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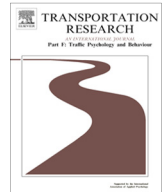
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How, and for whom, will activity patterns be modified by self-driving cars? Expectations from the state of Georgia



Sung Hoo Kim ^{a,*,1}, Patricia L. Mokhtarian ^{a,2}, Giovanni Circella ^{a,b,3}

^a School of Civil and Environmental Engineering, Georgia Institute of Technology, Atlanta, GA 30332, USA

^b Institute of Transportation Studies, University of California, Davis, Davis, CA 95616, USA

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ABSTRACT

Many studies have explored travelers' perceptions of self-driving cars (or autonomous vehicles, AVs) and their potential impacts. However, medium-term modifications in activity patterns (such as increasing trip frequencies and changing destinations) have been less explored. Using 2017–2018 survey data collected in the US state of Georgia, this paper (1) measures (at a general level) how people expect their activity patterns to change in a hypothetical all-AV era; (2) identifies population segments having similar profiles of expected changes; and (3) further profiles each segment on the basis of attitudinal, sociodemographic, and geographic characteristics. In the survey, respondents were asked to express their expectations regarding 16 potential activity modifications induced by AVs. We first conducted an exploratory factor analysis (EFA) to reduce the dimensionality of the activity-change vector characterizing each individual, and estimated non-mean-centered (NMC) factor scores (which have been rarely used in applied psychology). The EFA solution identified four dimensions of activity change: *distance*, *time flexibility*, *frequency*, and *long distance/leisure*. Next, we clustered Georgians with respect to these four-dimensional expectation vectors. The cluster solution uncovered six segments: *no change*, *change unlikely*, *more leisure/long distance*, *longer trips*, *more travel*, and *time flexibility & more leisure/long distance*. Using NMC factor scores identified considerably more inertia with respect to expectations for change than would have been apparent from the usual mean-centered scores. Finally, the various segments exhibit distinctive demographics and general attitudes. For example, those in the *more leisure/long distance* cluster tend to be higher income and are more likely to be Atlanta-region residents compared to other clusters, while those in the *no change* and *change unlikely* clusters tend to be older and are more likely to be rural residents.

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1. Background

Our transportation systems have been facing a variety of transformative technologies for several decades. Information and communication technologies (ICTs) have facilitated/substituted for travel (Mokhtarian, 2009). Mobile-internet-enabled shared mobility services such as bikesharing, carsharing, and ridehailing have offered new transportation options that potentially make people less reliant on privately-owned vehicles or conventional public transit. Most recently, new

* Corresponding author.

E-mail addresses: skim3020@gatech.edu (S.H. Kim), patmokh@gatech.edu (P.L. Mokhtarian), gcircella@gatech.edu (G. Circella).

¹ ORCID: <https://orcid.org/0000-0002-6748-0171>.

² ORCID: <https://orcid.org/0000-0001-7104-499X>.

³ ORCID: <https://orcid.org/0000-0003-1832-396X>.

micromobility services (e.g. dockless shared bicycles and/or e-scooters) are peppering the urban landscape. Looking to the future, it is becoming somewhat clichéd to expect that self-driving cars (or autonomous vehicles, AVs) will be the next technology to profoundly transform travel patterns and urban structure. At least, a sizeable number of experts agree that such changes will occur, aside from debates on when and how much. A key feature of AVs is its “passengerization” of erstwhile car drivers (Mokhtarian, 2018), which may transform how people engage in activities, whether in the vehicle or outside of it. For example, Mokhtarian (2018, p.5) suggested some examples of the cognitive logic of travelers:

- “Let’s go to this special place 50 miles away – we can do our last hour of work in the car on the way there, and watch our favorite TV show on the way back (as we would have done at home)”;
- “Since I can work and sleep in the car, I’m no longer really losing any work time during the travel itself”;
- “The time I saved by doing other things while traveling allows me to do x and still have time to go [somewhere else].”

The challenges to characterizing such behavioral changes, estimating their magnitudes, and identifying the people who exhibit such changes stem from the fact that fully-AVs are not yet on the roads. One clever approach is to deduce some hints from the current services that can be considered as precedents of true AVs. For example, some have argued that the impacts of automated ridehailing will be similar to those of current ridehailing services (e.g. Ozonder, Calderón, & Miller, 2019). Hardman, Berliner, and Tal (2019) envisioned the early adopters of AVs from considering electric vehicle (EV) owners in the U.S., while (Harb, Xiao, Circella, Mokhtarian, & Walker, 2018; Wadud, & Huda, 2019) drew implications on travel time use from current users of chauffeurs. Malokin, Circella, and Mokhtarian (2019) used the propensity to multitask on commuter rail to inform hypothetical AV adoption scenarios. However, aside from the fact that relevant studies about behavior changes are limited, such projections are also not perfect. EVs or partially-automated vehicles cannot offer real “hands-free” travel, while chauffeurs and public transit passengers may impede privacy and transit generally involves fixed routes and schedules. Accordingly, the way people react to these surrogates will be different from their response to fully AVs. In addition, even if a shared AV business model is plausible, the automobile-dependent settlement patterns and (related) strong inertia with respect to owning vehicle(s) in countries such as the United States will likely lead a sizable fraction of households to retain one or more vehicles, at the least in the medium term. Hence, how people travel may substantially differ between the current era of shared mobility and the coming AV era.

Surveying public opinion regarding perceptions of AVs and their impacts is far from perfect because the future is highly uncertain, and what people think now may be only loosely connected to what they will actually do when the time comes. However, current expectations can be an important benchmark and thus such surveys have been widely employed. In particular, people’s familiarity with AVs and acceptance of AVs has been explored (Kyriakidis, Happee, & de Winter, 2015; Payre, Cestac, & Delhomme, 2014).

A prevailing feature of such explorations is to examine the perceived benefits of and concerns regarding AVs (Cunningham, Regan, Horberry, Weeratunga, & Dixit, 2019; Liljamo, Liimatainen, & Pöllänen, 2018; Woldeamanuel & Nguyen, 2018). However, beyond investigating possible impacts on travel time use and valuation (e.g. Pudāne et al., 2019; de Almeida Correia, Loeff, van Cranenburgh, Snelder, & van Arem, 2019), a focus on the medium- and longer-term behavioral implications of AVs has been fairly limited. Perrine, Kockelman, and Huang (2020), by using the inter-regional *rJourney* travel demand model, analyzed changes in mode and destination choices for long distance trips with an AV option available. Olsen and Sweet (2019) explored commuters’ willingness to commute farther, while Kim, Mokhtarian, and Circella (2019c) analyzed potential changes in residential location and vehicle ownership in the AV era. On the whole, however, less attention has been paid to medium-term modifications in activity patterns such as increasing trip frequencies and changing destinations. Addressing this latter gap is the purpose of the present paper. Specifically, we aim (1) to measure (at a general level) how people expect their activity patterns to change in the AV era; (2) to identify population segments having similar profiles of expected changes; and (3) to further profile each segment on the basis of attitudinal, sociodemographic, and geographic characteristics.

The rest of this paper is structured as follows: Section 2 reviews related work. Section 3 describes the study design and relevant variables. Section 4 introduces the methodologies employed in this study and Section 5 presents the analysis results. Section 6 recapitulates the key findings and discusses implications of the findings and limitations of the study.

2. Related work

2.1. Sample and group differences in AV studies

Many studies have explored opinions of the general population regarding AVs, either in a specific city/neighborhood (Bansal, Kara, & Amit, 2016; Zmud, Ipek, & Wagner, 2016), nationwide (Cunningham et al., 2019; Liljamo et al., 2018; Nielsen & Haustein, 2018; Wu, Liao, Wang, & Chen, 2019), or multinationally (König & Neumayr, 2017; Kyriakidis et al., 2015). It is also notable that some studies have focused specifically on how certain sub-populations perceive AVs: older people (Rahman, Deb, Strawderman, Burch, & Smith, 2019), those with physical disabilities (Bennett, Vijaygopal, & Kottasz, 2019), and parents having at least one child between the ages of 0 and 14 (Lee and Mirman, 2018). In addition, Hohenberger, Spörrle, and Welp (2016) explored differences in willingness to use AVs by gender. The fact that certain population segments have distinctive perceptions/opinions suggests that diverse population segments may perceive the benefits

of AVs from the perspective of their own segment-specific needs, and thus it may be informative to disaggregate the population with respect to potential behavioral changes.

2.2. Market segments related to AVs

In the AV literature, there are a few studies that aimed to identify segments in the AV era. Nielsen and Haustein (2018) explored 3040 Danish adults' opinions and uncovered three segments (sceptics, 38%; indifferent stressed drivers, 37%; and enthusiasts, 25%). They conducted principal component analysis (PCA) on AV-related attitudes and cluster analysis based on mean scales, which are calculated from the PCA solution. Pettigrew, Dana, and Norman (2019) analyzed 1345 Australians and identified five groups (non-adopters, 29%; ride-sharing, 20%; AV ambivalent, 19%; likely adopters, 17%; and first movers, 14%). Next, they applied latent profile analysis to some AV-related indicators (knowledge about, intention to buy/share, perceived benefits of, and concerns about AVs). A parallel study to the present paper examined Georgia adults' mode-use propensities (Kim, Circella, & Mokhtarian, 2019a). In that research, we applied latent class cluster analysis to four mode-use propensities and identified seven relevant segments (AV enthusiast, 11%; AV-over-flight, 14%; flight-over-AV, 25%; AV occupant, 10%; pro-walk/transit, 20%; AV resistant, 10%; and anti-AV, 10%). Thus, these three prior studies investigated segmentation with respect to different indicators of interest compared to the present study: the revealed segments are related to general perceptions of AVs (Nielsen & Haustein, 2018), willingness to use/buy AVs (Pettigrew et al., 2019), and mode use under hypothetical transportation needs (Kim et al., 2019a). The current study is focusing on activity changes prompted by AVs.

2.3. Potential activity changes due to AVs

Such AV-triggered activity changes have been explored by a few studies in various ways. Gruel and Stanford (2016) discussed prospective impacts of AVs from a conceptual perspective. In their causal loop diagrams, increased comfort and utility of time in the car (i.e. an AV) could be one factor increasing the attractiveness of traveling by car; and then this attractiveness would lead to more trips per car per day and greater average trip length. Childress, Nichols, Charlton, and Coe (2015) applied an activity-based model to the Seattle region and found that vehicle-miles traveled could increase by 4% to 20% because of more/longer trips and some shifts away from other modes. LaMondia, Fagnant, Qu, Barrett, & Kockelman (2016) simulated statewide long-distance mode shifts by controlling the 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. Pudāne et al. (2019) conducted focus group interviews with 27 commuters about reshaping their daily activities by AVs. For example, interviewers asked (p. 225), "Would you like to perform such activities in the AV which you normally perform in traditional environment like at home or at work? If so, do you think you can save time for other things which you would like to (or have to) do?", "Would you change anything in your daily routine if you had an AV?", "Would you travel further or more frequently to perform activities if you had an AV?" The findings of the study suggested some types of on-board activities and complex re-arrangements of daily activity patterns. Harb et al. (2018) conducted a naturalistic experiment by providing a chauffeur to 13 subjects and thus mimicking the hands-free travel feature of AVs. The study found that the experiment increased total VMT (by 83% overall), vehicle-trips (58% more on average), and trip lengths (a 91% increase, between chauffeur and control weeks, in the average per-person number of trips longer than 20 miles).

2.4. Summary

Such studies are certainly informative, but to date they either rely on informed speculation, or on very small samples. What the literature is currently missing is a larger-scale empirical look at what people think about their behavioral responses (with respect to travel-related activities in particular) in the AV era. Do people really expect that they will take advantage of the reduced disutility of travel and thus do something that they would not have done if they were to drive themselves? Will there be subgroups having different expectations? The current study aims to provide an early glimpse of the answers to these questions, for a sample that (after weighting) is reasonably representative of the population of the US state of Georgia.

3. Empirical context

This study analyzes data collected from a cross-sectional survey targeting the adult population of Georgia (18 or older). The survey aimed to take a snapshot of attitudes and travel behaviors in Georgia, particularly emphasizing the use of new technologies including ICTs, ridehailing services, and (prospectively) AVs. To obtain a diverse and healthy-sized sample, we recruited respondents both through address-based stratified random sampling in the 15 Metropolitan Planning Organization (MPO) areas in Georgia,⁴ and

⁴ A key goal of the research project was to ensure representation of Georgia residents in all 15 MPO areas. However, since the single Atlanta-region MPO contains about 68% of the state's households, we deliberately undersampled Atlanta-region residents so as secure healthy-size samples in the smaller regions of the state. Specifically, we allocated 33% of the budgeted number of invitations to Atlanta-region residents. We purchased a contact list of 30,000 randomly selected households (and an adult in each household) from a commercial vendor: 10,000 from the Atlanta region, and 20,000 from the remaining MPO areas. Within each of these two regions, we ensured that the distribution of invited households across the counties comprising the region was proportional to the total number of households in the respective counties.

also through inviting Georgia participants in the 2016–17 National Household Travel Survey who expressed a willingness to be surveyed further (Westat, 2018). A paper copy of the survey, with a cover letter containing a link to the online version which could be completed instead, was sent to each individual. Data collection lasted about six months (October 2017 – April 2018), and since a majority (about 80%) of respondents completed the paper version of the questionnaire, we spent several months on data entry and cleaning. For this study, the sample size is 3244 after dropping cases with missing values on key variables. Because of nonresponse biases and our intentional sampling strategy (we oversampled non-Atlanta MPO residents to secure an adequate number of such cases), the sample under-/over-represented certain population groups. Hence, to improve the representativeness of the sample, we developed weighting factors based on American Community Survey (ACS) key demographics, using a mixture of cell weighting and iterative proportional fitting (IPF) (more details about the survey design and development of weighting factors can be found in Kim, Mokhtarian, & Circella, 2019b). To ensure that the full diversity of the sample was allowed to influence the analysis, we used the *unweighted* sample when conducting the factor and cluster analysis (since the weighted sample might have suppressed the “voice” of small segments). However, to ensure that population proportions were appropriately represented in the end, we used the *weighted* sample to compute cluster sizes and class-specific characteristics. Additional land use variables, related to respondents’ home locations, were appended by using Google API and American Community Survey (ACS) estimates (2017 5-year estimates). The sample distribution is reported later in Table 3, for easier comparison with the cluster-specific distributions.

It is important to note how the survey set up assumptions for the AV era since such assumptions will affect how people respond to the questions. The survey asked respondents to imagine that fully-mature AV technologies had replaced *all* conventional vehicles and were at least as safe and cost about as much as today’s vehicles, so as to focus on behavioral responses after sidestepping transitional, safety and cost issues. However, it is still an open question whether AVs can/will ever completely replace all conventional vehicles, and hence, this study treats only one of multiple plausible future scenarios. The survey provided descriptions and figures to help respondents envision that hypothetical future. To capture expectations on (travel-related) activity changes triggered by AVs (the focus of the present study), the survey asked respondents to express their expectations regarding 16 statements, using a five-point ordinal scale (very unlikely to very likely). A full list of statements, together with relevant statistics, will be shown in Table 1 in Section 5.1.

4. Methodology

4.1. Factor analysis and non-mean-centered scores

Because the 16 statements describing potential AV-initiated activity changes are intercorrelated (and constitute an unwieldy number to analyze individually), we conduct an exploratory factor analysis (EFA) to reduce the dimensionality of the activity-change vector characterizing each individual. EFA aims to identify the underlying latent constructs that best account for the patterns of covariance among the observed variables (Rummel, 1970). In particular, we map the 16-dimensional vector of raw response items for a given person into a lower-dimension space by estimating factor scores from the EFA solution. This is analogous to employing dimension-reduced scores from principal component analysis (PCA) in the machine learning field (e.g. Camacho, Pérez-Villegas, García-Teodoro, & Maciá-Fernández, 2016; Krishna, Weaver, & Sanders, 2015). In the applied psychology field, factor scores have been employed as estimated measures of latent factors (e.g., Casutt, Martin, Keller, & Jäncke, 2014; Ledesma et al., 2019; Biehl, Ermagun, & Stathopoulos, 2018). Multiple methods to estimate factor scores have been proposed, including regression and Bartlett methods (cf. DiStefano, Min, & Diana, 2009; Estabrook & Neale, 2013). Although the regression method has been most widely used as a “default” because of its simplicity, in this study, we employed Bartlett scores⁵. McDonald and Burr (1967) noted that Bartlett scores, unlike regression scores, are conditionally unbiased estimators of the true scores and have zero correlations with the non-corresponding true scores (the latter property meaning that they are “univocal”). In addition, the present authors’ empirical experience has been that Bartlett scores from an obliquely-rotated factor solution tend to have lower correlations among themselves compared to the regression scores from the same solution.

As noted by Thompson (1993), conventional methods for estimating factor scores involve computing linear combinations of the standardized responses to the original items (where the magnitude of the coefficient of a given item is related to the strength of its association with the factor in question). Since the standardized items will each have mean zero, their linear combinations will also have mean zero, and thus this process produces mean-centered (MC) factor scores. But once an item or a score is mean-centered, its original *prima facie* meaning is lost: a zero does not mean “neutral”, but rather “average”, which is not at all the same thing. For example, if the sample means of the items loading heavily on a given factor are all around 2 (which means “unlikely” in our case), the zero-point of the resulting factor will represent a response of “unlikely”. A slightly positive score on such a factor is easily misinterpreted as meaning “slightly likely”, or favorable, when in fact it only means “slightly more likely than average, but still unlikely”.

To address this issue, Thompson (1993) proposed an alternative, non-mean-centered (NMC), method of computing factor scores that can preserve the face-value neutral of the Likert-type scale. The authors are aware of only a few studies that have employed NMC factor scores (Deng, Mokhtarian, & Circella, 2015; Garrow et al., 2020). A distinction of the present study is to

⁵ The regression and Bartlett scores are similar to each other (their correlations are higher than 0.96 in our sample), and hence similar final results are expected regardless of the estimation method.

Table 1
Descriptive statistics, communalities, and pattern factor loadings for 16 prospective activity changes prompted by AVs.

Statements	Descriptive statistics		Communalities	Activity change factors – pattern loadings			
	Mean	SD		Distance	Time flexibility	Frequency	Long-distance/leisure
Eat out in restaurants more often.	2.04	0.95	0.763	0.062	0.069	0.782	0.043
Go to grocery stores or shopping malls more often.	2.06	0.96	0.830	0.076	0.066	0.822	0.023
Travel to social/leisure activities more often.	2.36	1.12	0.733	0.375	0.060	0.452	0.138
Go to more distant restaurants.	2.45	1.18	0.833	0.666	0.077	0.247	0.062
Go to more distant grocery stores or shopping malls.	2.28	1.11	0.776	0.630	0.114	0.254	0.027
Socialize with people who live farther away.	2.52	1.20	0.813	0.654	0.102	0.080	0.214
Travel to more distant locations for leisure.	2.73	1.26	0.800	0.504	0.049	0.038	0.444
Eliminate some overnight trips because it would be easier to come back the same day.	2.80	1.24	0.670	0.106	0.106	0.080	0.652
Make more overnight trips by car because it would be less burdensome to travel long distances.	2.87	1.25	0.797	0.086	0.054	0.047	0.789
Go to work/school at a different time to avoid traffic jams, since I can sleep/work in the car.	2.32	1.15	0.553	0.055	0.428	0.098	0.335
Take part in more leisure activities after dark, because I wouldn't need to drive myself.	2.63	1.22	0.617	0.185	0.147	0.184	0.457
Take vacations more often.	2.48	1.17	0.661	0.221	0.212	0.171	0.417
Reduce my time at the regular workplace and work more in the self-driving car.	2.03	1.00	0.586	0.039	0.614	0.127	0.120
Sleep less time at home and more time in the car, to be more efficient.	1.83	0.89	0.683	0.040	0.817	0.013	−0.025
More often eat meals in a self-driving car instead of at home or in a restaurant.	1.96	0.96	0.549	0.020	0.687	0.060	0.034
Cultivate new hobbies or skills with the time I saved.	2.25	1.06	0.581	0.181	0.463	0.117	0.196

Note: Responses comprise a five-point ordinal scale where 1 = “very unlikely” and 5 = “very likely”. There are no strict rules about what is a “large enough” pattern loading, but advice in the attitudinal measurement literature ranges between 0.3 and 0.5 (in magnitude) as a threshold (e.g., Fabrigar, Wegener, MacCallum, & Strahan, 1999; Rummel, 1970). Taking the middle ground and following, e.g., Ledesma, Shinar, Valero-Mora, Haworth, and Morandi (2019), loadings greater than 0.4 are bolded for emphasis and treated as meaningful in our interpretation of the solution. These numbers, together with the associated row and column labels, are reported in Kim et al. (2019c), but the other numbers have not been published previously.

use Bartlett scores, whereas the previous two applications employed regression scores. Equations for the conventional MC Bartlett scores and the alternative NMC Bartlett scores are as follows (cf. DiStefano et al., 2009):

$$\hat{F}_{i \times m}^{MC} = Z_{i \times n} U_{n \times n}^{-2} A_{n \times m} \left(A'_{m \times n} U_{n \times n}^{-2} A_{n \times m} \right)^{-1} \quad (1)$$

$$\hat{F}_{i \times m}^{NMC} = T_{i \times n} U_{n \times n}^{-2} A_{n \times m} \left(A'_{m \times n} U_{n \times n}^{-2} A_{n \times m} \right)^{-1}, \quad (2)$$

where \hat{F} is a matrix of estimated factor scores, i is the number of individuals, n is the number of items, m is the number of factors, Z is the matrix of standardized item responses, T is the matrix of non-mean-centered responses (obtained by adding the item mean back to each standardized response in Z), A is the pattern matrix of loadings, and U^{-2} is the inverse of the diagonal matrix of the uniquenesses (a diagonal element of U^2 is the share of the unit variance of the associated item that is unique to that item rather than in common with the other items; it is one minus the communality of the item [see Table 1]).

4.2. Cluster analysis and group differences

Cluster analysis has often been used as a way of market segmentation. In the present study, we aim to group people based on their expectations regarding their AV-prompted activity changes (as measured by EFA-based factor scores). Segmentation analysis based on factor analysis solutions has been used in various fields such as transportation/planning (Mokhtarian, Ory, & Cao, 2009; Pronello & Camusso, 2011), tourism/marketing (Guttenag, Smith, Potwarka, & Havitz, 2017; Sinclair-Maragh, Gursoy, & Vieregge, 2015), and geology (Wang, Zuo, & Caers, 2017). In the current study, this expectation-based segmentation could produce plausible market compositions with respect to potential behavioral changes. We apply K -means clustering, which is one of the most intuitive and widely used cluster analysis methods. After obtaining a preferred cluster solution and naming the clusters on the basis of their centroids (i.e. their mean activity change factor scores), we explore group differences on *other* variables in the data using the relevant statistical tests. Specifically, one-way analyses of variance

(ANOVAs) and Pearson's χ^2 tests are performed to test for mean differences across clusters for continuous variables, and distribution differences across clusters for discrete variables, respectively.

5. Findings

5.1. Identifying latent constructs

Considering that the expected constructs may not be independent of each other, we obliquely rotated the initial factor solution (which allows constructs to be orthogonal if they naturally are so, but does not force them to be). The direct oblimin rotation method, suggested by [Jennrich and Sampson \(1966\)](#), has been widely used in the literature and we apply it here. Delta is a parameter that can control the degree of obliqueness; [Harman \(1976\)](#) suggested that delta should range between zero (most oblique) and -4 (less oblique as delta gets smaller). We experimented with various delta values and determined that a value of -1 produced the fewest sizable “off-diagonal” pattern loadings, thus maximizing interpretability. Based on qualitative and quantitative criteria, we selected the 4-factor solution. This factor solution was also reported in [Kim et al. \(2019c\)](#), where the resulting *mean-centered* scores were used as explanatory variables in models of hypothetical impacts of AVs on vehicle ownership and residential location.

[Table 1](#) exhibits the descriptive statistics and factor solution measures (communalities and pattern loadings) for the 16 statements reflecting potential activity changes as a consequence of AVs. A given change is generally considered to be less likely when its mean is smaller than 3 (“neutral”), and it can be seen at a glance that all 16 statements are considered, on average, to be unlikely to varying degrees. In particular, two statements related to time use (“Sleep less time at home and more time in the car, to be more efficient” and “More often eat meals in a self-driving car instead of at home or in a restaurant”) present means below 2. Whether these results are reflecting genuinely minor effects of AVs or an inability of respondents to envisage some downstream consequences of AVs remains to be seen, but in any case they provide a useful benchmark of public perceptions.

Turning to the factor solution, the first and third factors capture two different dimensions of travel quantity, largely (but not exclusively) with respect to local travel. **Distance** represents a general inclination toward traveling longer distances. Four statements have loadings above 0.5, and “Go to more distant restaurants” has the highest loading (0.666). People who have a higher score on this factor consider it more likely that they will go to farther-away restaurants, places where they can socialize with others, shopping malls, and leisure destinations. **Frequency** captures a general inclination toward traveling more frequently. Two statements “Go to grocery stores or shopping malls more often” and “Eat out in restaurants more often” have distinctively high loadings (0.822 and 0.782). Those with a higher score on this factor think they will likely go shopping, to restaurants, and leisure destinations more often. The second factor is labeled **time flexibility** and it reflects a general inclination toward modifying one's time use. The first three items loading heavily on this factor relate to time freed up by bringing formerly “outside-the-trip” activities inside the trip; the fifth item suggests freeing up “within-trip” time by spending less time in congestion; and the fourth item relates to ways in which the newly-freed time (whether formerly within-trip or outside-the-trip) can be spent ([Mokhtarian, 2018](#)). Lastly, the fourth factor, which is labeled **long-distance/leisure**, represents a general inclination toward making specifically long-distance and leisure trips more often. In particular, “Make more overnight trips by car because it would be less burdensome to travel long distances” presents the highest loading of 0.789. Even the item representing the “eliminat[ion of] some overnight trips because it would be easier to come back the same day” might actually indicate the facilitation of more long-distance travel due to the added convenience and time savings of not spending the night away from home.

5.2. Clustering the sample

When applying the *K*-means algorithm, to avoid local optima we used 1000 sets of initial centroid values, and selected the set that yielded the minimum value of the objective function (namely, the within-cluster sum of squares). We compared quantitative measures (mainly the within-cluster sum of squares and total sum of squares) and qualitative characteristics for different values of *K* (numbers of clusters). In particular, we focused on how much each solution could provide useful insights while minimizing complexity. Ultimately, we selected the 6-cluster solution.

[Fig. 1](#) shows the six sets of cluster centroids, which can help characterize each cluster. Especially, in keeping with the point of the NMC factor solution, we interpret each cluster centroid relative to the vector of factor scores corresponding to “neutral” responses on all 16 items: as “likely” if above the neutral score and “unlikely” if below it.

The six clusters are roughly ordered by how likely behavior changes are perceived to be. The first cluster is labeled **no change**, because people in this segment present the most negative reactions to any activity changes. The second cluster, **change unlikely**, also exhibits less optimistic responses, with all four mean scores falling below neutral. The first and second clusters are distinguished from each other in that respondents in the former answered “very unlikely” to most of the original statements, whereas respondents in the latter tended to answer “unlikely”. The shares of these two segments are 20% and 26%, respectively, indicating that almost half of the respondents expressed a lack of enthusiasm for changing their activity patterns due to AVs. The third segment is labeled **more leisure/long distance** and its share is 15%. This cluster also shows “unlikely” reactions to three of the activity dimensions, but has distinctively high expectations of making more leisure

and long distance trips. In other words, members of this cluster expect little change in their daily travel, but would like to take advantage of AVs for occasional long distance trips. The fourth cluster, **longer trips**, has a share of 13%. People in this group expressed less enthusiasm for using time more flexibly and making trips more frequently, but they envisioned traveling to more distant places, for both daily (e.g. grocery, restaurant) and long-distance trips. The fifth, **more travel**, segment (14%) exhibits a higher level of enthusiasm for changing the quantity of their travel. However, they still think it unlikely that they will employ time more flexibly because of AVs. The last segment is labeled **time flexibility & more leisure/long distance**, having a share of 13%. This cluster shows a generally high level of enthusiasm. A distinctive observation is that this cluster is the only segment presenting positive reactions to time flexibility.

Fig. 2 exhibits pairwise scatter plots of the factor scores, by cluster, for all combinations of the four activity dimensions. Note that there are two sets of axes in each figure. The solid-line (NMC) axes cross at the “neutral” point for each score, whereas the dashed-line (mean-based) axes cross at the “mean” point for each score (i.e. at what would be the (0,0) origin of the MC solution). The discrepancies between these pairs of axes illustrate differences in the interpretation of MC versus NMC solutions. Because the prevailing perception for all items is “unlikely”, there are substantially fewer cases thinking that a given impact dimension is “likely” (i.e. falling above or to the right of the solid axes) than cases that have “above average” perceptions of likelihood (i.e. above or to the right of the dashed axes) – with the exception of the long-distance/leisure factor, for which the mean-based and NMC axes nearly coincide⁶. Put another way, many cases with positive MC factor scores actually still consider a certain type of change to be unlikely. Thus, the MC factor scores can give a misleading picture of the actual content of the original responses.⁷

With respect to the degree of discrepancy between the two axes, the factors are ordered as follows: time flexibility, frequency, distance, and long distance/leisure. This is a function of how much the means of the original statements deviate from neutral (i.e. a 3 on the 5-point scale). Statements highly loading on the time flexibility factor have the lowest means and those loading on the long distance/leisure factor have the means closest to 3 (see Table 1).

5.3. Exploring group differences

In this section, we flesh out the characteristics of each cluster, by exploring their central tendencies and distributions with respect to a number of other variables available in the dataset. Table 2 presents the results of χ^2 and ANOVA tests of differences in distribution and mean across clusters, while Table 3 provides the cluster-specific distributions and means for the variables tested. At a glance, there are statistically significant differences on demographics, land use attributes, and attitudes among clusters. We discuss the nature of each cluster in turn.

The **no change** cluster has distinctive demographics. This segment is the oldest, least-often working, and lowest-income compared to other clusters. In addition, it has the greatest share of residents in non-MPO (rural and associated small town) areas. These demographics are congruent with this segment’s attitudinal characteristics: they are the least tech-savvy and least favorable to AVs. They live, on average, in the least dense areas. Hence, “older people in rural areas” seem to have the lowest expectations regarding activity modifications by AVs. The **change unlikely** segment is, in general, close to the population average demographically, aside from tending to be older. Their “unlikely” status appears most closely related to their relatively low level of perceived benefits from AVs. The **more leisure/long distance** cluster has the greatest shares of male, middle generation (34–64), white, and high-income individuals, with an above average share of people living in the Atlanta region. People fitting this profile may have a higher demand for leisure or long-distance trips in general, and are thus expecting more benefits from employing AVs to meet that demand. The **longer trips** cluster shares some similarity of demographics with the **more leisure/long distance** cluster, including higher incomes and employment. One notable difference is that it has by far the greatest share of women (of any of the clusters), and it also has more members in both the youngest and the oldest age groups than the **more leisure/long distance** cluster. On average, its members live in the densest areas, and yet their urbanite attitudes are noticeably weaker than those of the remaining two segments. The **more travel** segment has the greatest share of non-white members and people with lower incomes and fewer household vehicles. However, they are favorable toward AVs, tech-savvy, and favorable toward urban life (with, accordingly, the lowest share of rural-area residents). The **time flexibility & more leisure/long distance** has the greatest expectations for activity changes, and present the opposite demographic and attitudinal profile to the **no change** cluster. They are the youngest and most tech-savvy, like traveling the most, and are most favorable toward non-car options. This segment has the greatest share of workers and Atlanta residents. Finally, they have the most favorable perception of the benefits of AVs among all the clusters.

⁶ In this case, the mean-based axis is a bit higher than the NMC axis. This may be surprising, given that the means of all 16 items are below neutral (i.e. below 3). It happens because of the factor score coefficients $[U_{n \times n}^{-2} A_{n \times m} (A'_{m \times n} U_{n \times n}^{-2} A_{n \times m})^{-1}]$ and the differences between mean and neutral for the 16 statements. The difference between the neutral point (3.00) and the mean point (3.14) is the inner product of the factor score coefficients vector and the difference between the vectors of NMC neutrals and means. The latter, difference vector, has all positive values (since all the means are below neutral), but coincidentally, for statements having positive factor score coefficients those differences are small, whereas for statements having negative coefficients those differences are relatively greater. Consequently, the sum of products is dominated by negative values, and the final difference (3.00–3.14) is negative.

⁷ The number of cases falling between the “neutral” and “mean” axes are: 224 (distance), 941 (time flexibility), 681 (frequency), and 146 (long distance/leisure; in this case alone, the “neutral” axis is higher than the “mean” axis).

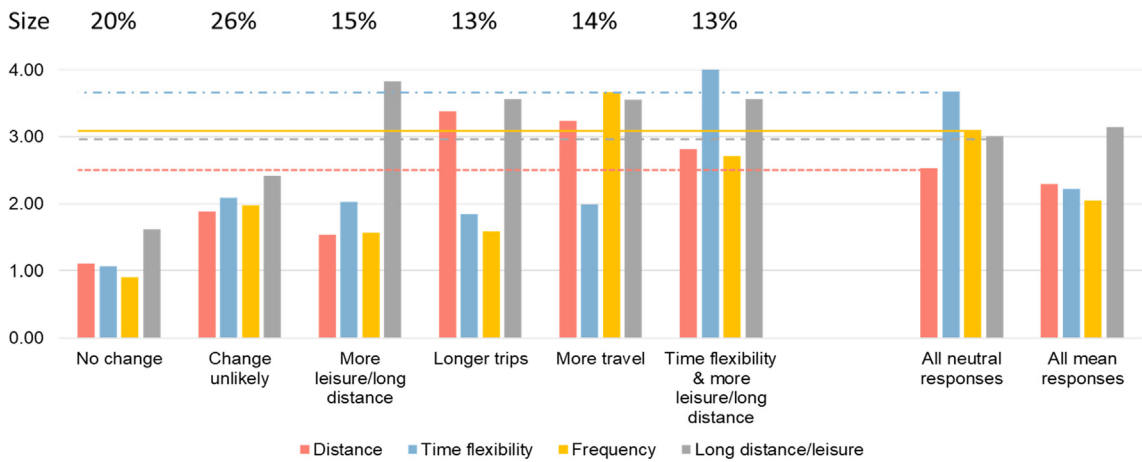


Fig. 1. Centroids of the six clusters.

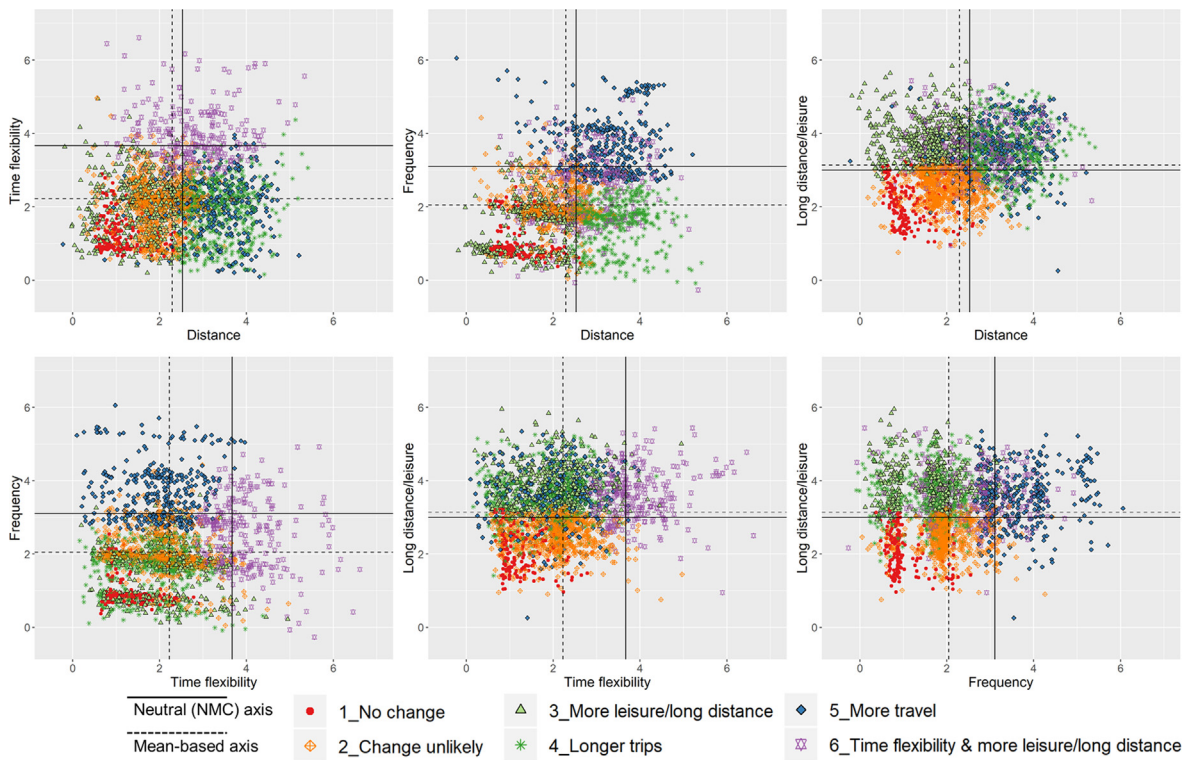


Fig. 2. Scatter plots of factor scores.

6. Conclusion

6.1. Summary of findings

This study examined potential (travel-related) activity changes caused by AVs, and identified population segments that have different expectations regarding such changes occurring to them personally. We surveyed more than 3000 Georgians with respect to their expectations regarding 16 potential changes, under the assumption of a hypothetical fully-AV era. In common with a previous paper using the same data for a different purpose (Kim et al., 2019c), we applied factor analysis to identify four latent dimensions underlying the 16 activity changes: *distance*, *time flexibility*, *frequency*, and *long distance/leisure*. We then estimated factor scores to measure how likely individuals perceive it to be that they will experience changes

Table 2
Statistical tests of group differences for selected variables.

Analysis of variance			Chi-squared test		
Variable	F statistic	P-value	Variable	Chi sq. value	P-value
Pro-non-car-mode	37.02	0.000	Gender	41.03	0.000
Tech-savvy	44.30	0.000	Generation	269.31	0.000
Urbanite	33.71	0.000	Work status	124.82	0.000
Travel-liking	10.76	0.000	Race	84.32	0.000
AV pros	382.20	0.000	Household income	98.29	0.000
Population density	4.56	0.000	Vehicle ownership	69.44	0.000
Household density	4.76	0.000	MPO tier	140.67	0.000
Job density	2.71	0.019			
Number of stores	6.60	0.000			
Number of restaurants	7.54	0.000			
Number of bars	8.10	0.000			

Note: The total number of cases is 3244. Some variables have missing values, so the number of cases varies (but is always more than 3200). For each variable, the null hypothesis is “no difference across clusters”, and the alternate hypothesis is “at least one cluster is different from the others”. See the [Table 3](#) footnotes for variable descriptions.

on each dimension due to AVs. In particular, distinctively from the conventional method used in the previous paper (namely mean-centered, MC, factor scores, which center the origin of each factor dimension using the *means* of the raw responses), we employed the alternative method of non-mean-centered (NMC) factor scores, which preserve the *prima facie* meaning of “neutral” in the raw responses. Because the prevailing sentiment on all 16 changes was that they were unlikely to occur, the NMC scores are positive for far fewer cases than the MC scores are, indicating that the traditional approach could provide a misleadingly optimistic view of the likelihood or pace of change.

To discover potential market segments, we applied the *K*-means clustering algorithm to the NMC factor scores. Six clusters appeared: *no change*, *change unlikely*, *more leisure/long distance*, *longer trips*, *more travel*, and *time flexibility & more leisure/long distance*. The clusters exhibited heterogeneous expectations with respect to their potential activity changes: nearly half the cases fell into the first two clusters, which expected changes on all four dimensions to be unlikely, but the remainder expected that change on one to three of the four dimensions is likely to some extent. We scrutinized group differences (with relevant statistical tests) to see what demographic, geographic, and/or attitudinal differences exist across clusters. Many relevant characteristics were statistically different across clusters. In particular, the favorability of individuals’ perceptions of AVs was strongly tied to their expectations of future activity changes. Perhaps not surprisingly, older and relatively lower-income people, as well as residents of smaller MPO regions, tended to expect fewer changes to their travel-related activities in the AV era.

6.2. Implications and limitations

This study contributes to the applied psychology and AV literature by (1) applying a rarely-used psychometric method (NMC factor scores) and demonstrating its value; and (2) obtaining empirical results, including market segments, with respect to prospective activity changes that have been currently understudied. This early glimpse of such activity changes hints at some implications.

First, although many experts speculate that AVs will be a “game changer” that significantly shifts behaviors, based on people’s current opinions (which are admittedly likely to be conservative), the shifts may be more modest on average. Among the four dimensions explored in this study, people reported particularly lower expectations with respect to time flexibility. This finding is congruent with other discussions about time use in the AV era. For example, [Singleton \(2019\)](#) also argued that impacts of AVs on the value of time (related to productive time use) may be more modest than expected. However, some fraction of people will take advantage of hands-free travel; such people are more likely to be tech-savvy, younger, and workers (the *time flexibility & more leisure/long distance* segment).

Second, when we consider two major dimensions of travel amounts, namely trip distance and frequency, the results (either the means of the raw statements in [Table 1](#) or the factor means in [Fig. 1](#)) of this study suggest that AVs will have stronger impacts on distance than on frequency. We speculate that this might be partly because it is relatively less burdensome to add more travel time to existing trips (especially if the time can be used pleasantly or productively) than to make entirely new trips (which are likely to impose a heavier time fragmentation and spatial constraint penalty, even if the impact of that penalty may be diminishing with the increased fungibility of travel time). This, in turn, suggests that it is important to distinguish between more versus longer trips in efforts to predict aggregate increases in travel time due to AVs. Increased overall trip distance implies that the service areas of some types of places (e.g. restaurants or shopping malls) could be enlarged in the AV era. However, the current study cannot estimate specific sizes of the incremental changes in trip distance and frequency. Furthermore, the study did not touch on the implications of employing zero-occupant AVs for errands; employing zero-occupant AVs may affect how people organize their daily activity schedules, and thence their trip frequencies and distances. Thus, caution is called for with respect to drawing specific conclusions at this point.

Table 3
Cluster-specific means/shares (weighted sample).

	No change	Change unlikely	More leisure/long distance	Longer trips	More travel	Time flexibility & more leisure/long distance	Sample
Share	20%	26%	15%	13%	14%	13%	
Cluster-specific means							
Pro-non-car-mode ^a	-0.34	-0.11	0.06	0.14	-0.01	0.47	-0.01
Tech-savvy ^a	-0.21	0.00	0.35	0.40	0.33	0.50	0.17
Urbanite ^a	-0.15	-0.01	0.10	0.18	0.47	0.46	0.13
Travel-liking ^a	-0.10	-0.11	0.03	0.11	0.04	0.28	0.01
AV pros ^a	-1.06	-0.20	0.20	0.53	0.69	0.79	0.04
Population density ^b	2.85	3.34	3.55	3.91	3.58	3.67	3.42
Household density ^b	1.12	1.25	1.42	1.60	1.38	1.52	1.35
Job density ^b	1.74	1.26	1.84	2.30	2.00	1.47	1.70
Number of stores ^c	10.46	<i>10.32</i>	10.49	12.58	12.00	11.61	11.06
Number of restaurants ^c	4.55	4.66	4.39	6.55	5.49	5.97	5.12
Number of bars ^c	1.08	<i>1.00</i>	1.27	2.26	1.41	1.47	1.33
Cluster-specific shares							
Gender							
Male	48%	50%	56%	37%	43%	53%	48%
Female	52%	50%	44%	63%	57%	47%	52%
Age							
18–34	14%	17%	24%	29%	28%	33%	23%
35–44	13%	13%	21%	17%	20%	26%	17%
45–64	37%	43%	43%	36%	39%	36%	39%
65+	36%	27%	13%	18%	13%	6%	21%
Work status							
Not working	55%	39%	31%	33%	33%	26%	38%
Working	45%	61%	69%	67%	67%	74%	62%
Race							
White	63%	66%	69%	65%	48%	57%	62%
Black	28%	27%	21%	26%	45%	36%	30%
Else	9%	7%	10%	9%	8%	7%	8%
Income							
Below \$50,000	52%	40%	34%	32%	52%	42%	42%
\$50,000–\$99,999	29%	35%	31%	34%	31%	29%	32%
\$100,000+	19%	26%	35%	34%	18%	29%	26%
Vehicle ownership							
Zero vehicle	8%	3%	2%	5%	10%	4%	5%
1 vehicle	36%	35%	31%	28%	38%	35%	34%
2+ vehicles	56%	62%	67%	67%	52%	61%	61%
MPO tier ^d							
Atlanta region	38%	48%	58%	60%	55%	59%	51%
Mid-size MPO regions	17%	20%	16%	18%	19%	17%	18%
Small-size MPO regions	17%	14%	8%	11%	15%	12%	13%
Non-MPO areas	29%	17%	17%	12%	<i>10%</i>	12%	17%

Notes: Bold indicates the highest value in the row and italicized indicates the lowest value. The total number of cases is 3244. Some variables have missing values, so the number of cases varies (but always exceeds 3200).

^a Factor scores: the first four were obtained from one EFA (which included other factors not used in this study), while the fifth came from a separate EFA (which included an additional factor not used here). Statements strongly loading on each factor are reported in the Appendix; see Kim et al., 2019a for additional details.

^b Census block-group level attributes (per acre). These are appended based on geocodes of home address.

^c Individual-level attributes that describe local accessibility (the number of amenities within a mile from the home location). These are appended based on a Google API.

^d We classified the 15 MPOs and the remaining regions into four tiers based on population: 1st tier (Atlanta region), 2nd tier (mid-sized MPO regions whose populations exceed 200,000), 3rd tier (small-sized MPO regions, whose populations are under 200,000), and non-MPO areas.

Lastly, how much more travel is generated in the AV era will vary across demographics and regions. For example, AVs could facilitate the potential travel needs of younger/middle-age adults, higher income individuals, and Atlantans more than others. In addition, such travel generation may occur only for long distance trips (e.g. holiday trips) for some, whereas others may employ AV benefits more in daily life, for example by using time more flexibly (either in-vehicle or out-of-vehicle). As such, future modeling for demand forecasting or prescriptive planning in preparation for the AV era should consider these heterogeneous responses of people.

Accordingly, it is pertinent to wonder about the extent to which the Georgia-specific findings of this study (or, indeed, the geographically-specific findings of any study) are transferable to other regions (whether to other states in the US, or elsewhere). We could certainly expect the shares of each segment in the population to differ across regions, and to some extent the nature of the segments could differ if the methodology of this study were replicated on similar data collected

elsewhere – expectations it would certainly be useful to test in future research. However, we believe that the study has identified some key dimensions along which activity impacts of AVs are likely to be felt (lengths and frequencies of local and long-distance trips, time use), and that the general nature of these dimensions is likely to be geographically robust. Given that we observed geographical differences (e.g. density measures and number of amenities near home) across segments, it is likely that differences in the extent to which each dimension of change is operative in other populations are partly a function of such geographical characteristics. From this perspective, it would be desirable to more deeply investigate the connection of specific empirical findings, across several studies similar to this one, to the geographical characteristics of each study area (e.g. how more- and less-urban areas are geographically distributed in the study area, how much of the area is urbanized overall, the possible role of geographic constraints such as mountains or bodies of water, whether there is an attractive long-distance destination located a “reasonable [AV] driving distance” away, and so on). Similar observations could be made about cultural differences across areas – for example, making efficient use of one’s time is more important in some cultures than in others (e.g. Kaufman-Scarborough, 2018; Lindquist, Knieling, & Kaufman-Scarborough, 2001; Plocher, Goonetilleke, Zhang, & Liang, 2002).

Some limitations of the study remain. Although we identified potential behavioral changes, it is unclear how much such changes will occur or specifically how much trips or vehicle-miles traveled will increase. Although a hypothetical bias is often toward a more rosy or favorable view of the new alternative being proposed, in this context there may be a bias in the opposite direction as well, due to some combination of ignorance, uncertainty, and fear with respect to AV technology and its possible implications (Loomis, 2011). To assess potential changes more quantitatively, a larger-scale chauffeur experiment (Harb, Xiao, Circella, Mokhtarian, & Walker, 2018; Wadud & Huda, 2019) could be informative. In addition, as in other AV studies, there are huge uncertainties at this point in time about the eventual nature of the AV era; hence, the “all-AV” future scenario presented to respondents in this study should be considered only one of many plausible scenarios.

CRedit authorship contribution statement

Sung Hoo Kim: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. **Patricia L. Mokhtarian:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Funding acquisition, Resources, Supervision, Writing - original draft, Writing - review & editing. **Giovanni Circella:** Conceptualization, Project administration, Funding acquisition, Resources, Supervision, Writing - review & editing.

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Appendix

Selected attitudinal factors and highly-loading statements

Factor	Statement	Pattern matrix loading
<i>Pro-non-car-mode</i>	I like the idea of walking as a means of travel for me.	0.666
	I like the idea of bicycling as a means of travel for me.	0.628
<i>Tech-savvy</i>	I like the idea of public transit as a means of travel for me.	0.336
	Learning how to use new technologies is often frustrating for me.	−0.866
<i>Modern urbanite</i>	I am confident in my ability to use modern technologies.	0.801
	I like the idea of having stores, restaurants, and offices mixed among the homes in my neighborhood.	0.417
<i>Travel-liking</i>	My phone is so important to me, it’s almost part of my body.	0.350
	I generally enjoy the act of traveling itself.	0.618
<i>AV pros</i> ^a	I like exploring new places.	0.593
	Having the vehicle drive itself would allow me to be more comfortable on trips.	0.746
	A self-driving car would enable me to enjoy traveling more (e.g. watching the scenery).	0.734
	I would gain a lot of useful time by sending my vehicle to do certain things (e.g. pick	0.705

Appendix (continued)

Factor	Statement	Pattern matrix loading
	up dry cleaning) without me.	
	I would more often travel even when I am tired or sleepy.	0.676
	I would reduce my parking costs because my self-driving car could drive itself to a cheaper parking space.	0.645
	A self-driving car would enable me to get to places faster than if I had to drive myself.	0.590
	I would be able to travel more often when under the influence of alcohol or medicines.	0.501
	Even if I could do other activities in the car while it drove itself, I would not gain that much useful time.	−0.424

a. Based on an EFA separate from the one that produced the remaining factors.

References

- Bansal, Prateek, Kockelman, Kara M., & Singh, Amit (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies*, 67, 1–14.
- Bennett, Roger, Vijaygopal, Rohini, & Kottasz, Rita (2019). Attitudes towards autonomous vehicles among people with physical disabilities. *Transportation Research Part A: Policy and Practice*, 127, 1–17.
- Biehl, A., Ermagun, A., & Stathopoulos, A. (2018). Modelling determinants of walking and cycling adoption: A stage-of-change perspective. *Transportation Research Part F: Traffic Psychology and Behaviour*, 58, 452–470.
- Camacho, J., Pérez-Villegas, A., García-Teodoro, P., & Maciá-Fernández, G. (2016). PCA-based multivariate statistical network monitoring for anomaly detection. *Computers & Security*, 59, 118–137.
- Casutt, G., Martin, M., Keller, M., & Jäncke, L. (2014). The relation between performance in on-road driving, cognitive screening and driving simulator in older healthy drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, 22, 232–244.
- Childress, S., Nichols, B., Charlton, B., & Coe, S. (2015). Using an activity-based model to explore the potential impacts of automated vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 2493, 99–106.
- Cunningham, M. L., Regan, M. A., Horberry, T., Weeratunga, K., & Dixit, V. (2019). Public opinion about automated vehicles in Australia: Results from a large-scale national survey. *Transportation Research Part A: Policy and Practice*, 129, 1–18.
- de Almeida Correia, G. H., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. *Transportation Research Part A: Policy and Practice*, 119, 359–382.
- Deng, H., Mokhtarian, P.L., & Circella, G. (2015). Modeling the adoption of full-day, part-day, and overtime telecommuting: An investigation of Northern California workers using non-mean-centered factor scores to segment on built environment attitudes. Paper presented at the 94th Annual Meeting of the Transportation Research Board, Washington, D.C.; available from the authors.
- DiStefano, Christine, Zhu, Min, & Mindrila, Diana (2009). Understanding and using factor scores: Considerations for the applied researcher. *Practical Assessment, Research and Evaluation*, 14(20), 1–11.
- Estabrook, R., & Neale, M. (2013). A comparison of factor score estimation methods in the presence of missing data: Reliability and an application to nicotine dependence. *Multivariate Behavioral Research*, 48(1), 1–27.
- Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., & Strahan, E. J. (1999). Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods*, 4(3), 272–299.
- Garrow, L., Mokhtarian, P.L., German, B., & Glodek, J. (2020). Market Segmentation of an Electric Vertical Take-Off and Landing (eVTOL) Air Taxi Commuting Service in Five Large U.S. Cities. Under review.
- Gruel, W., & Stanford, J. M. (2016). Assessing the long-term effects of autonomous vehicles: A speculative approach. *Transportation Research Procedia*, 13, 18–29.
- Guttentag, D., Smith, S., Potwarka, L., & Havitz, M. (2017). Why tourists choose Airbnb: A motivation-based segmentation study. *Journal of Travel Research*, 57(3), 342–359.
- Harb, M., Xiao, Y., Circella, G., Mokhtarian, P. L., & Walker, J. L. (2018). Projecting travelers into a world of self-driving vehicles: Estimating travel behavior implications via a naturalistic experiment. *Transportation*, 45, 1671–1685.
- Hardman, S., Berliner, R., & Tal, G. (2019). Who will be the early adopters of automated vehicles? Insights from a survey of electric vehicle owners in the United States. *Transportation Research Part D: Transport and Environment*, 71, 248–264.
- Harman, H. H. (1976). *Modern Factor Analysis*. Chicago, IL: University of Chicago Press.
- Hohenberger, C., Spörrle, M., & Welpe, I. M. (2016). How and why do men and women differ in their willingness to use automated cars? The influence of emotions across different age groups. *Transportation Research Part A: Policy and Practice*, 94, 374–385.
- Jennrich, R. I., & Sampson, P. F. (1966). Rotation for simple loadings. *Psychometrika*, 31(3), 313–323.
- Kaufman-Scarborough, C. (2018). Monochronic and Polychronic Time. In Y. Y. Kim (Ed.), *The International Encyclopedia of Intercultural Communication*. Wiley Blackwell.
- Kim, S. H., Circella, G., & Mokhtarian, P. L. (2019a). Identifying latent mode-use propensity segments in an all-AV era. *Transportation Research Part A: Policy and Practice*, 130, 192–207.
- Kim, S.H., Mokhtarian, P.L., & Circella, G. (2019b). The Impact of Emerging Technologies and Trends on Travel Demand in Georgia: Final Report, Georgia Department of Transportation, available online at g92018.eos-intl.net/G92018.
- Kim, S.H., Mokhtarian, P.L., & Circella, G. (2019c). Will autonomous vehicles change residential location and vehicle ownership? Glimpses from Georgia. Under review; available from the authors.
- König, M., & Neumayr, L. (2017). Users' resistance towards radical innovations: The case of the self-driving car. *Transportation Research Part F: Traffic Psychology and Behaviour*, 44, 42–52.
- Krishna, V.B., Weaver, G.A., & Sanders, W.H. (2015). PCA-based method for detecting integrity attacks on advanced metering infrastructure. In: Campos, J., Haverkort, B. (Eds.) *Quantitative Evaluation of Systems. QEST 2015. Lecture Notes in Computer Science*, (Vol. 9259). Cham: Springer.
- Kyriakidis, M., Happee, R., & de Winter, J. C. F. (2015). Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. *Transportation Research Part F: Traffic Psychology and Behaviour*, 32, 127–140.
- LaMondia, J. J., Fagnant, D. J., Qu, H., Barrett, J., & Kockelman, K. (2016). Shifts in long-distance travel mode due to automated vehicles: Statewide mode-shift simulation experiment and travel survey analysis. *Transportation Research Record: Journal of the Transportation Research Board*, 2566, 1–11.

- Ledesma, Rubén. D., Shinar, David, Valero-Mora, Pedro M., Haworth, Narelle, Ferraro, Ottavia E., Morandi, Anna Morandi, ... Sapliloglu, M. (2019). Psychosocial factors associated with helmet use by adult cyclists. *Transportation Research Part F: Traffic Psychology and Behaviour*, 65, 376–388.
- Lee, Yi-Ching, & Mirman, Jessica H. (2018). Parents' perspectives on using autonomous vehicles to enhance children's mobility. *Transportation Research Part C: Emerging Technologies*, 96, 415–431.
- Liljamo, T., Liimatainen, H., & Pöllänen, M. (2018). Attitudes and concerns on automated vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, 59, 24–44.
- Lindquist, J. D., Knieling, J., & Kaufman-Scarborough, C. (2001). Polychronicity and consumer behavior outcomes among Japanese and US students: A study of response to culture in a US university setting. In *Proceedings of the Tenth Biennial World Marketing Congress*.
- Loomis, J. (2011). What's to know about hypothetical bias in stated preference valuation studies? *Journal of Economic Surveys*, 25(2), 363–370.
- Malokin, A., Circella, G., & Mokhtarian, P. L. (2019). How do activities conducted while commuting influence mode choice? Using revealed preference models to inform public transportation advantage and autonomous vehicle scenarios. *Transportation Research Part A: Policy and Practice*, 124, 82–114.
- McDonald, R. P., & Burr, E. J. (1967). A comparison of four methods of constructing factor scores. *Psychometrika*, 32(4), 381–401.
- Mokhtarian, P. (2009). If telecommunication is such a good substitute for travel, why does congestion continue to get worse? *Transportation Letters*, 1(1), 1–17.
- Mokhtarian, P. L. (2018). The times they are a-changin': What do the expanding uses of travel time portend for policy, planning, and life? *Transportation Research Record*, 2672(47), 1–11.
- Mokhtarian, P. L., Ory, D. T., & Cao, X. (2009). Shopping-related attitudes: A factor and cluster analysis of Northern California shoppers. *Environment and Planning B: Planning and Design*, 36(2), 204–228.
- Nielsen, T. A. S., & Haustein, S. (2018). On sceptics and enthusiasts: What are the expectations towards self-driving cars?. *Transport Policy*, 66, 49–55.
- Olsen, Tyler, & Sweet, Matthias N. (2019). Who's Driving Change? Potential to Commute Further using Automated Vehicles among Existing Drivers in Southern Ontario Canada. *Transportation Research Record*, 2673(7), 50–61.
- Ozonder, G., Calderón, F., & Miller, E.J. (2019). TNC Demand in Toronto: Implications for Future AV Usage. Oral presentation at the 2019 Autonomous Vehicle Symposium, Orlando, Florida.
- Payre, W., Cestac, J., & Delhomme, P. (2014). Intention to use a fully automated car: Attitudes and a priori acceptability. *Transportation Research Part F: Traffic Psychology and Behaviour*, 27, 252–263.
- Perrine, K. A., Kockelman, K. M., & Huang, Y. (2020). Anticipating long-distance travel shifts due to self-driving vehicles. *Journal of Transport Geography*, 82, 102547.
- Pettigrew, Simone, Dana, Liyuwork Mitiku, & Norman, Richard (2019). Clusters of potential autonomous vehicles users according to propensity to use individual versus shared vehicles. *Transport Policy*, 76, 13–20.
- Plocher, T., Goonetilleke, R. S., Zhang, Y., & Liang, S.-F. (2002). Time orientation across cultures. *Proceedings of the 4th Annual International Workshop on Internationalisation of Products and Systems (IWIPS)*.
- Pronello, C., & Camusso, C. (2011). Travellers' profiles definition using statistical multivariate analysis of attitudinal variables. *Journal of Transport Geography*, 19(6), 1294–1308.
- Pudâne, B., Rataj, M., Molin, E. J. E., Mouter, N., van Cranenburgh, S., & Chorus, C. G. (2019). How will automated vehicles shape users' daily activities? Insights from focus groups with commuters in the Netherlands. *Transportation Research Part D: Transport and Environment*, 71, 222–235.
- Rahman, Md Mahmudur, Deb, Shuchisnigda, Strawderman, Lesley, Burch, Reuben, & Smith, Brian (2019). How the older population perceives self-driving vehicles. *Transportation Research Part F: Traffic Psychology and Behaviour*, 65, 242–257.
- Rummel, Rudolf J. (1970). *Applied Factor Analysis*. Evanston, IL: Northwestern University Press.
- Sinclair-Maragh, G., Gursoy, D., & Vieregge, M. (2015). Residents' perceptions toward tourism development: A factor-cluster approach. *Journal of Destination Marketing & Management*, 4(1), 36–45.
- Singleton, P. A. (2019). Discussing the "positive utilities" of autonomous vehicles: Will travellers really use their time productively? *Transport Reviews*, 39(1), 50–65.
- Thompson, B. (1993). Calculation of standardized, noncentered factor scores: An alternative to conventional factor scores. *Perceptual and Motor Skills*, 77 (3_suppl), 1128–1130.
- Wadud, Z., & Huda, F. Y. (2019). Fully automated vehicles: the use of travel time and its association with intention to use. *Proceedings of the Institution of Civil Engineers: Transport*.
- Wang, J., Zuo, R., & Caers, J. (2017). Discovering geochemical patterns by factor-based cluster analysis. *Journal of Geochemical Exploration*, 181, 106–115.
- Westat (2018). NHTS Main Study Retrieval Questionnaire. Report prepared under Contract #GS23F8144H for the US Federal Highway Administration, Washington DC, February. Available at https://nhts.ornl.gov/assets/2016/NHTS_Retrieval_Instrument_20180228.pdf, accessed July 3, 2019.
- Woldeamanuel, M., & Nguyen, D. (2018). Perceived benefits and concerns of autonomous vehicles: An exploratory study of millennials' sentiments of an emerging market. *Research in Transportation Economics*, 71, 44–53.
- Wu, J., Liao, H., Wang, J.-W., & Chen, T. (2019). The role of environmental concern in the public acceptance of autonomous electric vehicles: A survey from China. *Transportation Research Part F: Traffic Psychology and Behaviour*, 60, 37–46.
- Zmud, Johanna, Sener, Ipek N., & Wagner, Jason (2016). Self-driving vehicles: determinants of adoption and conditions of usage. *Transportation Research Record: Journal of the Transportation Research Board*, 16–1832, 57–64.