupant AV over occupied AV*, and *AV over transit*. The main goal of the paper was to segment the sample on the basis of these four mode-use propensities, to identify clusters with similar propensity profiles or response vectors. We applied latent class cluster analysis to do so, and identified seven potential market segments: some preferring AV options in general, others preferring non-AV options or having unique propensity patterns based on certain contexts (e.g. long distance travel and vehicle occupancy). In the model, socio-demographics, geography, attitudes, and perceptions of AVs help characterize those market segments, and this provides a basis for deeper interpretation and consideration of policy implications.

1. Introduction

New technologies are reshaping the landscape of urban transportation systems and daily lifestyles of society. A prominent focal point for a bundle of emerging technologies is the autonomous vehicle (AV, *a.k.a.* self-driving/automated car/vehicle, etc.). The U.S. National Highway Traffic Safety Administration (2017) released new federal guidance for automated driving systems based on six levels of automation, from "No automation" (Level 0) to "Full automation" (Level 5). Current technologies have already passed "Driver assistance" (Level 1) and reached "Partial automation" (Level 2) or "Conditional automation" (Level 3). Some experts are predicting that "High automation" (Level 4) or Level 5 full automation will be realized in the relatively near future, although when, or even whether, we will ever reach complete systemwide automation is far from certain. Nevertheless, it is widely acknowledged that even the mere *introduction* of AVs could bring massive changes in nearly everything related to transportation, because they can significantly affect interactions among humans, vehicles, and infrastructure. Consequently, the even greater changes that would occur if *full* automation were ever achieved are of keen interest to researchers, planners, policymakers, and industry alike.

Accordingly, AV studies are proliferating. Such studies use several kinds of approaches, including, but not limited to: *surveys* (e.g. Payre et al., 2014; Bansal et al., 2016; Daziano et al., 2017; Haboucha et al., 2017); *scenario-based projections* (e.g. Harper et al., 2016; Truong et al., 2017); *scenario-based simulations* (e.g. Liu et al., 2017; Zhang et al., 2018); and *naturalistic experiments* (Harb et al.,

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2018). Survey-based research to date has generally focused on general opinions about AVs, intention to use AVs, or willingness to pay for (Level 3 or 4) AVs (e.g. Daziano et al., 2017; Haboucha et al., 2017; Krueger et al., 2016). Because fully automated AVs have not been realized yet and from a customer's perspective, trust in technology matters (Becker and Axhausen, 2017), those topics have been of dominant interest. Looking forward, however, a critical question about AVs may be "*How will people change their travel-related behavior if personal vehicles are fully automated and replace all conventional vehicles?*" Will people still be suspicious of AVs and embrace other modes (walking, transit, etc.) as much as possible? Will an aversion to AVs compete with an aversion to the alternative (public transportation, active modes, or flying)? Or will travelers embrace the hands-free flexibility that AVs offer, and choose to travel by car even more?

In this context, this study aims to address the following questions, the first two being ancillary to the third, which is the main focus of interest: (1) how will people perceive AVs? (2) what will travelers' general inclinations, or propensities, be with respect to choices between AVs and other modes in various contexts? and (3) what distinctive market segments will exist with respect to those general inclinations? Of course, there are always difficulties associated with asking people to imagine their reactions to a technology that is still emerging. Whether the survey format is stated preference or direct questioning, there is no evading response errors due to ignorance, an inability to imagine new technologies, and/or difficulty in assessing the role of such technologies in future lifestyle options. However, both the technology (including precursors to full Level 5 that are already on the market) and the public conversation about the technology are evolving rapidly, and more and more "lay" citizens are growing well-formed opinions about an AV future. Although respondents' reactions offered now must still be considered somewhat volatile, we think it is not too soon to begin assessing responses to a prospective all-AV future – both for what they *can* tell us about future impacts, and also to establish a benchmark against which ongoing shifts in opinion can be measured and trends detected.

To address the questions we raised above, we designed and implemented a survey to measure AV perceptions and inclinations together with general travel-related attitudes, sociodemographic traits, and other variables. In the service of research questions (1) and (2), we apply factor analysis to distill the perceptions into two factors and the propensities into four factors. To address our main question (3), we use latent class cluster analysis to identify segments having similar vectors of scores on the latter four factors, i.e. similar bundles of propensities toward using AVs versus other modes. We then further analyze and interpret the resulting latent classes.

Accordingly, the remainder of this paper is organized as follows: Section 2 outlines literature relevant to our study. Section 3 delineates how we designed and implemented the survey and describes the data collected. Section 4 shows the modeling framework and corresponding models, while Section 5 presents the results of the factor analyses and the latent class cluster analysis. Lastly, Section 6 summarizes the study and discusses its implications and limitations.

2. Literature review

As mentioned in Section 1, the field of AV studies is rapidly growing. For brevity, we do not provide a comprehensive review of the AV literature; rather, we simply touch on some research themes that are relevant to this study. In this section, we present a skim of papers analyzing several behavioral responses in the AV era, and in particular, mode choice. Glimpses of some new types of mode use in the AV era are provided. Then, in terms of modeling, important variables in the literature and some contextual differences among previous studies, and between those studies and the present one, are identified. Lastly, we review some studies related to market segmentation, which is the key interest of our analysis.

Beyond the adoption of AVs (e.g. Payre et al., 2014; Zmud et al., 2016), various other behavioral responses have begun to be examined. The majority of studies have focused on *mode choice*, using stated preference (SP) surveys (e.g. Krueger et al., 2016; Yap et al., 2016; Steck et al., 2018). Household *vehicle ownership* (Zhang et al., 2018), *residential location* (e.g. Milakis et al., 2018; Zhang and Guhathakurta, 2018), and *time use* (e.g. Pudāne et al., 2018) have also been studied, involving stated preference, simulation, and conceptual approaches. Among the mode choice SP studies, the choice set varied by study. Haboucha et al. (2017) used regular car, private AV (PAV), and shared AV (SAV); Krueger et al. (2016) compared dynamic-shared SAV, non-dynamic-shared SAV, and respondent's current mode; and Yap et al. (2016) introduced bike, public transit, and AV as egress modes from a train station. Steck et al. (2018) used five options (walk, bike, public transit, PAV, and SAV).

With respect to mode use in particular, many researchers agree that AVs will prompt shifts to new modes and new types of behavior. One example is the use of zero-occupant vehicles (ZOVs) to run errands, reposition to pick up a passenger, or park after dropping off a passenger (Zhang et al., 2018). Another example concerns long-distance trips. LaMondia et al. (2016) found that various socioeconomic/demographic (SED) variables (especially income) and trip characteristics (e.g. distance, purpose) affect mode choice for long-distance trips, and they simulated statewide mode shifts by controlling the (assumed) perceived travel time of AVs. They found that AVs draw shares from personal vehicles and airlines equally for less-than-500-mile trips, whereas airlines remain preferred for greater-than-500-mile trips.

Diverse variables have been tested in modeling the behavioral impacts of AVs (e.g. intention to use, mode choice, acceptance). Among SED traits, gender, age, education, and income have played critical roles in the models. In general, *male* (e.g. Payre et al., 2014; Schoettle and Sivak, 2015; Zmud et al, 2016), *younger* (e.g. Dong et al., 2019; Haboucha et al., 2017; Abraham et al., 2016), *more highly educated* (e.g. Haboucha et al., 2017), and *higher-income people* (e.g. Bansal et al. 2016) are more positive toward AVs or more likely to adopt AVs. Several studies have found that attitudes or lifestyle factors are important to AV-related behavioral changes (Lavieri et al., 2017; Nielsen and Haustein, 2018; Yap et al., 2016; Zmud et al., 2016).

It is worth noting contextual differences among AV studies, since the future is highly uncertain and thus each study has its own assumptions and setting. Specifically, past studies differ with each other in how they set up the future (i.e. assumptions about the AV era), research focus (i.e. dependent variable and key covariates of interest), demographic context (i.e. geography or target population), modeling structure, and/or outcome of interest (e.g. adoption, willingness to pay, etc.). In many studies (1) the focus is on the transition period or the initial introduction of AVs rather than on a longer-term future when the technology is more mature[1]; (2) the mode choice context is the transition period, during which conventional vehicles as well as AVs are available; (3) the target population tends to be one specific neighborhood/city rather than a more general population; and (4) the key outcome of interest is generally AV "adoption", rather than some other indicators that are relevant to mode use. In addition, as new technologies will be introduced, there will be heterogeneous groups that react to such a new environment differently, and yet to the authors' knowledge, studies on market segmentation in the AV era are currently very limited. We aim to address some of these knowledge gaps, as improving our understanding of the future AV market is informative to both research (e.g., models in a simulation framework could consider this heterogeneous market) and policy (e.g., how can sustainable travel best be encouraged in a fully-AV era).

A particular interest of this study is to identify market segments characterized by mode-use propensities in the AV era. Hence, the vast literature on clustering methodologies is pertinent. Common segmentation methods include K-means clustering (e.g. Mokhtarian et al., 2009; Li et al., 2013) and latent class cluster analysis (LCCA, e.g. Deutsch and Goulias, 2013; Molin et al., 2016); we use the latter and will describe it in detail in Section 4. Nielsen and Haustein (2018) is relevant to our study in that they classified the Danish population into three clusters (Sceptics, Indifferent stressed drivers, and Enthusiasts) based on attitudes toward AVs and traditional car driving. They found that Enthusiasts are more often male, young, highly educated, and living in large urban areas, whereas Sceptics tend to be older, car-reliant, and living in less densely-populated areas. Differences from the present study include that they segmented the population based on perceptions of AVs rather than on mode-use propensities, and they used different modeling approaches (principal component analysis vs. our common factor model; K-means clustering vs. our LCCA).

3. Survey administration and design

3.1. Survey administration

This study employs survey data collected in 2017–2018. Funded by the Georgia Department of Transportation (GDOT), the main purpose of the survey was to illuminate the impacts of new technologies and emerging trends on travel behavior/demand in Georgia. By agreement with the study sponsor, primary sampling consisted of inviting randomly-selected members of randomly-selected households living in the 15 metropolitan planning organization (MPO) regions in Georgia. Residents outside those areas (i.e. in largely rural parts of the state) were also represented by means of a secondary sample comprising Georgia respondents to the 2016–17 National Household Travel Survey who had agreed to be surveyed further and who accepted the invitation to complete our survey. Prospective respondents in both samples were sent a paper copy of the survey, together with a cover letter containing a link to the online version which could be completed instead. As an incentive, two-dollar bills (relatively novel in U.S. currency) were promised in the cover letter, and later sent, to those who completed the survey. The sampling and survey design descriptions are abridged here due to space limitations; more detailed descriptions are available in Kim et al. (2019). In brief, this study can capture a more diverse cross-section of opinions because (1) we used address-based random sampling rather than a commercially-recruited online panel, and (2) the survey was administered with both paper and online formats rather than exclusively online. Accordingly, we minimized the biases associated with an all-online administration, although the usual survey nonresponse biases still apply. The initial sample size was more than 3000, but for this study it was reduced to 2890 due to missing values on relevant variables. The descriptive statistics of the data will appear in Tables 4 and 5 of Section 5 (to ease comparison with the model results).

3.2. Survey design

The survey was designed to capture information on general transportation-related attitudes, lifestyle, use of technology/transportation services, travel behaviors, opinions on AVs, and socio-demographics. The section ordering just specified was intentional, so that respondents will have reflected on their opinions, lifestyle, and behaviors when envisioning an AV era. Within the section devoted to AVs, we also intentionally ordered the questions to progress from AV familiarity, perceptions of potential AV benefits and drawbacks, willingness to use some AV configurations (privately owned AVs, sequentially shared AVs, and simultaneously shared AVs), the propensity to use other modes (as will be described in more detail below), and longer-term impacts of AVs on activity patterns, vehicle ownership, and residential location. As introduced earlier, one notable difference from other studies is that we bypassed transitional concerns about safety and cost to focus on a possible "simpler" future period in which AV technologies are *fully mature* and in fact *ubiquitous and mandatory* (i.e. with conventional personal vehicles removed from the choice set). The survey gave descriptions and figures to help respondents envision such a fully automated future.

With respect to mode-use propensities, the survey includes a block of 12 items, each presenting a brief hypothetical transportation "need" (see the lower half of Table 1, below), and offering an AV-based alternative for meeting that need, versus an alternative generally involving another appropriate mode, such as walk/bike, bus/train, and plane (for three items, the two alternatives were an occupied and unoccupied AV, respectively). Respondents were asked to indicate, on a continuous/ordinal scale anchored at each end

[1] In this study, we are conjecturing a future where AVs completely replace *all* conventional vehicles. However, it is still an open question whether AVs can/will *ever* completely replace all conventional vehicles. Hence, this study should be considered an investigation of only one of multiple plausible future scenarios.

Table 1
Pattern matrix factor loadings for the AV-related constructs.

Advantages/disadvantages of AVs

Dimension	Statement	*AV pros*	*AV overuse cons*
Comfort	Having the vehicle drive itself would allow me to be more comfortable on trips.	0.751	
Fun	A self-driving car would enable me to enjoy traveling more (e.g. watching the scenery).	0.732	
Productivity	I would gain a lot of useful time by sending my vehicle to do certain things (e.g. pick up dry cleaning) without me.	0.704	
Impaired driving	I would more often travel even when I am tired or sleepy.	0.677	
Parking	I would reduce my parking costs because my self-driving car could drive itself to a cheaper parking space.	0.646	
Mobility	A self-driving car would enable me to get to places faster than if I had to drive myself.	0.588	
Impaired driving	I would be able to travel more often when under the influence of alcohol or medicines.	0.505	
Productivity	Even if I could do other activities in the car while it drove itself, I would not gain that much useful time.	−0.424	0.345
Time/money use	A self-driving car would reduce by too much the exercise I get through walking or biking.		0.662
Relationship	I am concerned that the self-driving car would lead to spending less time with family or friends (e.g. because of having more work trips).		0.652
Time/money use	I am concerned that the self-driving car would lead to me using a car too much.		0.602
Fun	I would miss the joy of driving and the feeling of being in control.		0.339

Mode-use propensities*

	AV over walk/bike	*ZOV over OV*	*AV over flight*	*AV over transit***
Walk/bike for 20 min to get to work/school vs. Take a **self-driving car** to get to work/school	0.953			
Walk/bike for 20 min to get to a transit station vs. Take a **self-driving car** to get to a transit station	0.872			
Walk/bike for 20 mins to social activities or to do personal business vs. Take a **self-driving car** to social activities or to do personal business	0.771			
Walk/bike for 20 mins to go shopping vs. **Take a self-driving car** to go shopping	0.711			
Go with the car to bring other people who are not able to drive vs. **Send an empty self-driving car** to bring others who are not able to drive		0.895		
Go with the car to pick up meals vs. **Send an empty self-driving** car to pick up meals		0.581		
Go with the car to bring my child vs. **Send an empty self-driving car** to bring my child		0.526		
Fly to a vacation in a distant state vs. **Take a self-driving car** to a vacation in a distant state			0.859	
For a one-day trip, **fly** for 3 h each way (including access/wait time) vs. For a one-day trip, **take a self-driving car** for 6 h each way			0.592	
Take a bus or train to go shopping vs. **Take a self-driving car** to go shopping				0.912
Take a bus or train to social activities or to do personal business vs. **Take a self-driving car** to social activities or to do personal business				0.877
Take a bus or train to get to work/school vs. **Take a self-driving car** to get to work/school	0.309			0.533

Note: factor loadings under 0.3 are suppressed for clarity.
* Higher response values on the items shown signify a greater inclination toward the second of the two options presented.
** To simplify interpretation, we reversed the directionality of this scale by multiplying the original loadings and factor scores by (−1).

by AV and the alternative, where their inclination fell. For the paper version, we intentionally designed the responses as visual analogue scales (VAS), i.e. rating scales in a continuous graphical format (Fig. 1), for multiple reasons: (1) mode-use propensity in the AV-era is somewhat uncertain due to its hypothetical nature and thus it is better to allow for a degree of general inclination rather than forcing a dichotomous or even ordered categorical response; (2) many studies have shown that VAS has superior measurement qualities compared to traditional Likert-type scales (Kuhlmann et al., 2017); and (3) by that point (page 12) in the 14-page survey we wanted to break the monotony and maintain respondent attention by using a new response format, specifically one with greater visual interest. Due to limitations of the software, however, the online version of the survey (completed by 20.7% of the sample analyzed in this study) offered a five-point ordinal response scale; the two types of scales were combined for the present study[2]. These 12 items were factor-analyzed to obtain four mode-use propensity measures, the key variables defining the structure of our latent classes (see Sections 4 and 5.1). In asking these questions, we left unspecified the form that AV service would take (i.e. private, shared sequentially, or shared simultaneously), because in this block of questions we considered respondents' views of "generic" AV technology to be more relevant than their views of specific service configurations of that technology. Further, since the question

[2] For the paper survey, we used the original scale (continuous values between 0 and 5). For the online survey, we converted the five ordinal points into the midpoints of the five units composing the continuous scale by subtracting 0.5 from each response (e.g. 1 became 0.5; 5 became 4.5). As described in the text, a majority of respondents completed the paper survey and we factor-analyzed the responses; hence the impact of the difference in scales is expected to be marginal.

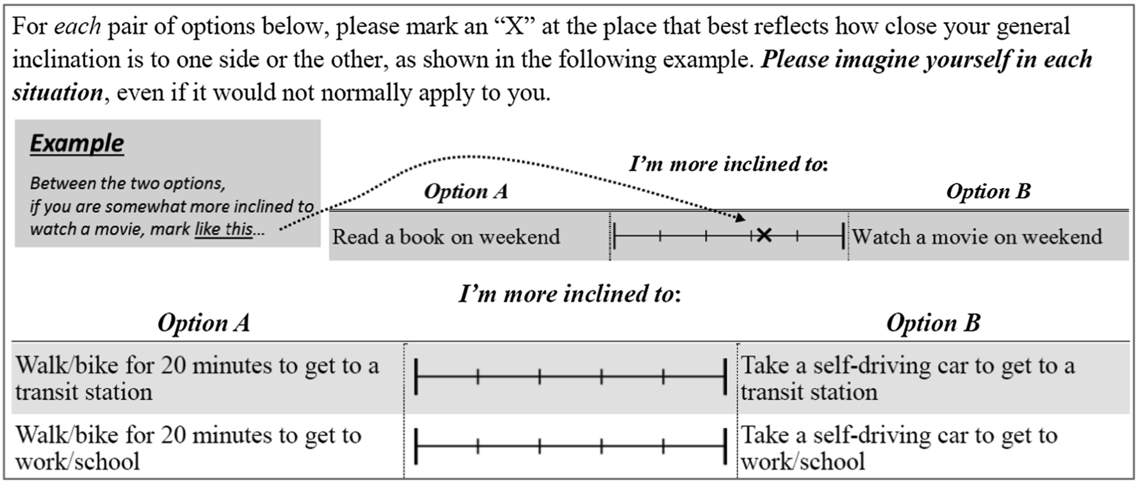

Fig. 1. Paper survey version of the mode-use propensity block of items (excerpt).

immediately preceding this block asked specifically about each of those configurations, treating them as equally possible, we expected respondents to have all of them in mind as they answered the mode-propensity questions.

Several other sets of variables are pertinent to this study. The first section of the survey contains 46 attitudinal statements with five-point Likert-type scale ("strongly disagree" to "strongly agree") responses. We extracted 15 attitudinal constructs through factor analysis, and selected those which are relevant to mode preference. Specifically, we use factor scores for *non-car-alternative*, *tech-savvy*, *pro-environmental*, *pro-exercise*, *family/friends-oriented*, *wait-tolerant*, and *pro-car-owning* attitudes in this paper (see Appendix A for the selected constructs and associated statements). The *perceptions of AVs* that were included in the model are described in Section 5.1. As found in other studies, *SED traits* may be strongly associated with the behavioral response to AVs, and thus we incorporate key SED variables. In addition, we hypothesize that geographic location will also affect mode-use propensity; hence we adopt variables capturing two types of geography – MPO level (regional) and neighborhood type (local). With respect to *MPO level*, we classify the 15 MPOs and the remaining regions into four tiers based on MPO population: 1st tier (Atlanta MPO), 2nd tier (other MPOs with population over 200,000), 3rd tier (MPO population under 200,000), and non-MPO areas. The *neighborhood type* is classified into urban, suburban, small town, and rural.

4. Methodology

To address the research questions mentioned above, we use two types of latent variable models – factor analysis and latent class cluster analysis. For the first type, specifically, we use exploratory factor analyses, which aim to find a relatively small number of underlying *latent* variables or constructs (common factors) that sufficiently account for the patterns of covariance among the observed variables (Loehlin and Beaujean, 2017; Rummel, 1970). After identifying the latent constructs, we obtain estimated factor scores and use them as covariates (attitudes and perceptions) and indicators (four mode-use propensities) in the next step (consistent with the approach taken by Narati et al. (2018) and others). In the factor analysis (by contrast to the next model), both observed and latent variables are *continuous*.

The second type of latent variable model we use is latent class cluster analysis (LCCA). The basic idea of LCCA is that a single nominal (latent) variable, representing class membership, explains a set of indicators (Eq. (1)) – in our case, the bundle or vector of mode-use propensity factor scores. Here, we need to clarify several things because various types of models are interrelated, nomenclature is similar and not always standardized, and thus different models can easily be confused. First, in LCCA, as mentioned, a single nominal variable can take on one of two or more categorical values that corresponds to the class membership of the case. It is latent because the true class membership is unknown (or unobserved). Second, LCCA is sometimes confused with latent class choice modeling (LCM). Although LCCA and LCM are, in fact, based on similar probabilistic structures, LCCA focuses on differences in group means of the indicators, whereas LCM concerns differences in model coefficients across groups (Oberski, 2016). In other words, LCM is a way to deal with taste heterogeneity (see, e.g., Bhat, 1997; Vij et al., 2013; and Kim and Mokhtarian, 2018). Furthermore, specifically for our application, our observed indicators are continuous, whereas the observed indicator in LCM is discrete (the "choice" in question). Some researchers employ the term "latent profile analysis (LPA)" for the case of latent class analysis with continuous indicators, to distinguish it from that with discrete indicators (e.g. Norman et al., 2010; Oberski, 2016; Muthén and Muthén, 2017). However, to the present authors' knowledge, there is no clear consensus and thus latent class analysis with continuous indicators is also called LCCA (e.g. Vermunt and Magidson, 2002). In this paper, we use the term LCCA.

The LCCA model can be expressed as:

$$f_2(\boldsymbol{y}_n|\boldsymbol{z}_n) = \sum_{k=1}^{K} P(k|\boldsymbol{z}_n) f_1(\boldsymbol{y}_n|k), \tag{1}$$

where n is the case subscript, k is a nominal latent variable (the latent class membership), $\boldsymbol{z}_n$ is a vector of covariates, $\boldsymbol{y}_n$ is a vector of indicators, $P(k|\boldsymbol{z}_n)$ is the membership probability (a.k.a. mixing weight) for a certain latent class given covariates, $f_1(\boldsymbol{y}_n|k)$ is the probability density of $\boldsymbol{y}_n$ given k, and $f_2(\boldsymbol{y}_n|\boldsymbol{z}_n)$ is the probability density of $\boldsymbol{y}_n$ given $\boldsymbol{z}_n$. Specifically, in the case of multivariate continuous indicators, $f_1(\boldsymbol{y}_n|k)$ is generally assumed to be a (class-specific) multivariate normal density function, and therefore $f_2(\boldsymbol{y}_n|\boldsymbol{z}_n)$ is also multivariate normal (Vermunt and Magidson, 2002). The normal distribution assumption is reasonable, since theoretically any continuous density can be approximated by a mixture of normal densities by selecting the proper number of classes (Bishop, 2006). Applied to the sample as a whole, a useful interpretation of Eq. (1) is that the point of the model is to delineate the set of latent classes (as represented by the $P(k|\boldsymbol{z}_n)$) that will best explain the *joint distribution* of the indicators (the $f_2(\boldsymbol{y}_n|\boldsymbol{z}_n)$), in view of the fact that different latent classes will exhibit different distributions of those indicators ($f_1(\boldsymbol{y}_n|k)$). Thus, the latent classes are designed to be "optimally different" from each other (loosely speaking) with respect to their bundle of means on the indicator vector $\boldsymbol{y}_n$ – their "cluster centroids", in the language of deterministic cluster analysis. Accordingly, the mean indicator vectors for each class offer a key basis for interpreting the class.

The expected value (mean) of the t^{th} element of the $\boldsymbol{y}_n$ vector for class k is expressed in terms of the mean of the reference class, plus the deviation from that mean for class k:

$$\eta_{k,t} = \beta_{0,t} + \beta_{k,t}, \tag{2}$$

where t = indicator index (t = 1, 2, 3, 4 for the mode-use propensity factor scores in our study);
$\eta_{k,t}$= mean of the normally-distributed indicator t for cluster k;
$\beta_{0,t}$= intercept (mean of the reference cluster on indicator t);
$\beta_{k,t}$= effect of cluster k on the mean of the t^{th} indicator $y_{n,t}$ (i.e. the deviation of the k^{th} cluster-specific mean, $\eta_{k,t}$, from the reference cluster's mean, $\beta_{0,t}$).

Fig. 2 presents the modeling framework for our LCCA. There are four continuous indicators, namely the mode-use propensity factor scores. We identify latent mode-use propensity groups with respect to the four indicators, and then further characterize the membership of each group by employing the covariates SEDs, general attitudes, perceptions of AVs, and geographical types. In addition, we will investigate current behaviors by segment as "inactive covariates" (those that are of interest as class-specific descriptive measures but do not affect the model estimation).

5. Results

5.1. Factor solutions

For this study, we developed three sets of exploratory factor analysis solutions (all using principal axis factoring with oblique rotation and standardized Bartlett scores): for perceptions of AVs, mode-use propensities, and general attitudes. We use factor

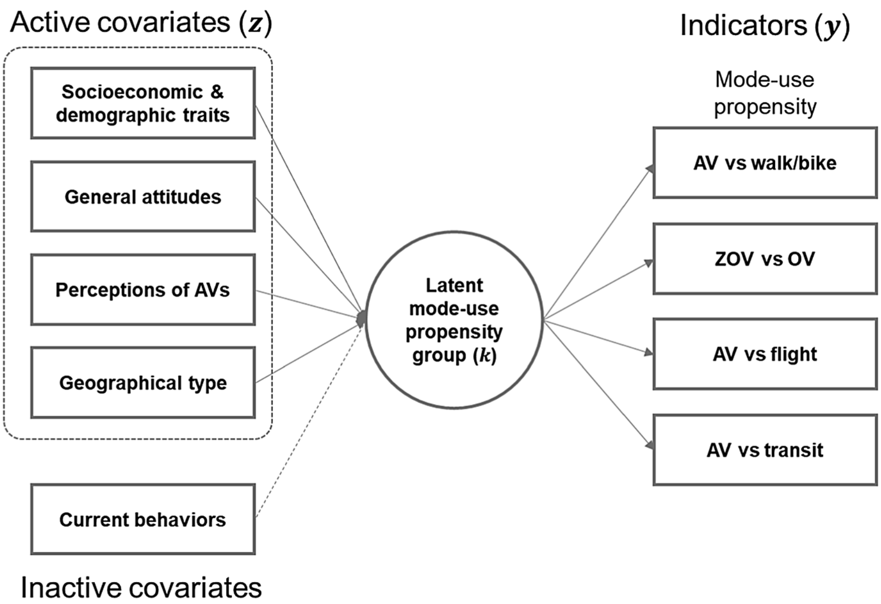

Fig. 2. Modeling framework of our latent class cluster analysis.

solutions to (1) capture underlying attitudinal constructs rather than responses to individual attitudinal indicators, and (2) reduce the number of variables for a more parsimonious and interpretable model.

We designed a block of 12 statements on the perceived advantages and disadvantages of AVs, to tap several dimensions such as mobility, time-use productivity, enjoyment of driving, and comfort. The preferred factor analysis for this set of AV perceptions identifies two attitudinal constructs (Table 1). The first construct is oriented toward the advantages or benefits offered by AVs. For example, respondents could indicate whether they would be more comfortable while taking an AV, or gain more time by sending an AV for errands, and thus we label it as ***AV pros***. Although we conceived of separate dimensions for productive versus hedonic benefits (Shaw et al., 2019), they loaded on the same factor here, signifying that for the current sample, on average, respondents envision both types of benefits as being closely associated. The second construct is oriented toward a somewhat negative perspective, which raises the question of how it is distinguished from the negative direction of the first factor. However, the two constructs have a correlation of only −0.2, and the second factor is specifically related to negative outcomes *due to the excessive use of AVs* (e.g. reducing exercise, time with family/friends because of AVs) rather than AVs themselves; thus we label it as ***AV overuse cons***. A crosstabulation of the signs of the two factor scores for each case (not shown) indicates that nearly 40% of the (weighted) sample have scores that are either both positive (23.1%) or both negative (16.6%), signifying that many people can simultaneously perceive both advantages and disadvantages of AVs – a nuance that would have been lost if there had only been a single factor.[3] This result is further distinctive in that respondents were (in principle) considering a hypothetical situation in which AV technology is fully mature ("*at least as safe* as today's cars are, and *cost[ing] about as much*"), whereas most other studies measured perceptions of AVs that may be confounded with (dis)trust in AV technologies.

For mode-use propensities, we obtained four constructs (Table 1): *AV over walk/bike*, *zero-occupant vehicle (ZOV) over occupied vehicle (OV)*, *AV over flight*, and *AV over transit*. ***AV over walk/bike*** captures a general inclination toward using AVs rather than walking or bicycling for several types of short trips. All types of short-trip purposes tested load strongly on this factor (from 0.953 to 0.711). ***ZOV over OV*** is about a new type of mode choice in the AV era. AVs will offer a new option: "let the AV go for errands". Thus, this construct is capturing a general preference between deploying an empty AV versus taking an AV in person for errands. Sending an empty car to pick up other people who cannot drive loads especially highly (0.895). Picking up "my child" with an empty AV is a similar situation but it loads least strongly among the three items associated with this factor (0.526) – probably because of the particular vulnerabilities of the young. ***AV over flight*** is related to the long-distance mode choice between an automated ground vehicle and flight. A statement related to "a distant state" loads highly (0.859) and a statement involving travel time is comparatively less-strongly loaded (0.592). ***AV over transit*** measures a general inclination toward AVs over transit. In particular, compared to a commuting situation (0.533), items associated with non-commuting situations load more heavily (0.912 and 0.877).

We also factor-analyzed a block of general attitudinal statements and identified fifteen latent constructs. In this study, we selected several attitudinal constructs relevant to mode-use propensities for modeling. For brevity, we do not present the entire factor solution for the general attitudes, but the six factors used in the present study are more fully described in Appendix A.

5.2. Identification and description of latent classes

This study aims to uncover population-wide market segments that will have different profiles of mode-use propensities. Although we employed stratified address-based random sampling, Atlanta residents were intentionally undersampled (to ensure greater geographic diversity by preventing the Atlanta region from dominating the sample), and because of typical non-response biases, the sample overrepresented certain demographic segments (such as older people, those with higher incomes, and the more highly educated). To obtain more population-representative results, we developed and applied case weights using a mixture of cell-weighting and iterative proportional fitting with respect to key Census demographics, namely sex, age, race, education, work status, MPO tier, income, household size, and vehicle ownership (more details about the weights can be found in Kim et al., 2019). The weights were developed on the full sample and we did not repeat the process on the working sample of this study, so they correct for sample biases slightly less effectively than before. However, we did re-normalize the weights for the working sample, so that the unweighted and weighted sample sizes are both equal to 2890.

Once developed, the weights could be applied at two key points in the analysis: (1) when estimating the parameters of the LCCA model, or (2) afterwards, when analyzing the nature and sizes of the clusters. We selected the latter option in this study because we wanted to discover more diverse mode-use propensity segments. If we had applied the weights during estimation, certain types of people (notably Atlanta residents) could overwhelm the estimation and lead to identifying fewer and/or less diverse segments. On the other hand, in view of the biases described above, not weighting the sample at all would mean that we would have no sense of the true size of each segment in the population at large. By applying the weights after the segments have been identified, we can have confidence that the relative size and demographic/attitudinal composition of each segment is reasonably representative of its population-level counterpart.

For estimation, we employed Latent GOLD 5.1. Considering fit indices and interpretability, we chose seven latent mode-use propensity groups. Specifically, the Bayesian Information Criterion (BIC, 25381.47) and Consistent Akaike Information Criterion (CAIC, 25623.47) indicated that seven clusters were more suitable than other cluster solutions after penalizing for the number of parameters. Table 2 presents the estimated values of the β parameters in Eq. (2), while Fig. 3 plots the η values – i.e. the cluster means

[3] More than a third (33.8%) of the sample was more uniformly favorable toward AVs, having a positive score on the pros and a negative score on the overuse cons, while about a quarter (26.6%) were in the opposite position.

Table 2
Joint estimation results of the LCCA parameters (N = 2890).

	Intercepts	AV enthusiast	AV-over-flight	Flight-over-AV	AV occupant	Pro-walk/transit	AV resistant	Anti-AV
AV over walk/bike	0.020	**1.146**	−0.032	–	**0.897**	**−0.511**	**−0.529**	**−1.050**
ZOV over OV	**0.310**	**0.603**	0.108	–	**−1.206**	**−0.187**	**−1.430**	**−0.705**
AV over flight	**−0.517**	**0.758**	**1.799**	–	**0.698**	**0.722**	**−0.361**	**0.297**
AV over transit	**0.419**	**0.541**	0.016	–	**0.321**	**−1.457**	**−1.018**	**−1.649**

Notes: The bolded numbers indicate coefficients that are significantly different from zero at the 0.05 level. Flight-over-AV is the reference class. Intercepts are the indicator means (the $\beta_{0,t}$s) for the reference class; the remaining coefficients are the class-specific deviations from the reference class means on each indicator (the $\beta_{k,t}$s).

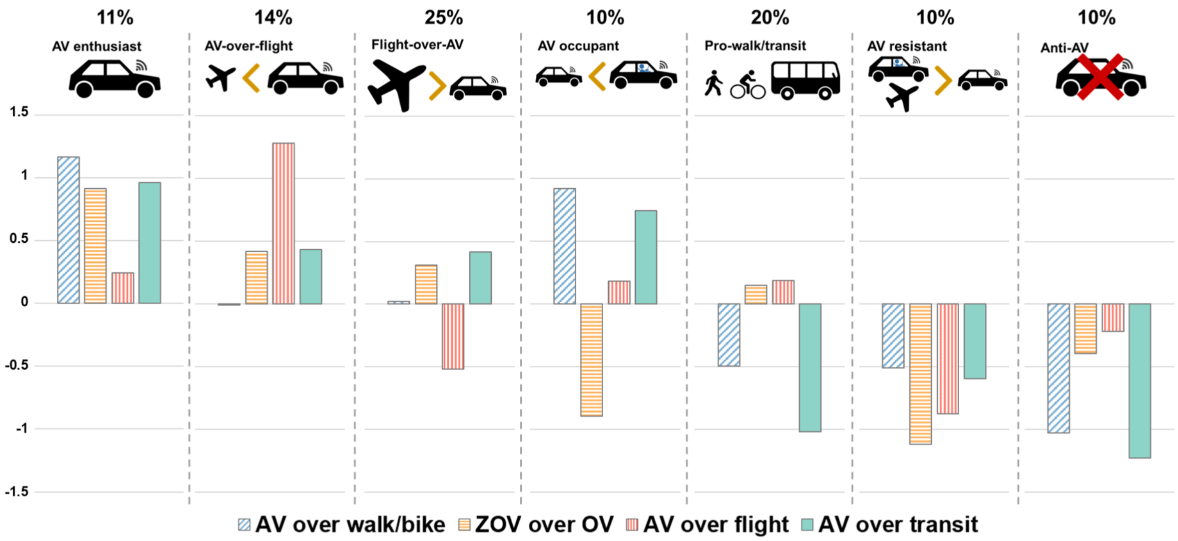

Fig. 3. Seven latent segments and their mode-use propensity means (weighted N = 2890).

on each indicator. The latter constitutes the basis for labeling the classes. Many SED traits and attitudes are statistically significant in the membership model (Table 3). For Tables 2 and 3, however, not every parameter is statistically significant for each class. In addition, even if parameters are statistically significant, they indicate statistical differences from those of the reference group ("flight-over-AV"); hence they are not necessarily different from the parameters of other groups. Nevertheless, all groups have a distinctive share/mean for at least one variable, even though not every group has a distinctive share/mean for every variable. Hence we retain variables in the model more liberally than in usual modeling situations.

In LCCA applications, it is common to interpret group characteristics based on the means or distributions of variables for each group (Tables 4 and 5). In this paper, clusters are ordered (conceptually) from more favorable to less favorable toward AVs. Below, we sketch the distinctive characteristics of each cluster in turn. In Section 5.3, we compare selected pairs of clusters and explore the distribution of cluster membership within specific demographic groups.

The ***AV enthusiast*** segment, which has a share of 10.6 percent, is the class that heavily favors AVs in general, with all four types of mode-use situations having mean propensities more inclined toward AV options. This segment has a notable set of attitudes – not surprisingly, members strongly perceive benefits from AVs (0.842) and have low expectations of negative effects due to AV overuse (−0.459). In addition, considering general attitudes, this cluster is highly inclined toward driving options rather than non-car options. On average, this segment is the least pro-environmental and wait-tolerant among the classes. Moreover, considering current technology usage (smartphone, social media, online purchasing) and attitude toward technologies, this segment is notably tech-savvy. These facts help suggest why people in this segment are enthusiastic about AVs. The segment has a 50 percent share of women, which is close to the samplewide share, and, compared to the whole sample, it is younger and more white. This segment has the highest share of middle-income respondents among the classes (40%). It is somewhat more Atlanta-region-based, and notably more suburban, than the sample overall.

The second segment is labeled "***AV-over-flight***" and its share is 13.7 percent. The label was chosen because there are no clear differences in the *other* mode-use propensities when compared to the propensities of the flight-over-AV segment (next cluster), but there *is* a notable difference in mean flight-use propensity (1.282 vs. −0.517). This segment does not have notable general attitudinal characteristics, although it strongly perceives benefits from AVs (mean factor score 0.420). The segment has the smallest share of women (42%), whereas the shares of generation, race (white), and income categories are quite close to those of the sample overall. Some clear discrepancies from the other segments (especially the first) are the geographical distributions: this segment has smaller shares of Atlanta MPO residents (43%) and urban residents (14%) compared to the shares in the entire sample. The current behaviors

Table 3
Membership model (N = 2890).

Cluster Weighted share	AV enthusiast 0.11	AV-over-flight 0.14	Flight-over-AV 0.25	AV occupant 0.10	Pro-walk/transit 0.20	AV resistant 0.10	Anti-AV 0.10
Intercept	**−1.670**	0.051	–	−0.832	**1.414**	0.113	−0.075
General attitude							
Non-car-alternatives	**−0.921**	0.034	–	**−0.611**	0.096	0.076	0.012
Tech-savvy	−0.057	−0.050	–	−0.052	−0.027	0.003	−0.179
Pro-environmental	**−0.272**	0.103	–	−0.030	**0.327**	0.026	0.140
Pro-exercise	**0.241**	−0.042	–	0.058	−0.034	−0.176	−0.067
Family/friends-oriented	**−0.249**	−0.092	–	−0.071	−0.135	**0.248**	−0.150
Wait-tolerant	−0.058	0.098	–	**0.193**	**0.220**	**0.211**	**0.231**
Pro-car-owning	**0.304**	**0.201**	–	**0.560**	**−0.177**	0.075	−0.150
AV perception							
AV pros	**1.061**	0.113	–	0.033	**−0.885**	**−1.324**	**−1.589**
AV overuse cons	−0.172	0.145	–	**0.195**	**0.686**	**0.606**	**0.741**
Gender							
Male	–	–	–	–	–	–	–
Female	−0.105	−0.204	–	−0.055	0.107	0.280	**0.451**
Generation							
18–44	–	–	–	–	–	–	–
45–64	0.308	0.040	–	0.185	**−0.514**	−0.333	−0.247
65+	−0.061	0.208	–	0.251	−0.453	−0.161	−0.161
Ethnicity							
Non-white	–	–	–	–	–	–	–
White	−0.032	**−0.561**	–	0.014	**−0.835**	**−0.801**	**−0.828**
Education							
High school or less	–	–	–	–	–	–	–
Some college	−0.366	−0.418	–	−0.305	**−0.744**	0.022	**−0.907**
4-year degree or higher	−0.009	**−0.852**	–	−0.379	−0.462	0.263	**−1.035**
Annual household income							
Below $50,000	–	–	–	–	–	–	–
$50,000–$99,999	−0.312	**−0.629**	–	**−0.554**	**−0.757**	**−0.875**	**−0.770**
$100,000+	**−0.767**	**−0.663**	–	**−0.908**	**−1.368**	**−1.023**	**−0.725**
MPO tier							
Atlanta MPO	–	–	–	–	–	–	–
2nd-tier MPO	0.269	**0.558**	–	0.146	0.257	0.209	**0.603**
3rd-tier MPO	0.338	**0.610**	–	0.308	0.368	0.118	0.377
Non-MPO	−0.694	0.524	–	−0.578	−0.493	−0.992	0.203
Neighborhood type							
Urban	–	–	–	–	–	–	–
Suburban	0.455	0.422	–	0.367	0.059	0.030	0.013
Small town	0.516	0.368	–	**0.775**	**0.580**	0.237	−0.035
Rural	0.689	**0.760**	–	**0.848**	**0.660**	0.239	0.311

Note: The bolded numbers indicate coefficients that are statistically significant (i.e. different from the reference class, flight-over-AV) at the 0.05 level.
'–' indicates reference class or category.

shown in Table 5 are, in general, close to those of the overall sample and thus this class is not clearly characterized by behavior.

Flight-over-AV (labeled oppositely from the second one) constitutes the largest segment (25.4%) in the sample. Regarding mode-use propensities, this segment is more inclined toward AV options compared to transit (average score 0.419) and somewhat more inclined to employ an empty AV compared to taking an AV in person for errands (0.310). The segment does not have a clear preference between walk/bike and AV on average (0.020), but the preference for flight over AV is its most distinctive characteristic (-0.517). In terms of attitudes, this segment is the most tech-savvy (0.454) and the second least waiting-tolerant (0.150). Even though the segment is positive toward public transit and active transportation, and despite preferring flight over AVs for long-distance trips, the segment also strongly perceives benefits from AVs and thus its members are generally pro-AV. With respect to SED characteristics, the segment has a slightly higher proportion of males (52%) compared to the sample (50%), and contains relatively younger individuals. The education and income levels are highest among the segments. The most intriguing characteristics of the segment can be observed in the geographical types. The segment has the highest shares of Atlanta MPO residents (65%) and urban dwellers (23%), and the second-highest share of suburban dwellers (52%). Considering these SED and geographical characteristics, the unique pattern of mode-use propensities is understandable. Because the majority of people belonging to this segment are relatively affluent and live near a major airport (the Hartsfield-Jackson International Airport, located in the Atlanta MPO, was one of the busiest airports in the U.S. in 2017), they may benefit less from using AVs for long distance trips. In terms of current behaviors, as supported by their tech-

Table 4
Segment-specific means/shares of covariates (N = 2890).

Cluster	AV enthusiast	AV-over-flight	Flight-over-AV	AV occupant	Pro-walk/transit	AV resistant	Anti-AV		
Unweighted size	320	396	775	320	506	335	239		
Weighted size	306	395	733	281	587	302	285		
Weighted share	0.11	0.14	0.25	0.10	0.20	0.10	0.10		
Segment-specific means									
General attitudinal factors									
Non-car-alternatives	−0.522	0.202	0.320	−0.479	0.114	−0.050	−0.236		
Tech-savvy	0.438	0.222	0.454	0.119	0.136	0.211	−0.217		
Pro-environmental	−0.461	0.046	−0.146	−0.240	0.163	−0.101	0.016		
Pro-exercise	0.199	−0.049	−0.165	0.213	0.115	−0.065	0.295		
Family/friends-oriented	−0.239	−0.131	0.057	−0.042	−0.235	0.151	−0.157		
Wait-tolerant	−0.309	0.020	−0.150	0.018	0.256	0.162	0.232		
Pro-car-owning	0.334	0.118	−0.246	0.441	−0.237	0.093	0.002		
AV perceptions									
AV pros	0.842	0.420	0.462	0.158	−0.228	−0.645	−0.986		
AV overuse cons	−0.459	−0.022	−0.340	0.033	0.426	0.232	0.396		
Segment-specific shares								Weighted sample share	Weighted sample count
Gender									
Male	0.50	0.58	0.52	0.49	0.48	0.41	0.46	*0.50*	*1436*
Female	0.50	0.42	0.48	0.51	0.52	0.59	0.54	*0.50*	*1454*
Generation									
18–44	0.50	0.38	0.49	0.36	0.43	0.45	0.27	*0.43*	*1233*
45–64	0.39	0.42	0.39	0.43	0.36	0.36	0.41	*0.39*	*1124*
65+	0.11	0.20	0.12	0.21	0.21	0.19	0.32	*0.18*	*534*
Ethnicity									
Non-white	0.31	0.37	0.25	0.27	0.48	0.45	0.41	*0.36*	*1035*
White	0.69	0.63	0.75	0.73	0.52	0.55	0.59	*0.64*	*1855*
Education									
High school or less	0.22	0.32	0.14	0.34	0.41	0.23	0.54	*0.30*	*857*
Some college	0.54	0.52	0.54	0.52	0.40	0.52	0.36	*0.49*	*1408*
4-year degree or higher	0.23	0.16	0.32	0.15	0.18	0.25	0.11	*0.22*	*625*
Annual household income									
Below $50,000	0.33	0.42	0.18	0.41	0.56	0.42	0.56	*0.39*	*1132*
$50,000–$99,999	0.40	0.30	0.36	0.36	0.30	0.32	0.29	*0.33*	*962*
$100,000+	0.27	0.28	0.46	0.23	0.14	0.25	0.15	*0.28*	*796*
MPO tier									
Atlanta MPO	0.59	0.43	0.65	0.49	0.46	0.58	0.36	*0.52*	*1516*
2nd-tier MPO	0.18	0.18	0.13	0.17	0.20	0.19	0.20	*0.17*	*500*
3rd-tier MPO	0.13	0.13	0.07	0.16	0.18	0.13	0.15	*0.13*	*379*
Non-MPO	0.09	0.25	0.15	0.18	0.16	0.11	0.29	*0.17*	*495*
Neighborhood type									
Urban	0.15	0.14	0.23	0.11	0.18	0.17	0.14	*0.17*	*502*
Suburban	0.56	0.47	0.52	0.46	0.42	0.54	0.42	*0.48*	*1392*
Small town	0.16	0.19	0.14	0.24	0.22	0.17	0.20	*0.18*	*528*
Rural	0.14	0.21	0.11	0.20	0.17	0.12	0.24	*0.16*	*469*

savvy attitude, people belonging to this segment use smartphones, social media, and online purchasing more often than average. In addition, the segment has distinctively higher fractions of Uber/Lyft users and long distance travelers.

The ***AV occupant*** segment has a share of 9.7 percent and it shows strong inclinations toward AV options rather than walk/bike and transit. It favors AVs over flight for long distances, but, interestingly, it exhibits strong preferences for taking an AV in person over deploying an empty AV for errands. Compared to other segments, this segment has less intense perceptions of both the benefits and the overuse side-effects of AVs (mean scores of 0.158 and 0.033). On average, this segment is the most-strongly car/driving-oriented, considering the attitudinal constructs of *non-car alternatives* and *pro-car-owning*, as well as the facts that it has the highest average number of vehicles (2.17) and second highest weekly vehicle-miles driven (VMD, 163.51 mi). This strong preference for cars may illuminate the preference for occupied AVs over empty ones. In terms of SED characteristics, the segment is whiter and older than the sample at large. It has relatively higher shares of 3rd-tier MPO residents and small town or rural area residents.

The ***pro-walk/transit*** segment has a share of 20.3 percent and is characterized by its inclination toward walk and transit, whereas the other two indicators slightly favor AV options. This segment has the highest average pro-environmental attitude (0.163), and its general attitudes also favor non-motorized options (averages on two relevant constructs – *non-car alternatives* and *pro-car-owning* – are

Table 5
Segment-specific means/shares of inactive covariates (N = 2890).

Cluster	AV enthusiast	AV-over-flight	Flight-over-AV	AV occupant	Pro-walk/transit	AV resistant	Anti-AV	Sample	
Weighted share	0.11	0.14	0.25	0.10	0.20	0.10	0.10	1.00	
Segment-specific means									
Number of household vehicles	2.14	2.10	2.12	2.17	1.82	1.94	1.89	2.02	
Vehicle-miles driven	180.53	155.20	162.65	163.51	123.58	139.86	115.09	148.74	
Segment-specific shares								Sample share	Sample count
Smartphone use									
Never/rarely	0.08	0.15	0.07	0.14	0.18	0.13	0.28	*0.14*	*397*
Sometimes	0.03	0.06	0.04	0.07	0.08	0.07	0.09	*0.06*	*176*
Often	0.33	0.36	0.38	0.37	0.37	0.39	0.35	*0.37*	*1051*
"Constantly"	0.56	0.43	0.51	0.42	0.37	0.41	0.28	*0.43*	*1240*
Social media ever used									
Facebook	0.76	0.72	0.77	0.72	0.70	0.72	0.64	*0.72*	*2089*
Twitter	0.28	0.25	0.34	0.23	0.22	0.24	0.16	*0.26*	*746*
Instagram	0.42	0.32	0.44	0.33	0.32	0.37	0.23	*0.36*	*1033*
Internet use: check traffic to plan the route/departure time									
Never/rarely	0.20	0.24	0.15	0.28	0.32	0.28	0.47	*0.26*	*746*
At least once a year	0.10	0.11	0.08	0.12	0.10	0.10	0.09	*0.10*	*280*
At least once a month	0.17	0.19	0.19	0.21	0.19	0.20	0.17	*0.19*	*541*
At least once a week	0.26	0.25	0.32	0.21	0.23	0.25	0.16	*0.25*	*720*
Daily	0.28	0.21	0.26	0.18	0.17	0.17	0.11	*0.20*	*586*
Buy goods online									
Not during the last 6 months	0.14	0.17	0.10	0.18	0.25	0.19	0.32	*0.18*	*529*
Once or twice	0.20	0.26	0.20	0.26	0.28	0.26	0.25	*0.24*	*691*
Three or more times	0.65	0.57	0.70	0.56	0.47	0.55	0.42	*0.57*	*1640*
At least one overnight trip made in past 12 months									
Within Georgia	0.64	0.64	0.67	0.63	0.61	0.62	0.56	*0.63*	*1820*
Within TN,FL,NC,SC,AL*	0.67	0.66	0.75	0.65	0.58	0.63	0.52	*0.65*	*1879*
Elsewhere in the US	0.55	0.50	0.65	0.46	0.46	0.51	0.38	*0.52*	*1497*
Ride-hailing services ever used									
Uber/Lyft use	0.48	0.38	0.58	0.33	0.34	0.41	0.24	*0.42*	*1191*

* Tennessee (TN), Florida (FL), North Carolina (NC), South Carolina (SC), and Alabama (AL) are the states adjacent to Georgia.

0.114 and 0.237 respectively). Regarding AV attitudes, this segment generally perceives less benefit from AVs. At a glance, this segment has "opposite" SED and geographical characteristics against those of the third segment (*flight-over-AV*). This class has more women (52%), and the largest share of non-whites (48%). The education and income levels are below sample averages. The shares of 3rd-tier MPO residents and small-town residents are relatively high (18%, 22% for the cluster; 13%, 18% for the overall sample respectively). Hence, the preferences for walking and transit over AVs but AVs over flight for long-distance trips seem to be the confounded outcomes of SED, attitudinal, and geographical characteristics. The segment also shows smaller fractions of technology users than does the sample overall.

Among the seven clusters, there are two segments which are negative toward AVs, but with conceptual differences between them. The first one is labeled ***AV resistant***, and has a share of 10.5 percent. All its average mode-use propensities favor non-AV options, with propensities concerning empty AVs or long-distance trips being especially negative (−1.120 and −0.878). On average, they are more skeptical about AV benefits (−0.645). This is the most family-oriented among the segments (0.151), which may help explain the strong aversion to using an empty AV. Compared to the entire sample, the segment contains more women (59%) and older people. Although this segment is opposite to the *AV enthusiasts* in its mode-use propensities, it is similar to that segment in its geographic tendencies: members of this group are somewhat more likely than average to live in the Atlanta MPO and/or in a suburban neighborhood.

The last segment, which has a share of 9.9 percent, is labeled ***anti-AV***. This segment most strongly perceives the disadvantages of AVs, based on the two AV-related attitudinal constructs. The segment contains more non-tech-savvy and waiting-tolerant people than average. It has high shares of women (54%), and the highest shares of seniors (32%), least-educated (54%), and lowest-income (56%) respondents. In addition, it has the lowest share of Atlanta MPO residents (36%) and highest share of rural residents (24%). Clearly, this segment presents opposite demographic/geographical traits compared to the *flight-over-AV* or *AV enthusiast* segments. This class contains the smallest shares of smartphone/ social media/internet users. Furthermore, they are the least mobile, in terms of average VMD, fraction of Uber/Lyft users, and share of overnight travelers.

As indicated by Eq. (1) of Section 4, the distribution of each mode-use propensity can be viewed as a composite or mixture of the class-specific normal distributions for that variable. Fig. 4 shows the composite (marginal) distributions of the four mode-use propensities, together with the underlying class-specific distributions uncovered by the LCCA. The gray bars are the sample histograms of

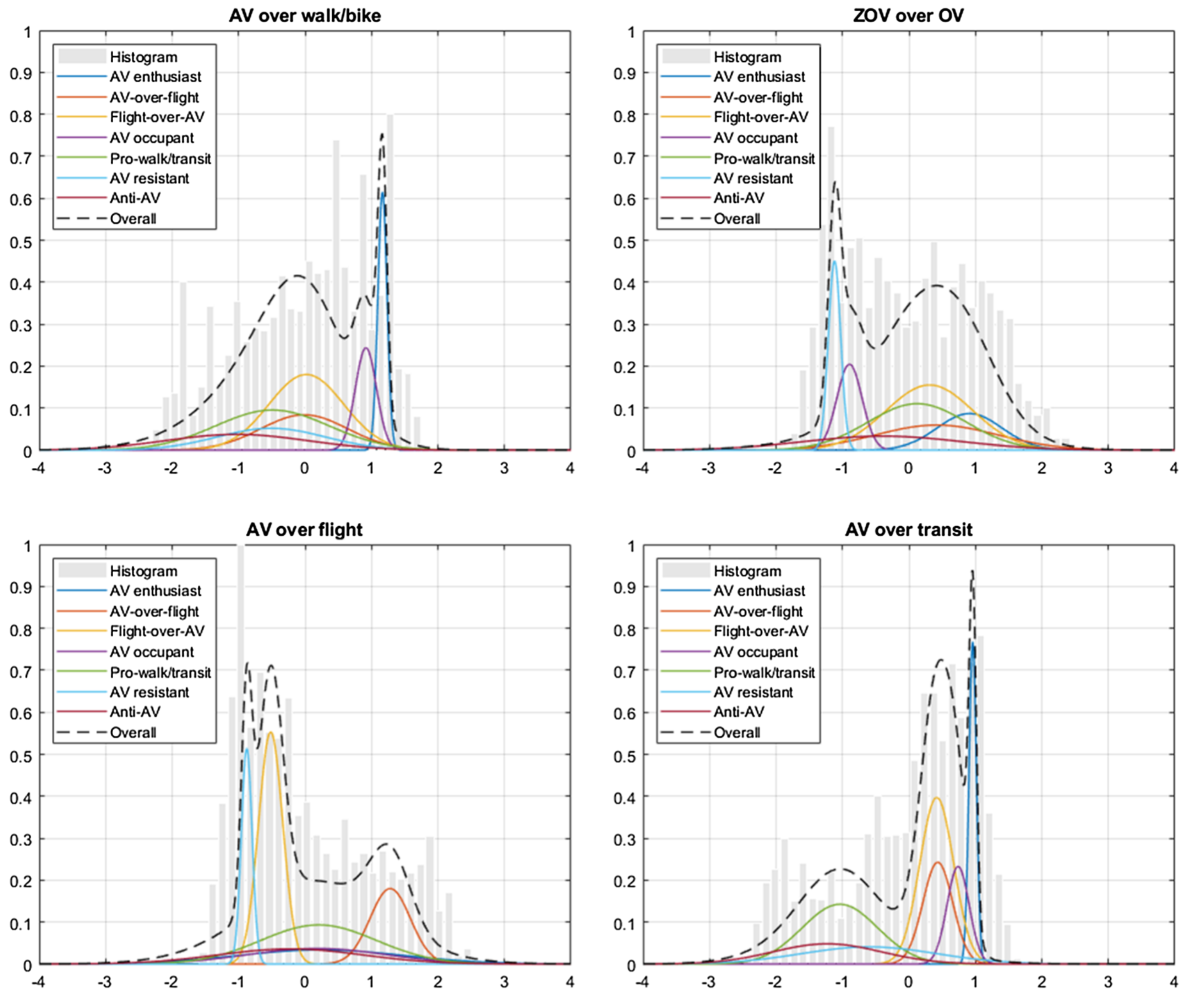

Fig. 4. Sample histogram and cluster distributions of mode-use propensities (weighted N = 2890).

the mode-use propensities (for the unweighted sample, since the LCCA parameters were obtained for the unweighted sample), and the estimated distributions for the seven latent classes are superimposed onto those histograms. The "overall" distributions shown by the black dashed lines constitute the probability-weighted superpositions of the seven constituent normal distributions. Each mean of a normal distribution is, in fact, already presented as a bar in Fig. 3. For example, for the AV occupant segment (purple lines), the means of the propensities for AV over walk/bike and AV over transit are between 0.5 and 1 in Fig. 4, and we can also see the same means in Fig. 3. By assumption, the mode-use propensities for each cluster are multivariate ("quadrivariate" in this case) normally distributed. They are plotted by marginal distribution because we cannot visually present four dimensions. It can be seen that the sample distributions of the mode-use propensities are well approximated by the LCCA results. Indeed, Fig. 4 illuminates/explains those highly irregular distributions, by separating and revealing the distinct and sometimes counteracting contributions of each latent segment to them. This is a visual demonstration of the value of LCCA for uncovering underlying segments in the population.

5.3. Discussion

5.3.1. Comparisons of selected segment pairs

This study decomposes the population into more detailed segments than standard classes such as enthusiast, neutral, and resistant. Each mode-use propensity segment displays different demographics, geography, and/or attitudinal motivations. The results of the study imply that mode use patterns in the AV era will probably be heterogeneous by such market segments. The ultimate goal of market segmentation is to target people (customers) more effectively and properly. Common bases for segmentation are demographic, geographic, and psychographic variables, which we have incorporated as covariates in the membership model for this study. If we take a closer look into differences between segments (Table 4), we obtain some hints regarding potential certain mode users and their key drivers.

For example, the *Flight-over-AV* and *AV-over-flight* segments have similar average propensities for other modes, differing primarily in their propensity related to long-distance travel. Attitudinal drivers that differ between these two segments are AV overuse cons (respective means of 0.022 and −0.340), wait-tolerant (0.020 and −0.150), and pro-car-owning (0.118 and −0.246). In other words, people who are more concerned about the downsides of AV overuse, less wait-tolerant (likely a proxy for time-sensitivity) and like owning/driving cars will tend to keep using flight *or* start flying (when they can no longer drive a car as they would have preferred) for long-distance trips. Such potential flight choosers (even in the AV era) are higher income (46% versus 28% for the $100,000+ income share of each segment), higher educated (32% versus 16% for the share having some graduate school), more likely Atlantan (65% versus 43%), and more likely urban dwellers (23% versus 14%). Some experts are expecting changes in the mode shares for long-distance trips (LaMondia et al., 2016; Rice and Winter, 2018), but the findings of the present study indicate that those changes will happen asymmetrically across population segments. The findings also suggest that the general catchment area of airports could shrink in an all-AV era. At the same time, oppositely, the impact of AVs on long-distance trips may not be dramatic in that today's frequent flyers are already more likely to have higher incomes and live "close enough" to an airport. For a better understanding of an asymmetric change in the landscape of long distance travel, future mode choice studies should not only capture the usual tradeoffs between access time from home to (and in) the airport and line-haul time between origin and destination, but also pay careful attention to market heterogeneity.

Another new type of mode use will be employing zero-occupant vehicles for some errands. Our results indicate that, in general, people who perceive more AV benefits are more inclined to use them in this way. In particular, the *AV enthusiast* and *AV occupant* segments mirror each other's mode-use propensities except for the propensity related to employing zero-occupant vehicles (mean scores of 0.603 and −1.206, respectively; Table 2 and Fig. 3). This notable gap relates (Table 4) to how wait-tolerant people are (as a proxy for time-sensitivity; mean scores of −0.309 for *AV enthusiasts* and 0.018 for *AV occupants* – those who are *not* inclined to send out ZOVs), and how much they perceive AV overuse cons (-0.459 and 0.033). Distributions of socio-demographics and geography give some glimpses of the kinds of people who will rely more on employing zero-occupant vehicles for errands. There is no clear difference in some demographics, but people who prefer using zero-occupant vehicles for errand trips tend to be younger, more educated, have a bit higher income, are more likely to be urban/suburban residents, and more likely to be Atlantan. This suggests that this issue will generate discussions similar to those currently underway regarding the impact of cruising/deadheading ridehailing vehicles on urban traffic. In other words, the incremental impact of zero-occupant vehicles will occur more in Atlanta, in more urbanized areas, and in neighborhoods where young adults and high-income people live. Prospective policies (e.g. pricing or physical restrictions) oriented toward discouraging ZOV travel may need to be stricter in such areas than in others.

For a final paired comparison, the *AV occupant* and *pro-walk/transit* segments have opposite mode-use propensity patterns with respect to local trips (the latter group, in keeping with its name, favoring walk and transit, while the former group favors AVs under similar circumstances), but similar propensities toward AVs over flight (average scores of 0.698 and 0.722, respectively; Table 2). There are no distinctive differences with respect to how they live. However, people in the pro-walk/transit segment tend to be more favorable toward non-car-modes (0.114 versus −0.479), more pro-environmental (0.163 versus −0.240), and less favorable toward owning/driving a car (-0.237 versus 0.441 on the *pro*-car-owning attitude). Encouraging more people to join this more sustainable segment calls for targeted social marketing aimed at influencing attitudes in these directions.

5.3.2. How are the segments distributed within a given socioeconomic/demographic slice?

Until now, the discussion has focused on describing and interpreting each segment in terms of its defining characteristics. That is, we have been answering the question, "conditional on being in segment k, what are its central tendencies?" However, it is also informative to reverse the direction of conditionality, and ask, "conditional on being in a certain SED-defined group, what is the distribution of latent class membership?" To answer this question, we apply Bayes' rule (actually, just the definition of conditional probability) to the conditional probabilities associated with the discrete-valued covariates in Table 4 (the lower panel of the table), to obtain Table 6[4].

By comparing the latent class distributions in each row of Table 6 (corresponding to a specific "demographic") to the overall shares shown at the top of the table, a number of interesting insights emerge. Consider, for example, age. Previously we saw that (consistent with expectations) members of the *anti-AV* segment tend to be older than average. Here, we can ascertain the share of

[4] Specifically, to obtain the elements of Tables 4 and 5, we use the equation

$$\widehat{E}(z_{nr}|k) = \frac{\sum_{n=1}^{N} w_n z_{nr} \widehat{P}(k|\boldsymbol{z}_n)}{\sum_n w_n \widehat{P}(k|\boldsymbol{z}_n)} \tag{3}$$

where z_{nr} is the r^{th} element of $\boldsymbol{z}_n$, and w_n is the case weight for the n^{th} person. When z_{nr} is a binary (0–1) variable indicating a discrete covariate value (e.g., = 1 for male), we can replace the left-hand side of Eq. (3) with $\widehat{P}_{wt}(z_{nr}=1|k)$, where the *wt* subscript denotes weighted. To obtain the elements of Table 6, we need

$$\widehat{P}_{wt}(k|z_{nr}=1) = \frac{\widehat{P}_{wt}(z_{nr}=1|k)\widehat{P}_{wt}(k)}{\widehat{P}_{wt}(z_{nr}=1)} \tag{4}$$

The first term of the right-hand side is given by Eq. (3); $\widehat{P}_{wt}(k) = \sum_n w_n \widehat{P}(k|\boldsymbol{z}_n)$ is the weighted marginal share of class k in the sample; and $\widehat{P}_{wt}(z_{nr}=1) = \frac{\sum_{n=1}^{N} w_n z_{nr}}{\sum_n w_n}$ is the weighted share of cases for which the r^{th} element of $\boldsymbol{z}_n = 1$. For example, if $z_{nr} = 1$ for Atlanta MPO residents and 0 else, we find (in Table 6) that 12 percent of Atlanta residents belong to the *AV enthusiast* segment by making the following computation based on numbers in Table 4: $(0.59 \times 0.11)/0.52 = 0.12$.

Table 6
Distribution of segment shares within each value of discrete active covariates (N = 2890).

Cluster	AV enthusiast	AV-over-flight	Flight-over-AV	AV occupant	Pro-walk/transit	AV resistant	Anti-AV		
Share	**0.11**	**0.14**	**0.25**	**0.10**	**0.20**	**0.10**	**0.10**		
Distribution of segment shares conditional on covariate value								Total	Sample share
Gender									
Male	0.11	0.16	0.26	0.10	0.20	0.09	0.09	***1.00***	*0.50*
Female	0.11	0.11	0.24	0.10	0.21	0.12	0.11	***1.00***	*0.50*
Generation									
18–44	0.12	0.12	0.29	0.08	0.21	0.11	0.06	***1.00***	*0.43*
45–64	0.11	0.15	0.25	0.11	0.19	0.10	0.10	***1.00***	*0.39*
65+	0.06	0.15	0.17	0.11	0.23	0.11	0.17	***1.00***	*0.18*
Ethnicity									
Non-white	0.09	0.14	0.18	0.07	0.27	0.13	0.11	***1.00***	*0.36*
White	0.11	0.13	0.30	0.11	0.16	0.09	0.09	***1.00***	*0.64*
Education									
High school or less	0.08	0.15	0.12	0.11	0.28	0.08	0.18	***1.00***	*0.30*
Some college	0.12	0.15	0.28	0.10	0.17	0.11	0.07	***1.00***	*0.49*
4-year degree or higher	0.11	0.10	0.38	0.07	0.17	0.12	0.05	***1.00***	*0.22*
Annual household income									
Below $50,000	0.09	0.15	0.12	0.10	0.29	0.11	0.14	***1.00***	*0.39*
$50,000–$99,999	0.13	0.12	0.27	0.11	0.18	0.10	0.08	***1.00***	*0.33*
$100,000+	0.11	0.14	0.42	0.08	0.10	0.10	0.06	***1.00***	*0.28*
MPO tier									
Atlanta MPO	0.12	0.11	0.31	0.09	0.18	0.12	0.07	***1.00***	*0.52*
2nd-tier MPO	0.11	0.15	0.19	0.09	0.23	0.11	0.11	***1.00***	*0.17*
3rd-tier MPO	0.11	0.14	0.14	0.12	0.28	0.10	0.11	***1.00***	*0.13*
Non-MPO	0.06	0.20	0.22	0.10	0.19	0.06	0.16	***1.00***	*0.17*
Neighborhood type									
Urban	0.09	0.11	0.34	0.06	0.21	0.10	0.08	***1.00***	*0.17*
Suburban	0.12	0.13	0.27	0.09	0.18	0.12	0.09	***1.00***	*0.48*
Small town	0.09	0.14	0.19	0.13	0.25	0.10	0.11	***1.00***	*0.18*
Rural	0.09	0.17	0.17	0.12	0.22	0.08	0.15	***1.00***	*0.16*

segment membership by age group, and note that 6% of even the youngest age group, 18–44-year-olds, belong to the *anti-AV* segment. Together with the *AV resistant* segment, a non-trivial 17% (1 in 6 members) of this age group is rather wary of AVs – not a statistic often seen. Similarly, 20% of the 45–64-year-olds are *AV resistant* or *anti-AV*. Looking at these two segments across the entire table shows that 16–28% of every single demographic group (including those with higher incomes, higher education, urban dwellers, and Atlanta MPO residents) lean away from AVs. From a policy perspective this suggests sizable and diffuse opposition (at the present time) to an eventual only-AV environment, while from a marketing perspective it illustrates that even among markets considered most favorable toward AVs, there appears to be a sizable fraction of people still needing to be convinced.

Looking at other demographic slices in Table 6, we can spotlight some additional interesting features. Among rural (non-MPO) residents, for example, we find negative AV tendencies as might be expected (demonstrated by their lower-than-average shares of *AV enthusiasts* and higher-than-average shares of *AV resistant* and *anti-AV* members), but a relative willingness to take *AVs over flying* for long-distance trips. Similarly, we have already discussed older people's relative disfavor toward AVs, and yet they have a substantially lower-than-average share of *flight-over-AV* segment members. It would be useful for further research to explore the reasons for these findings, perhaps due to a fear of flying that exceeds a fear of AVs, or perhaps from the reasonable expectation that, as today, ground travel will be cheaper than air. Either way, it suggests that in the future, one avenue for increasing acceptance of AVs among the resistant could be to market their advantages for long-distance travel.

Conversely, as we have glimpsed earlier, higher-educated and higher-income people are more favorable toward AVs in general, but are substantially more likely than average to belong to the *flight-over-AV* segment – presumably in part confounded with residential location (closer to the Atlanta airport), but also reflecting a greater ability to afford presumably more expensive air travel, and a higher value of time which favors faster modes. Value of time may also be a reason why these groups have lower-than-average membership in the *AV occupant* class, indicating a preference for sending empty AVs on errands.

6. Conclusion

Using responses to a survey of 2890 Georgia residents, this study considered a potential future transportation landscape in which AV technologies are fully mature and have replaced all traditional cars. We focused on how people react to such an all-AV era, particularly exploring mode-use propensity profiles. Mode-use propensity was measured using continuous factor scores that were extracted from a series of responses to hypothetical transportation needs that had an AV-based option and an alternative (such as walk/bike, bus/train, and plane) for fulfilling them. In our factor analysis, four mode-use propensities emerged: *AV over walk/bike,* *zero-occupant vehicle over occupied vehicle, AV over flight, and AV over transit*. In addition, we identified two perceptions of AVs – *AV pros* and *AV overuse cons* – based on a series of statements about advantages and disadvantages of AVs. We employed latent class cluster analysis (LCCA) to uncover latent segments with respect to the indicators (the four AV-related mode-use propensities) and to associate covariates with segment membership, thus allowing us to predict segment membership probability given a set of key variables such as socio-demographics. We identified seven clusters in our sample: *AV enthusiast*, *AV-over-flight*, *flight-over-AV*, *AV occupant*, *pro-walk/transit*, *AV resistant*, and *anti-AV*. Each segment has a unique mode-use propensity pattern. Some segments are more favorable toward the AV options (*AV enthusiast* and *AV-over-flight*), while other segments are more favorable toward the non-AV options (*AV resistant* and *anti-AV*). For some segments, inclinations with respect to AV are shaped by preferences for another travel option (*flight-over-AV*, *AV occupant*, and *pro-walk/transit*). Attitudinal motivations will play critical roles in the AV era, just as they do today. How people perceive the advantages/disadvantages of AVs will affect mode use, but the extent of the effect may differ by the transportation situation. The authors believe the key variables of this study – mode use propensities – will be associated with or affect longer-term behavioral responses such as residential choice, vehicle ownership, willingness to use shared AVs (especially with strangers), and induced activity participation. Future analyses of the survey data will investigate such behavioral shifts with an aim of helping to inform transportation policy and planning.

There are some limitations of this study. First, our target variables are mode-use propensities. We wanted to understand people's general inclinations in an all-AV-era, but these propensities will not necessarily result in behaviors. Second, because mode use will be highly uncertain in the AV era, we intentionally used a question format that allows respondents to report their degree of inclination between an AV option and an alternative, for a series of transportation situations; this non-standard format may not support some desired analyses, such as estimating mode shares. In addition, of course, transportation/ technology/land use landscapes in the coming AV era are highly uncertain. Therefore, respondents' current projections may not match their actual choices in the future.

Uncovering market segments does not provide a clear-cut prescription for policymaking. The goals of MPOs, departments of tax revenue, public transit agencies, automobile companies, the airline industry, insurance companies, and urban planners are far from congruent, and even within the public sector alone, objectives such as reducing congestion, economic development, public health, increasing equity, and improving personal and societal well-being are sometimes at odds. In addition, many objectives will differ by geography (is the policy targeting dense urban cores, suburbia, medium-to-small towns, or rural areas?). The impending AV era raises numerous policy issues that are under vigorous discussion. We believe that improving our understanding of population heterogeneity in this domain, through studies such as this one, can contribute to better informed and more nuanced policy discussions and policymaking.

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Appendix A. Selected attitudinal constructs and strongly-associated statements

Factor	Statement	Loading
Tech-savvy	Learning how to use new technologies is often frustrating for me	−0.866
	I am confident in my ability to use modern technologies	0.801
Pro-environmental	Cost or convenience takes priority over environmental impacts (e.g. pollution) when I make my daily choices	−0.914
	I am committed to an environmentally-friendly lifestyle	0.481
Pro-exercise*	The importance of exercise is overrated	−0.669
	I am committed to exercising regularly	0.663
Family/friends-oriented*	Family/friends play a big role in how I schedule my time	0.612
	It's okay to give up a lot of time with family and friends to achieve other worthy goals	−0.468
Waiting-tolerant	Having to wait is an annoying waste of time	−0.831
	Having to wait can be a useful pause in a busy day	0.533
Pro-car-owning	I definitely want to own a car	0.748
	I am fine with not owning a car, as long as I can use/rent one any time I need it	−0.576
	I like the idea of driving as a means of travel for me	0.535
	As a general principle, I'd rather own things myself than rent or borrow them from someone else	0.404

* To simplify interpretation, we reversed the directionality of these scales by multiplying the original loadings and factor scores by (−1).

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