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How attractive is it to use the internet while commuting? A work-attitude-based segmentation of Northern California commuters

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Will autonomous vehicles change residential location and vehicle ownership? Glimpses from Georgia

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ABSTRACT

Many studies have begun investigating possible transportation landscapes in the autonomous vehicle (AV) era, but empirical results on longer-term decisions are limited. We address this gap using data collected from a survey designed and implemented for Georgia residents in 2017–2018. Focusing on a hypothetical all-AV future, this section of the survey included questions regarding advantages/disadvantages of AVs, short-term mode choice impacts, medium-term impacts on activity patterns, and long-term behavioral changes – specifically, whether/how AVs will influence individuals to change residential location and the number of cars in the household. We hypothesize that AVs could act in concert with attitudinal preferences to stimulate changes in these long-term decisions, and that some medium-term activity changes triggered by AVs could motivate people to relocate their residence or shed household vehicles. We applied exploratory factor analysis to measure the perceived likelihood that AVs would prompt various medium-term changes. We then included some of those measures, among other variables, in a cross-nested logit (CNL) model of the choice of the residential location/vehicle ownership bundle. Although more than half of respondents expected "no change" in their bundle, we found that younger, lower income, pro-suburban, and pro-non-car-mode individuals were more likely to anticipate changing their selections. In addition, some expected medium-term impacts of AVs influenced changes in these longer-term choices. We further applied the CNL model to two population segments (Atlanta and non-Atlanta-region residents). We found notable improvement in goodness of fit and different effects of factors across segments, signifying the existence of geography-related taste heterogeneity.

1. Introduction

Autonomous vehicles (AVs) are seen as a game changer in areas such as system management, transportation planning, and land use policy, among others. In current transportation research, AV studies are probably one of the fastest growing areas, a sign of how much interest there is in AVs and how crucial they are for future planning. There have been multiple streams of literature. In the beginning (and still ongoing), research focused on people's familiarity with AVs and acceptance of AVs (Payre et al., 2014; Kyriakidis et al., 2015), making diverse assumptions about the level of automation and timing of technology realization and acceptance. Some studies have also entailed brainstorming potential changes and impacts from the broader point of view (Fagnant and Kockelman, 2015; Gruel and Stanford, 2016; Milakis et al., 2017). Recently, many active discussions focus on mode choice or willingness to own/

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use different types of AV configurations (e.g. private AVs, shared AVs, shared AVs with others). These can be considered "***short-term***" decisions in that, from the behavioral perspective, they can be made by many people as soon as AVs become feasible options. Some studies implemented stated preference surveys for choice experiments, either with other non-AV options or only among AV configurations (Krueger et al., 2016; Haboucha et al., 2017; Steck et al., 2018; Stoiber et al., 2019). Several studies modeled willingness to use different types of AV configurations, especially focusing on whether people are willing to share (Nazari et al., 2018; Lavieri and Bhat, 2019). Using the same dataset as the current study, Kim et al. (2019a) modeled mode-use propensities (between an AV-based option and an alternative such as walk/bike, bus/train, or plane to fulfill hypothetical transportation needs) in the fully-AV era and found seven population segments having different mode-use propensities.

An important implication of AVs is that people will be "passengerized" (Mokhtarian, 2018) and thus can benefit from physically/mentally more comfortable travel (i.e. a reduced disutility of travel, e.g., Singleton, 2019) and/or availability of on-board activities (e.g. Pudāne et al., 2019). Hence, this passengerization can trigger some activity changes that can be considered "***medium-term***" decisions. For example, people may use time more productively (either in vehicle or out of vehicle) or travel to more distant places. Some research has investigated ways of incorporating the overlay of activities while traveling into conventional models of time allocation (Pudāne et al., 2018), value of travel time savings (Wardman et al., 2019), or mode choice (Malokin et al., 2019), while at least one study examined the potential willingness to commute farther (Olsen and Sweet, 2019). However, our understanding of how AVs will reshape people's (travel-related) activities is still limited.

Ultimately, the combinations of short-/medium-term decisions and people's personal preferences may shift their "***long-term***" decisions. Major long-term decisions potentially changed by AVs will be vehicle ownership (e.g. the availability of shared AVs may motivate people to shed vehicles) and residential location (e.g. the ability to use travel time productively may motivate people to move "farther away" and thus exacerbate sprawl). Some studies have started to explore changes in vehicle ownership or residential location (e.g. Carrese et al., 2019; Menon et al., 2019). These societal shifts may produce the greatest implications for future transportation planning/policy. In particular, aggregate changes in vehicle ownership or residential location could have significant environmental implications, since these decisions in turn feed back to choices regarding daily travel/activities that are closely related to emissions or energy consumption (see more discussion in Milakis et al., 2017). However, much is yet to be learned about the extent to which, and how, people expect their vehicle ownership and residential location to change in the AV era and what factors/motives can affect those decisions (e.g. linkage between medium-term and long-term decisions). To address this knowledge gap, we analyze the AV-related responses to a statewide survey, to provide a current snapshot of individuals' expectations regarding potential changes in travel-related activities and long-term decisions. Our investigation presumes a "holding everything else [cost, regulatory environment, opportunity to share] constant" scenario (i.e. everything except the need for a driver in the vehicle), and evaluates the impacts of AVs under those circumstances. That is, we focus primarily on the influence of that one factor – the disappearance of the need for a driver in the vehicle – on people's activity patterns and medium- /long-term choices.

The rest of this paper is organized as follows: Section 2 reviews relevant literature. Section 3 delineates how the study was designed and explores key variables. Section 4 describes the modeling approach taken in this study, while Section 5 explores the empirical results. Section 6 summarizes the major findings and discusses some limitations and directions for future research.

2. Literature review

2.1. *Modeling of residential location choice and vehicle ownership*

Residential location choice and vehicle ownership have been extensively explored for several decades. A comprehensive literature review on those topics is beyond the scope of this study; readers can refer to some papers specializing in the modeling perspective, such as Schirmer et al. (2014) for residential location choice and Anowar et al. (2014) for vehicle ownership. Various models, factors, and types of dependent variables have been used. Some key explanatory variables include socio-demographics, built environment attributes, and attitudes or lifestyle. Specifically regarding vehicle ownership in the AV era, most previous studies have paid attention to the interest in buying, willingness to buy, or timing of buying AVs. However, some researchers have studied the level of household vehicle ownership, which is the topic closest to the present study.

For example, Zhang et al. (2018) modeled potential reductions in the Atlanta metropolitan area; results indicated that 18% of households could reduce vehicles (equivalent to a 9.5% reduction in private vehicles) while maintaining their current travel patterns. However, the study's perspective is more that of optimizing the number of vehicles than a behavioral investigation. Menon et al. (2019) modeled the likelihood of relinquishing a household vehicle, "given the availability of [shared autonomous vehicles]". Using random parameters ordered probit models, they found that diverse socioeconomic factors and commuting patterns affected the likelihood. For example, for single-vehicle households, millennials were more willing than others to relinquish the vehicle, whereas people who travel more than 90 min every day were less willing than others to do so. For multivehicle households, millennials and those who commute a one-way distance less than 10 miles are more willing than others to relinquish a vehicle, whereas whites and people who spend 5 min or less looking for parking are less likely to do so. However, one limitation is that the study employed convenience sampling methods, namely targeting students/faculty/staff of the University of South Florida (likely to be highly educated) and members of the American Automobile Association South (likely to be more auto-friendly).

Related to residential location, some experts expect that AVs will effect urban form changes in two opposite but simultaneous ways: densification of city centers and expanded urban sprawl (Milakis et al., 2018). Some people may move farther away from city centers for the usual reasons (larger and/or more affordable housing, more amenities), taking advantage of the reduced disutility of travel afforded by the ability to conduct a wider range of activities while traveling (including sleeping/relaxing). Other people may move closer to city centers, since the pain of congestion as well as the cost and hassle of owning and parking a car in a dense area can be more easily avoided in the AV era, and since shared AV options will be better in such areas (Duarte and Ratti, 2018; Bansal et al., 2016).

Zhang and Guhathakurta (2018) implemented an agent-based simulation in a scenario where shared AVs are popular, and the results indicated that commuters may relocate to better neighborhoods with the aid of reduced commute costs. Carrese et al. (2019) estimated a logit model with a binary indicator of willingness to relocate based on 201 residents in Rome, Italy. After applying the model to predict residential relocation, they implemented traffic assignment with a modified origin-destination matrix and quantified the change in systemwide travel time due to relocation triggered by AVs. They found that about 40 percent of respondents indicated a willingness to relocate under an AV regime and, based on simulation, that congestion reduction was observed in the central area, whereas suburban commute times increased. Krueger et al. (2019) administered a stated preference (SP) survey to 512 commuters in the Sydney metropolitan area. They employed mixed logit to model a joint choice of housing option and commute mode, with options characterized by housing attributes and commute attributes, when AVs are available (but so are conventional vehicles and public transit). Their findings suggest that the impact of AVs on residential location preferences may be relatively modest, and that the mean value of travel time savings for commuting by AV is between those for commuting by conventional car and by public transit.

In a nutshell, there have been some studies investigating future residential location or vehicle ownership, but some limitations remain. Beyond the small number of empirical findings on potential long-term decisions in the AV era, consideration of attitudinal or behavioral drivers is scarce. In this study, we hypothesize that AVs could act in concert with attitudinal preferences to stimulate changes in these long-term decisions. For example, pro-suburban people may be more likely to move farther (from the places to which they most often travel) if AVs could allow them to travel more conveniently. We particularly conjecture that some medium-term changes in daily activities that are triggered by AVs could motivate people to relocate their residence or shed household vehicles. For example, people who expect AVs to allow them to use their time more flexibly may be more willing to move farther away. Finally, together with others (e.g. Menon et al., 2019; Krueger et al., 2019) we speculate that there is population heterogeneity with respect to the factors influencing these long-term decisions. We explore all of these hypotheses in our analysis.

2.2. Multidimensional choice modeling

Many papers have focused on only one of the two topics (vehicle ownership and residential location), or have modeled them separately. Others have modeled the direct effects of one on the other (i.e. the effect of vehicle ownership on residential location choice or vice versa). Still other studies have used multidimensional structures to model the two choices simultaneously, to allow the unobserved attributes influencing those choices to be correlated (e.g. Pinjari et al., 2011). In a discrete choice context, multidimensional models are called for because "some of the [outcome *bundles*, such as a {residential location, vehicle ownership} bundle,] in a multidimensional choice set are logically related by virtue of the fact that they share a common [*individual* outcome, such as the same residential location]" (Ben-Akiva and Lerman, 1985, p. 277). Various methods have been used to model multidimensional choices, depending on the nature of these shared outcomes. If the shared outcomes have only *observed* attributes in common, we can reflect this in the specification of the utility functions for each bundle (referred to by Ben-Akiva and Lerman (1985) as joint logit). If both *observed* and *unobserved* attributes are shared across outcome bundles, shared error components are added to the first case above.

The most popular way to consider correlations among unobserved terms is to use a member of the nested logit family. The nested logit (NL) model allows interdependence between the pairs of alternatives in a common *nest* or *group* (Koppelman and Wen, 1998; Train, 2009). The cross-nested logit (CNL) structure can allow for the joint representation of inter-alternative correlation among multi-dimensional choices; hence it has been applied in several contexts having more than one dimension of choice (albeit less widely employed than the standard nested logit). Empirical examples include joint choice of airport, airline, and access mode in the Greater London area (Hess and Polak, 2006), joint choice of vehicle type and fuel type (Hess et al., 2012), and joint choice of residential location, travel mode, and departure time in Beijing (Yang et al., 2013). In fact, CNL (sometimes also called generalized nested logit, GNL) is a more general form having multinomial logit (MNL) and standard nested logit as special cases, and it has been theoretically explored by several scholars (Vovsha, 1997; Wen and Koppelman, 2001; Bierlaire, 2006). Unlike standard nested logit, which requires alternatives to belong to only one nest, CNL can allow alternatives to partially belong to multiple nests by introducing additional parameters. In theory, standard multi-level nested logit can be used to model multidimensional choices, but (1) doing so requires a decision of how to order the choice dimensions; (2) a full correlation structure can be accommodated only in the highest level of nesting (Hess et al., 2012); and (3) some empirical studies have found that CNL outperforms multi-level nested logit (e.g. Hess and Polak, 2006; Hess et al., 2012). Accordingly, in the present study we chose to model the joint choice of vehicle ownership and residential location changes using CNL.

3. Data collection and key variables

This study uses data collected in 2017–2018, from a broad-ranging survey aimed at exploring the impacts of emerging technologies and trends on travel behavior in Georgia. The survey design was based on a variety of past surveys created by the authors, most recently Circella et al. (2016). For more details on the present survey design, data collection, data cleaning, sample weighting, and initial analyses, see Kim et al. (2019b). We used a combination of sampling approaches, namely (1) recruiting respondents through address-based stratified random sampling in the 15 Metropolitan Planning Organization (MPO) areas in Georgia, and (2) recontacting survey participants who took the 2016–17 National Household Travel Survey (Westat, 2018) in Georgia and agreed to

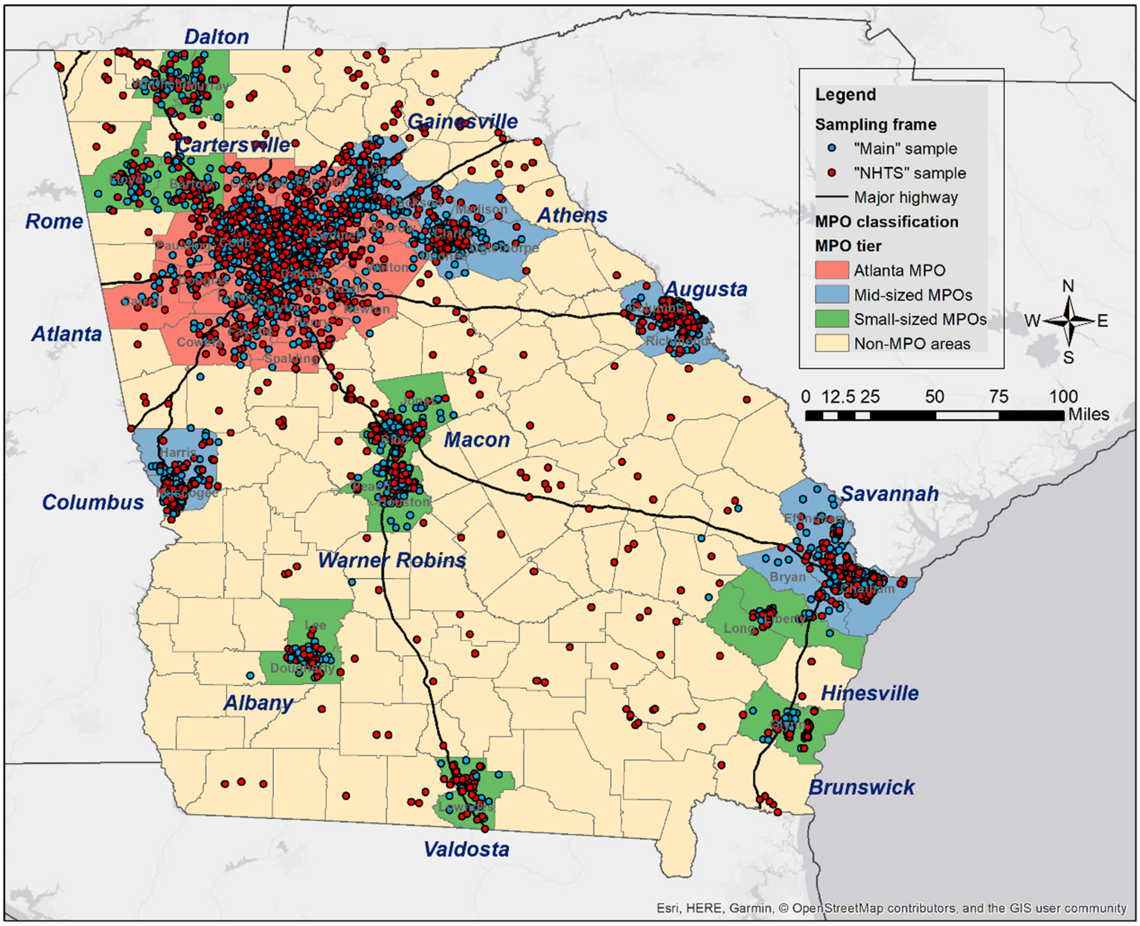

Fig. 1. Distribution of the sample.

be surveyed further. For the former sample, randomly-selected adults (18 or older) in the 15 MPO areas 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. The full sample size was 3288, but for this study it was reduced to 3106 due to missing values on relevant variables. The geographic distribution of the sample is shown in Fig. 1 and the descriptive statistics of the data appear in Table 1. It can be seen from the latter that, although we employed random sampling strategies, due primarily to nonresponse biases the respondents we ultimately obtained were demographically skewed: in general, affluent, highly educated, and older people were overrepresented (as is common with survey data). We also intentionally oversampled non-Atlanta MPO residents, to help better capture the diversity *outside* the Atlanta region (which, comprising more than half of the state's population, would otherwise have dominated the sample). 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).[1] All empirical analyses in this paper are based on the weighted sample unless otherwise specified.

Part G of the eight-part survey dealt with AVs. We introduced the section with figures (not shown here, for copyright reasons) and descriptions (Fig. 2) to help respondents envision a hypothetical AV future. Clearly, there is considerable uncertainty about what such a future will look like, so for the purposes of this study, we asked respondents to assume that fully-mature AV technologies will replace *all* conventional vehicles, and will cost as much and be at least as safe as today's vehicles. Our goal was not to be able to obtain precise demand forecasts, but rather to obtain a glimpse of people's inclinations, all else equal – the only difference from today being that the role of the driver has been eliminated, which allows for some changes in vehicle design and functionality. We intentionally ordered the questions in this section to relate sequentially to advantages/ disadvantages of AVs, short-term mode choices, medium-term activity changes, and long-term behavioral changes. We believe this could help people assess their long-term decisions

[1] For developing weights, we employed nine factors (particularly focusing on the ones used by NHTS to weight that sample): MPO size (four categories), income, household size, vehicle ownership, sex, education, race, age, and work status. We believe these variables comprise not only the most important and most commonly used demographic variables in general, but also those most pertinent to residential location and vehicle ownership.

Table 1
Descriptive statistics of the data (weighted N = 3106).

Variable	Category	Unweighted count	Unweighted share	Weighted count	Weighted share
Composite choice (RL & VO)	Closer & Reducing	119	3.8%	180	5.8%
	Closer & Not reducing	142	4.6%	186	6.0%
	Same & Reducing	930	29.9%	838	27.0%
	Same & Not reducing	1649	53.0%	1561	50.3%
	Farther & Reducing	112	3.6%	151	4.9%
	Farther & Not reducing	161	5.2%	190	6.1%
Age	18–34	289	9%	728	23%
	35–44	323	10%	540	17%
	54–64	1264	41%	1227	40%
	65 +	1237	40%	611	20%
Income	Below $50,000	976	31%	1281	41%
	$50,000–$99,999	1133	36%	999	32%
	$100,000 or more	1004	32%	827	27%
Vehicle ownership[a]	Zero/deficit	388	13%	615	20%
	Sufficient	1806	58%	1694	55%
	Surplus	910	29%	785	25%
Neighborhood type[b]	Urban	453	15%	531	17%
	Suburban	1585	51%	1481	48%
	Small town	611	20%	582	19%
	Rural	464	15%	513	17%

[a] In this study, vehicle ownership categories are based on the ratio of number of vehicles to number of driving-age household members (18 or older). Zero/deficit indicates a household having zero vehicles or less than one vehicle per driving-age household member; sufficient indicates a household having as many vehicle(s) as driving-age household members; surplus indicates a household having more vehicles than driving-age household members.
[b] Self-reported: respondents were asked to characterize the area where they live, given these four options.

Section G: What if cars could drive themselves?

In this section, we'd like to know your opinions on ***self-driving (or driverless) cars***. Such vehicles drive themselves and control all operating and safety functions, and are even able to travel without a human inside. For our purposes, we want you to ***imagine*** a future where all cars are *fully automated* and do not need humans driving them (we will later ask you how far off you think this future is). Specifically, please assume that …

- Traditional cars can no longer be used in regular traffic – self-driving cars are the *only way to go by car*.
- Driverless cars are *at least as safe* as today's cars are, and *cost about as much* as today's cars do.
- You could *furnish* your self-driving car with a TV, kitchenette, recliner, light exercise equipment, etc.
- You could send an empty self-driving car somewhere to *pick up other people or things, or to park* after dropping you off at work or the ball game.
- You could let a self-driving car take you places *while you are sleeping*.

Fig. 2. Introduction to the AV section of the survey.

more reflectively, after completing previous questions and considering their corresponding reactions.

This study specifically focuses on two long-term decision dimensions. In particular, the survey includes questions about whether/how AVs will influence individuals to change residential location and the number of cars in the household. The residential location question asked "Where would you prefer to live, if self-driving cars were available?", with respondents instructed to choose the single best answer: (1) "I would like to move closer to the locations I travel to most often (e.g. workplace or school)"; (2) "Having a self-driving car would not influence me to move somewhere else"; and (3) "I would like to move to a more attractive location, even if it means being farther from the locations I travel to most often" (for brevity, we call these three options "closer", "same", and "farther").

The vehicle ownership question asked, "Considering the number of cars your household currently owns, how would that change if self-driving cars were the only cars available?", with responses "Very likely to own *fewer* cars"; "Somewhat likely to…"; "Most likely to own the *same* number of cars"; "Somewhat likely to own *more* cars"; and "Very likely to …". In this study, for simplicity and in view of small counts for some responses[2], we collapse the five categories into two: (1) "reducing" the number of vehicles (combining the

[2] Unweighted counts for the original categories are: 620 (19.9%) for "very likely to own fewer cars", 541 (17.4%) for "somewhat likely to own fewer cars", 1857 (59.7%) for "most likely to own the same number of cars", 59 (1.9%) for "somewhat likely to own more cars", and 36 (1.2%) for "very likely to own more cars".

first two responses) and (2) "not reducing" the number of vehicles (combining the remaining three responses). As presented in Table 1, sizable majorities of the sample expect to maintain their residential location (77.3%, weighted) or vehicle ownership (62.4%) when considered separately. When considered jointly, 50.3% of Georgia residents expect to change neither their residential location nor their vehicle ownership because of AVs. These results are likely consequences of the relative stability of major long-term decision processes, uncertainty about the form the AV future may take, and the difficulties respondents may have in imagining their behavior in a future that could be very different from the present.

In the scenario offered to respondents (Fig. 2), some of the assumptions are agnostic about ownership, while others are more likely to apply to personal AVs (PAVs) than to shared AVs (SAVs). However, before asking the questions about residential location and vehicle ownership, we asked respondents, "If self-driving cars were the only cars available, how likely would you be to ***own*** a self-driving car, ***use*** self-driving services (such as a driverless taxi), or do both?", with each of the following choices answered separately on a five-point ordinal scale from "Very unlikely" to "Very likely": (1) "I would own a self-driving car"; (2) "I would use a driverless taxi alone or with others I know"; and (3) "I would use a driverless taxi with other passengers who are strangers to me (like UberPOOL)". Accordingly, it is reasonable to assume that respondents were answering the subsequent vehicle ownership and residential location questions with their preferred scenario(s) (sharing and/or owning) in mind.

Based on relevant literature and our modeling experiments, we selected various explanatory variables to test for inclusion in the models. Among socio-demographics, age and income are key factors in the residential location and vehicle ownership literature, as well as in AV studies. Measures of the current residential location and vehicle ownership are also included. Attitudes have been found important to explaining travel behavior in numerous previous studies; hence in the final model, we include the *pro-suburban* and *pro-non-car-modes* (i.e. walk, bike, and transit) scores from an exploratory factor analysis[3], which are relevant to our two choice dimensions (Kim et al., 2019b contains more details about the attitudinal constructs). In addition, we incorporate factor scores measuring the propensity for activity changes, which will be described in Section 5.1.

4. Methodology

4.1. Cross-nested logit for multidimensional choice modeling

The cross-nested logit (CNL) model is a member of the generalized extreme value (GEV) family and is consistent with random utility maximization theory (Wen and Koppelman, 2001; Bierlaire, 2006). It relaxes the Independence of Irrelevant Alternatives (IIA) restriction that is inherent in the simpler multinomial logit (MNL) model. One of its merits is that the choice probabilities can be written in closed form, and thus it does not require the simulation that is needed for some competing models (e.g. probit or mixed logit). The CNL model can be expressed as follows, where individual subscripts have been suppressed for simplicity:

$$P_i = \sum_{m=1}^{M}\left[\frac{(\alpha_{im}e^{V_i})^{1/\lambda_m}}{\sum_{j=1}^{J}(\alpha_{jm}e^{V_j})^{1/\lambda_m}} \times \frac{\left(\sum_{j\in S_m}(\alpha_{jm}e^{V_j})^{1/\lambda_m}\right)^{\lambda_m}}{\sum_{l=1}^{M}\left(\sum_{j\in S_l}(\alpha_{jl}e^{V_j})^{1/\lambda_l}\right)^{\lambda_l}}\right] \quad (1)$$

where i and j index alternative (bundle), P_i is the probability of choosing alternative i, m and l index nest, S_m is the set of alternatives in nest m, V_i is the observed portion of utility for alternative i, α_{im} is a parameter expressing the "share of allocation" of alternative i to nest m (which can be interpreted as its degree of belongingness to that nest relative to the others), and λ_m is the logsum parameter of nest m ($0 < \lambda_m \leq 1$), a measure of the degree of independence of unobserved utilities among the alternatives (Train, 2009). This equation can be decomposed into two parts, corresponding to the two terms of Eq. (1) – the probability of alternative i given nest m ($P_{i|m}$) and the probability of nest m (P_m):

$$P_i = \sum_{m=1}^{M} P_{i|m} \times P_m \quad (2)$$

The role of the allocation parameters is to represent the membership of an alternative in different nests, where $0 \leq \alpha_{jm} \leq 1$ and $\sum_{m=1}^{M}\alpha_{jm} = 1$ for all j. The correlations of the error terms of the alternatives are a function of the logsum parameters and allocation parameters. In theory, all allocation parameters can be estimated, yielding the most unconstrained model. However, in practice, doing so can add to the complexity of optimization and thus bring convergence issues. Furthermore, whereas in the context of a single

[3] Statements loading strongly on the pro-suburban factor are "I prefer to live in a spacious home, even if it's farther from public transportation or many places I go to" (pattern matrix loading 0.609) and "I see myself living long-term in a suburban or rural setting" (0.387); statements loading strongly on the pro-non-car-modes factor are "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), and "I like the idea of public transit as a means of travel for me" (0.336). Ideally, these attitudinal statements would be directly included in the choice models as indicators of the corresponding latent variables, via hybrid choice (or integrated choice and latent variable, ICLV) modeling. However, ICLV models have been produced in multinomial single choice contexts. To our knowledge, ICLV models based on the CNL model used in the present study have not yet been developed. Because of the high-level complexity of the model, we decided to include the attitudinal factor scores as estimated manifest variables (via the separately conducted factor analysis) rather than as latent variables. Such a process is not able to explicitly account for measurement errors in the estimated scores, but in practice many empirical studies have used such a two-step framework (e.g. Nazari et al., 2018). We think such an approach offers a reasonable tradeoff between rigorous complex modeling and practical, intuitive results.

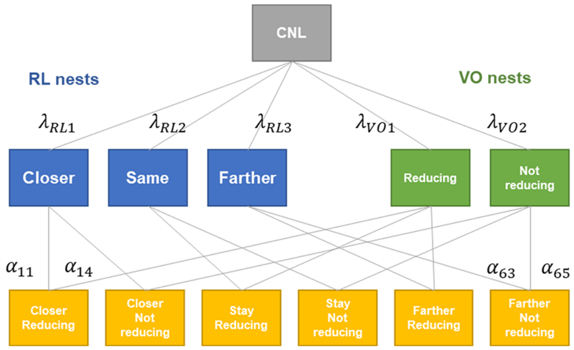

Fig. 3. Schematic structure of our CNL model.

choice an estimated allocation parameter can be meaningful (for example, finding that the taxi mode, for women, empirically belongs 58% to a "scheduled modes" nest also containing rideshare and transit, and 42% to an "unscheduled modes" nest also containing car; Shahangian et al., 2012), in the context of multidimensional models it seems less useful (e.g., how should we interpret a result that a given choice bundle belongs to a residential location nest and vehicle ownership nest in proportions of 0.6 and 0.4, respectively, rather than half and half?). Accordingly, most studies using CNL for multidimensional models have fixed the allocation parameters so as to assign equal membership in all applicable nests (e.g. Hess and Polak, 2006; Hess et al., 2012; Yang et al., 2013). We follow suit in this study, i.e. we fix some of the allocation parameters at 0.5 and others at zero, reflecting that each alternative "belongs by the same *proportion*" (Hess et al., 2012, p. 609) to one residential location nest and one vehicle ownership nest. For example, in Fig. 3, $\alpha_{11} = \alpha_{14} = 0.5$, reflecting the equal membership of alternative 1 (Closer & Reducing) in the "Closer" RL and "Reducing" VO nests, while $\alpha_{12} = \alpha_{13} = \alpha_{15} = 0$.

4.2. Accounting for (dis)similarity of individuals: Taste heterogeneity models

An implicit assumption of many models is that "one size fits all" – i.e. constant population coefficients for everyone. To relax this assumption, various types of models have been used to account for dissimilarity of individuals (taste heterogeneity). In particular, grouping individuals either by deterministic (conventional segmentation modeling) or by stochastic (latent class modeling, LCM) means has been widely employed (see more detailed discussion in Kim and Mokhtarian, 2018). The CNL modeling approach can be considered to be a form of *grouping alternatives*, whereas taste heterogeneity modeling can be considered to be *grouping individuals*. Conceptually and empirically, stochastic segmentation models generally outperform deterministic segmentation models. However, in this study, we use deterministic segmentation because (1) it is simpler, and we are superimposing it onto the already complex CNL model, and (2) in our experiments, LCM was not stable given the modeling context. There are numerous possible ways to segment the population, but we hypothesize that geography (where individuals live) could introduce taste heterogeneity. Specifically, the Atlanta region is distinctive from other areas in Georgia in terms of infrastructure and economic structure; hence we segment the data into Atlanta-region residents and non-Atlanta-region residents, which can represent similar distinctions between a major metropolitan area and smaller agglomerations in other regions.

5. Results and discussion

As mentioned in Section 2.1, we speculate that the prospect of medium-term changes prompted by AVs could influence longer-term decisions. Accordingly, in this section we first describe how we measured respondents' perceptions of such changes, which is a novel contribution of the study. Next, we present and discuss our pooled CNL model, as a benchmark for the segmented CNL model, which concludes the section.

5.1. Potential activity changes prompted by AVs

The increased physical and mental freedom while traveling that AVs make possible could (1) permit the spatio-temporal re-organization of activities (e.g., Pudāne et al., 2019); and (2) reduce the disutility of travel, which, in turn, could result in more travel occurring through a variety of mechanisms (Mokhtarian, 2018). To measure people's expectations of such changes occurring, we designed 16 statements (Table 2) representing possible changes, with responses offered on a 5-point ordinal scale ranging from "very unlikely" to "very likely". We factor-analyzed those statements to consolidate related items into a smaller number of latent constructs. Based on several criteria including quantitative measures (e.g. eigenvalues) and interpretability, we selected the four-factor solution. ***Travel longer distances*** represents a general inclination toward making longer trips. People who have a higher score on this factor are more willing to go to *farther-away* restaurants, places where they can socialize with others, shopping malls, and leisure destinations. ***Gain time flexibility*** 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"

Table 2
Substantial pattern matrix loadings for likely activity changes stimulated by AVs.

"How likely is it that self-driving cars would change your behavior, in each of the following ways?"	*Travel longer distances*	*Gain time flexibility*	*Travel more frequently*	*Make more long-distance/leisure trips*
Go to more distant restaurants.	0.666			
Socialize with people who live farther away.	0.654			
Go to more distant grocery stores or shopping malls.	0.630			
Travel to more distant locations for leisure.	0.504			0.444
Sleep less time at home and more time in the car, to be more efficient.		0.817		
More often eat meals in a self-driving car instead of at home or in a restaurant.		0.687		
Reduce my time at the regular workplace and work more in the self-driving car.		0.614		
Cultivate new hobbies or skills with the time I saved.		0.463		
Go to work/school at a different time to avoid traffic jams, since I can sleep/work in the car.		0.428		0.335
Go to grocery stores or shopping malls more often.			0.822	
Eat out in restaurants more often.			0.782	
Travel to social/leisure activities more often.	0.375		0.452	
Make more overnight trips by car because it would be less burdensome to travel long distances.				0.789
Eliminate some overnight trips because it would be easier to come back the same day.				0.652
Take part in more leisure activities after dark, because I wouldn't need to drive myself.				0.457
Take vacations more often.				0.417

Notes: Factor loadings under 0.3 in magnitude are suppressed for clarity. Factors were obliquely rotated; the highest correlation between factors was 0.602 (between *Travel longer distances* and *Travel more frequently*). Ultimately, we included the first two factors in the CNL models; their correlation is 0.383, which, in view of the sample size, is not particularly problematic. Factor scores are Bartlett scores that have been standardized afterwards.

Table 3
Model summary (N = 3106).

Model	Number of parameters	$LL(0)$	$LL(\beta)$	ρ^2	$\bar{\rho}^2$
Pooled MNL	60	−5565.687	−3880.119	0.303	0.292
Pooled CNL	65	−5565.687	−3848.715	0.308	0.297
Atlanta region	65	−2897.892	−1979.312	0.317	0.295
Non-Atlanta region	65	−2667.795	−1728.724	0.352	0.328
Overall segmented model	130	−5565.687	−3707.527	0.334	0.311

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). ***Travel more frequently*** captures a general inclination toward making more trips. Those with a higher score on this factor think they will likely go shopping, to restaurants, and leisure destinations *more often*. Lastly, the ***make more long-distance/leisure trips*** factor represents a general inclination toward making specifically those kinds of trips more often. 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.

As mentioned, we hypothesize that these potential activity changes could trigger changes in residential location and/or vehicle ownership; hence we use the scores computed for each factor as explanatory variables in the models of the next section. In practice, we employ two scores (*longer distances* and *time flexibility*) rather than all four scores because (1) including all scores brings about multi-collinearity issues and (2) *make more long-distance/leisure trips* may not be a strong motive to relocate home or shed vehicles, even if it is an important activity change.

5.2. Pooled CNL model of residential location/vehicle ownership bundle

Table 3 (top two rows) exhibits summary statistics for an MNL base model and CNL as an error correlated model. We used the Biogeme program for estimation (Bierlaire, 2018). By adding five parameters to represent the similarities of some alternatives, the goodness-of-fit of the CNL model improves over that of MNL. However, the incremental increases in ρ^2 and $\bar{\rho}^2$ are marginal. Table 4

Table 4
Pooled MNL and CNL models (reference: Same RL/Not reducing VO).

Alternative bundle	Closer & reducing		Closer & not reducing		Same & reducing		Farther & reducing		Farther & not reducing	
Variable	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value
Pooled MNL										
Constants	**−2.179**	**−12.15**	**−2.082**	**−12.35**	**−0.962**	**−9.59**	**−2.561**	**−12.85**	**−2.230**	**−12.49**
Age 18–34 (ref: 35–64)	0.132	0.69	0.349	1.87	**−0.241**	**−1.99**	0.208	1.04	−0.062	−0.33
Age 65+ (ref: 35–64)	−0.430	−1.67	0.086	0.40	0.176	1.55	−0.516	−1.71	−0.316	−1.29
$50–100k (ref: < $50k)	**−0.710**	**−3.54**	−0.277	−1.50	−0.160	−1.46	−0.251	−1.19	0.142	0.76
$ 100k+ (ref: < $50k)	**−1.331**	**−5.65**	**−1.026**	**−4.28**	**−0.309**	**−2.63**	**−0.521**	**−2.30**	−0.369	−1.74
Neighborhood type (urban = 1)	−0.057	−0.26	0.651	3.41	0.076	0.59	0.306	1.34	**0.561**	**2.83**
Pro-suburban	−0.126	−1.55	0.090	1.17	**−0.140**	**−3.15**	−0.006	−0.06	**0.316**	**3.99**
Pro-non-car-modes	**0.814**	**9.20**	−0.021	−0.25	**0.277**	**5.98**	**0.272**	**3.00**	0.157	1.94
Travel longer distances	0.127	1.56	**0.167**	**2.08**	**−0.117**	**−2.47**	**0.322**	**3.76**	**0.433**	**5.58**
Gain time flexibility	0.108	1.51	**0.142**	**1.95**	−0.052	−1.11	**0.263**	**3.58**	**0.214**	**3.11**
Vehicle deficit (ref: sufficient)	**0.758**	**3.86**	**0.409**	**2.19**	**0.599**	**4.93**	0.143	0.58	−0.048	−0.22
Vehicle surplus (ref: sufficient)	**0.582**	**2.64**	**−0.927**	**−3.12**	**1.199**	**11.43**	**0.806**	**3.94**	−0.402	−1.79
Pooled CNL										
Constants	**−1.727**	**−9.04**	**−1.570**	**−10.07**	**−0.254**	**−3.61**	**−1.322**	**−9.80**	**−1.296**	**−11.47**
Age 18–34 (ref: 35–64)	0.189	1.23	**0.499**	**6.16**	**−0.123**	**−2.31**	0.074	1.17	0.073	1.15
Age 65+ (ref: 35–64)	−0.283	−1.34	0.191	2.21	0.033	0.93	**−0.385**	**−2.44**	**−0.354**	**−2.23**
$50–100k (ref: < $50k)	**−0.472**	**−2.63**	**0.171**	**2.85**	**−0.076**	**−1.99**	−0.036	−0.54	−0.028	−0.41
$ 100k+ (ref: < $50k)	**−1.068**	**−5.45**	**−0.822**	**−3.94**	**−0.151**	**−3.29**	**−0.345**	**−2.98**	**−0.339**	**−2.86**
Neighborhood type (urban = 1)	0.060	0.35	**0.606**	**8.00**	0.068	1.69	**0.354**	**4.55**	**0.359**	**4.49**
Pro-suburban	−0.045	−0.65	**0.182**	**5.10**	**−0.058**	**−3.46**	**0.171**	**4.65**	**0.192**	**5.77**
Pro-non-car-modes	**0.602**	**6.31**	0.017	0.63	**0.097**	**3.67**	**0.144**	**3.84**	**0.137**	**3.67**
Travel longer distances	**0.144**	**2.34**	**0.184**	**5.40**	−0.009	−0.67	**0.292**	**8.41**	**0.309**	**9.68**
Gain time flexibility	**0.106**	**2.01**	**0.154**	**5.47**	−0.007	−0.55	**0.190**	**7.39**	**0.188**	**7.42**
Vehicle deficit (ref: sufficient)	**0.564**	**3.81**	**0.494**	**6.52**	**0.188**	**3.02**	−0.067	−0.61	−0.087	−0.80
Vehicle surplus (ref: sufficient)	0.199	0.98	**−1.131**	**−3.88**	**0.396**	**4.75**	0.033	0.31	−0.019	−0.20
Logsum parameters ($1/\lambda$)[a]	1.210	0.81	**12.756**	**2.07**	75.685	0.60	**1.823**	**2.18**	**57.511**	**2.49**

Note: The bolded numbers indicate coefficients that are statistically significant at the 0.05 level.

[a] Biogeme estimates $1/\lambda$, so these values should be inverted to obtain λ, as needed. The corresponding t-statistics are based on H_0: $1/\lambda = 1$, which is equivalent to testing H_0: $\lambda = 1$.

presents the estimation results of the models; given the number of alternatives and explanatory variables, we discuss specifics selectively. The parameters are generally statistically significant and have plausible signs. For the most part, coefficients in both models have the same signs. The differences usually occur when the estimated coefficients are not statistically significant. Among the parameters common to both models, more of them are statistically significant for CNL than for MNL, suggesting an efficiency advantage due to acknowledging the correlations of unobserved variables across alternatives.

To interpret specific relationships, we focus on the CNL coefficients for brevity. Because the *reference* alternative is “same RL/not reducing VO”, a negative coefficient means that an increase in the associated variable, on average, decreases the likelihood of choosing the *other* alternative. In terms of general attitudes, compared to the base reference, pro-suburban propensities increase the likelihood of expecting to move, particularly moving farther away than the current location (coefficients of 0.171 and 0.192 for the “farther RL/reducing” and “farther RL/not reducing” choices, respectively). Favoring non-car-modes increases the probability of changing the status quo in general, but specifically, the biggest change is in the probability of moving closer and shedding vehicles (0.602). Hence, the effects of these two general attitudes are consistent with their effects found in many studies of the current non-AV era.

Two activity change effects of AVs (*travel longer distances, gain time flexibility*) are also important influences on potential choices of residential location and vehicle ownership. In particular, as the propensities for these changes increase, the choice probabilities of moving farther away increase the most. In other words, the more people expect AVs to benefit them by increasing their time flexibility and making it easier to travel longer distances, the more likely they are to move farther away from work and other currently frequently-visited places. This signals some direct ways in which introducing AVs could trigger long-term behavioral shifts through the medium-term relaxation of constraints. Thus, our hypothesis that attitudinal preferences and potential activity changes could trigger changes in long-term decisions is supported.

As proxies for current choices, neighborhood type and vehicle sufficiency are generally statistically significant and have logical signs. People having zero or a deficit of vehicles in the household have higher likelihoods of moving closer to places where they travel most. There is an ambiguous effect of current neighborhood type: urban residents are apparently both more likely to move closer and more likely to move farther away, compared to the reference alternative of not moving. This result suggests potential taste heterogeneity among this group of people.

Additional insight from the CNL model is offered by its logsum parameters and the corresponding error correlations. Three of the five logsum parameters are statistically significant. Similar to the standard nested logit model, the smaller the logsum parameters (i.e., the larger the inverted parameters produced by Biogeme and presented in the table), the higher the error correlations between alternatives. Unlike the usual nested logit, CNL has additional (allocation) parameters that enable the overlapped nest structure and influence error correlations; hence the error correlation matrix is informative for understanding the outcome of using the allocation and logsum parameters. The correlation between error terms ε_i and ε_j of two alternatives in the CNL model can be calculated as in Eq. (3), proposed by Papola (2004). Note that this correlation is only different from zero when (1) $1 < \lambda_m$ (i.e. $1/\lambda_m > 1$); and (2) both α_{im} and α_{jm} are greater than zero, which occurs only when one member of the bundle is shared between alternatives i and j. Note also that in contrast to the standard NL model, where the asymptotic maximum error correlation is unity, here it is only $\sum_{m=1}^{M} \alpha_{im}^{1/2} \alpha_{jm}^{1/2}$, which in our case is always either 0.5 or 0, and thus here the asymptotic maximum would be 0.5. As shown in Fig. 4, CNL has some non-zero correlations in off-diagonal cells, whereas the error correlation matrix of MNL is an identity matrix. The empirical error correlation matrix for the CNL model shows generally substantial correlations between unobserved variables for joint alternatives that share a member (e.g. among all combinations involving fewer vehicles), which supports using CNL instead of MNL so as to account for the unmeasured sources of similarity between alternatives. However, as previously mentioned, the improvement in this case is arguably marginal.

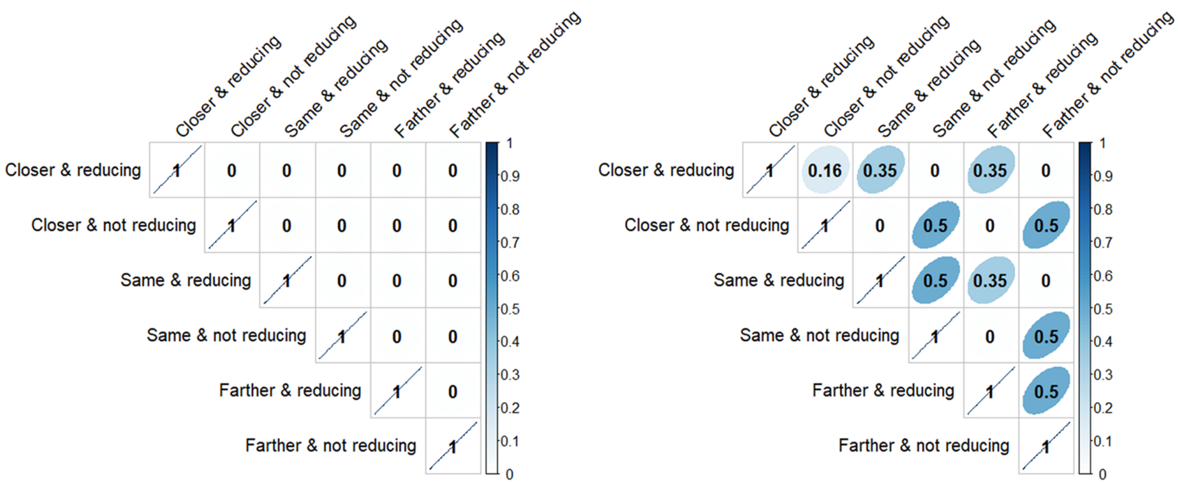

Fig. 4. Error correlation matrices (upper triangle).

Table 5
Segmented CNL models (reference: Same RL/Not reducing VO).

Category	Closer & reducing		Closer & not reducing		Same & reducing		Farther & reducing		Farther & not reducing	
Variable	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value	Parameter	t-value
Atlanta region										
Constants	**−1.569**	**−5.29**	**−1.121**	**−5.04**	**−1.130**	**−6.74**	**−1.001**	**−6.11**	**−0.934**	**−11.62**
Age 18–34 (ref: 35–64)	**−0.450**	**−2.56**	0.081	0.66	**−0.475**	**−4.68**	−0.172	−1.91	−0.147	−1.74
Age 65+ (ref: 35–64)	**−0.633**	**−2.92**	**−0.790**	**−2.34**	0.086	0.67	**−0.345**	**−2.50**	**−0.402**	**−3.38**
\$50–100k (ref: < \$50k)	**−0.397**	**−2.61**	−0.237	−1.38	**0.265**	**2.99**	−0.096	−1.38	−0.086	−1.09
\$ 100k+ (ref: < \$50k)	**−0.851**	**−3.08**	**−0.936**	**−3.11**	**0.505**	**3.42**	−0.172	−1.19	**−0.221**	**−3.07**
Neighborhood type (urban = 1)	0.104	0.52	0.289	1.84	**−0.269**	**−1.99**	0.021	0.14	0.109	1.31
Pro-suburban	0.081	0.94	**0.179**	**2.16**	−0.105	−1.24	0.057	0.60	**0.117**	**2.20**
Pro-non-car-modes	**0.732**	**5.19**	−0.090	−1.74	**0.301**	**6.91**	**0.274**	**6.37**	**0.258**	**7.49**
Travel longer distances	0.104	1.40	**0.308**	**3.88**	0.006	0.08	0.119	1.52	**0.160**	**4.62**
Gain time flexibility	**0.281**	**4.52**	−0.005	−0.09	0.049	1.27	**0.167**	**4.68**	**0.142**	**3.64**
Vehicle deficit (ref: sufficient)	**0.558**	**2.91**	**0.638**	**4.07**	**0.925**	**6.88**	**0.315**	**2.67**	**0.369**	**4.82**
Vehicle surplus (ref: sufficient)	**0.755**	**2.91**	**−1.113**	**−2.19**	**0.830**	**3.90**	**0.716**	**3.20**	**0.601**	**7.74**
Logsum parameters[a]	1.000	0.00	1.000	0.00	45.677	0.41	**112.636**	**2.85**	**56.970**	**2.68**
Non-Atlanta region										
Constants	**−1.306**	**−6.95**	**−1.341**	**−6.54**	**−0.385**	**−2.98**	**−1.647**	**−6.98**	**−1.703**	**−7.53**
Age 18–34 (ref: 35–64)	**0.415**	**3.51**	**0.701**	**4.52**	0.002	0.02	0.084	0.48	−0.161	−1.14
Age 65+ (ref: 35–64)	**0.308**	**2.22**	**0.533**	**3.43**	0.137	1.54	**−1.147**	**−1.99**	−0.433	−1.21
\$50–100k (ref: < \$50k)	**−0.486**	**−3.41**	−0.259	−1.61	**−0.235**	**−2.19**	−0.128	−0.79	0.145	0.88
\$ 100k+ (ref: < \$50k)	**−0.957**	**−3.11**	**−0.787**	**−2.61**	**−0.449**	**−2.44**	−0.384	−1.51	−0.468	−1.56
Neighborhood type (urban = 1)	0.066	0.50	**0.318**	**2.86**	0.161	1.51	−0.178	−0.71	**0.336**	**3.07**
Pro-suburban	**−0.143**	**−2.80**	−0.026	−0.78	**−0.070**	**−2.10**	−0.047	−0.68	0.148	1.89
Pro-non-car-modes	**0.322**	**3.23**	−0.004	−0.15	**0.139**	**2.89**	0.154	1.57	−0.073	−0.86
Travel longer distances	−0.018	−0.41	0.052	1.55	−0.014	−0.42	**0.286**	**3.69**	**0.559**	**5.87**
Gain time flexibility	**0.195**	**4.22**	**0.235**	**5.64**	0.000	−0.01	**0.326**	**5.43**	**0.147**	**3.48**
Vehicle deficit (ref: sufficient)	**0.712**	**4.59**	**0.446**	**4.83**	0.134	1.56	0.318	1.58	−0.116	−0.52
Vehicle surplus (ref: sufficient)	−0.242	−0.82	**−0.741**	**−2.54**	**0.623**	**3.42**	−0.021	−0.09	−0.006	−0.04
Logsum parameters ($1/\lambda$)[a]	**2.502**	**2.06**	4.229	1.05	2.183	0.85	114.599	1.83	84.661	1.66

Note: The bolded numbers indicate coefficients that are statistically significant at the 0.05 level.
[a] Biogeme estimates $1/\lambda$, so these values should be inverted to obtain λ, as needed. The corresponding t-statistics are based on H_0: $1/\lambda = 1$, which is equivalent to testing H_0: $\lambda = 1$.

$$Corr(\varepsilon_i, \varepsilon_j) = \sum_{m=1}^{M} \alpha_{im}^{1/2} \alpha_{jm}^{1/2} (1 - (\lambda_m)^2) \tag{3}$$

5.3. Segmented CNL models of residential location/vehicle ownership bundle

As aforementioned, we are interested in potential heterogeneity across the population, and presume that geography (Atlanta region versus non-Atlanta areas) could be a source of heterogeneity. Table 3 (last three rows) summarizes the deterministically-segmented CNL models. Overall, the ρ^2 of the model is higher than that of the pooled MNL and CNL models, as would be expected since it is less constrained. However, the segmented model is quite parameter-greedy in that when adding segments, the number of parameters is multiplied by the number of segments (of course, this applies at least as strongly to other finite-class segmentation models – for example, the latent class model has not only those parameters, but the parameters of the class membership model as well). Nevertheless, even after penalizing for lack of parsimony, the goodness of fit ($\bar{\rho}^2$) is still notably higher than the adjusted ρ^2s of the pooled MNL and CNL models. This indicates that segmenting by geography is meaningful and can (partially) address taste heterogeneity in this context.

Table 5 exhibits the estimation results of the model, containing parameters and their t-statistics. By segmenting into more homogeneous population groups, parameters tend to be more statistically significant because the model can allow effects of variables to differ across groups. However, although the magnitudes and signs of the coefficients can provide a general sense of the effects, we cannot directly compare coefficients across the two segments. This is because coefficients are confounded with the scale parameter of the Gumbel distribution, which in turn is related to the variance of the error term of the utility function. Without additional restrictions, it is therefore impossible to distinguish differences in the coefficients themselves from differences across segments in the variability of the unobserved characteristics influencing choice[4]. Hence, to compare effects, we employ scenario analyses that explore the change in aggregate share of each alternative given a change in the explanatory variable (a detailed description/ justification can

[4] One exception (which we observe in this study) is when coefficients have opposite signs between segments: since the scale parameter is always strictly positive, it cannot be the source of a sign reversal. The same is true if a coefficient is zero for one segment and non-zero for another, although in our case we retain non-zero estimates for all coefficients, even when they are not statistically significant.

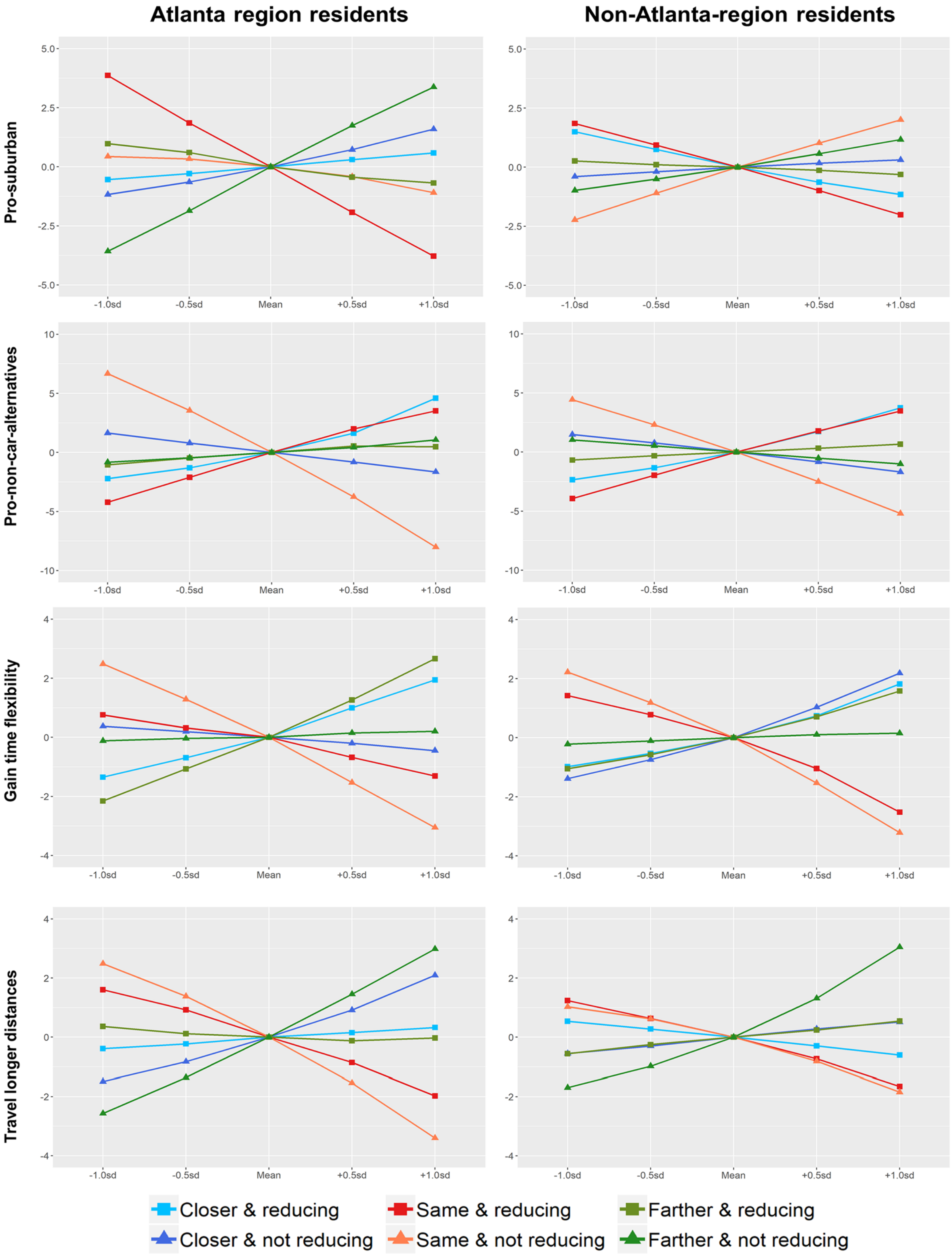

Fig. 5. Comparison across segments of effects of attitudinal and activity change measures on aggregate shares (percentage point changes).

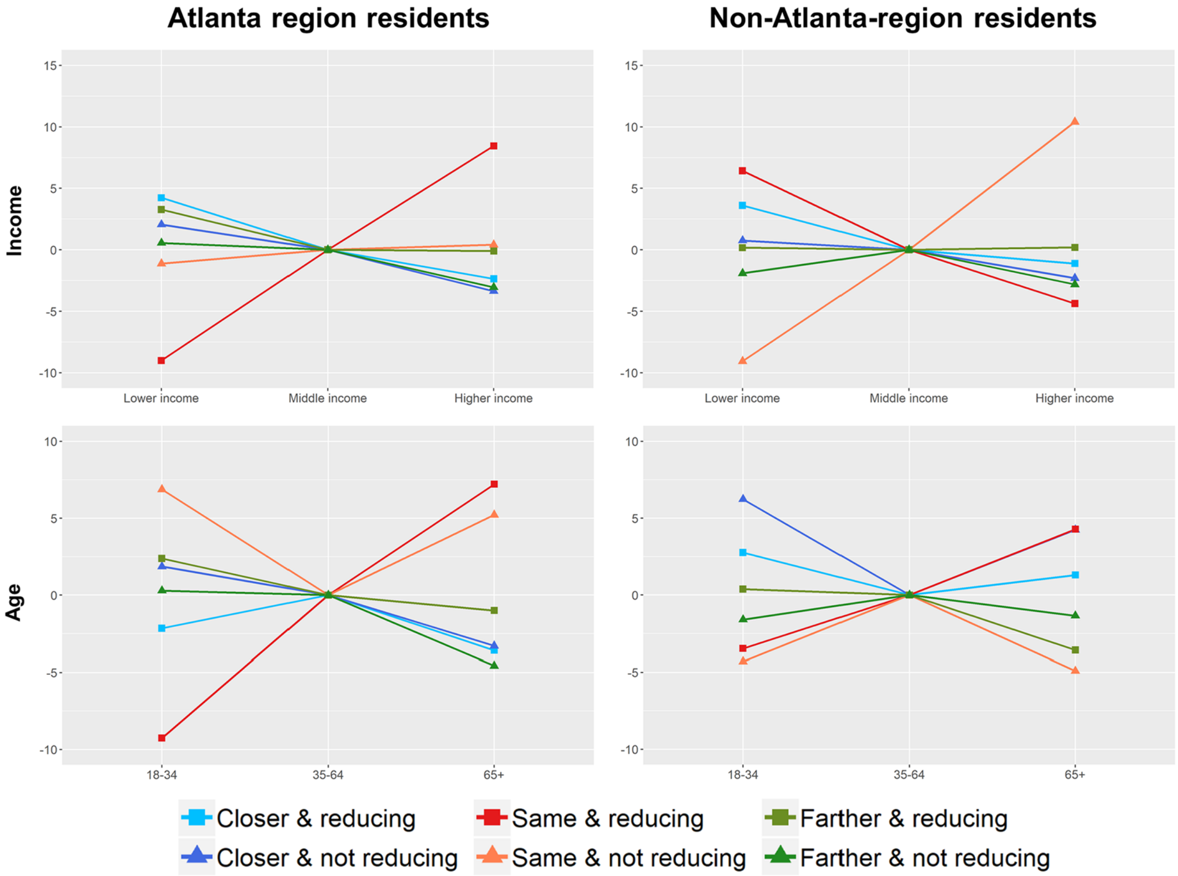

Fig. 6. Comparison of effects of demographics on aggregate shares.

be found in Kim and Mokhtarian (2018)).

Figs. 5 and 6 present the percentage point changes in aggregate shares if all cases were to have the specified values of the target variable, holding all other variables as they are. For example, compared to a case where everyone has the mean pro-suburban propensity, if everyone's propensity increases by half a standard deviation, the aggregate share of choosing "farther RL and not reducing VO" increases by about 2 percentage points. From this perspective, we can compare the effects of selected variables on the shares of each alternative bundle; the two population segments exhibit different sensitivities to these variables. The following observations are especially notable.

As found in Section 5.2, a pro-suburban attitude increases the likelihood of choosing a more distant residential location. However, Atlanta residents are more sensitive to the effect of that attitude (as shown by the wider vertical spread of the changes in share). Furthermore, for Atlanta residents, increasing favorability toward suburbs has the largest positive effect on the share of moving farther away and not reducing vehicles, whereas for non-Atlanta residents the largest positive effect is on *not* moving and not reducing vehicles. One plausible reason might be that differences in levels of urbanization are more extreme within the Atlanta region, and thus moving could represent a more profound change for pro-suburban Atlanta residents. In other words, even if a non-Atlanta resident's favorability toward suburbs increases, it may not prompt a move in a region that is already lower-density and "suburban-like", and more uniformly so, than Atlanta is. For example, as shown in Table 6, there is greater variability in population density and job density (by census block group, which can be considered a proxy for neighborhood) in the Atlanta region than in non-Atlanta areas.

We also see that attitudes toward non-car modes carry more weight for Atlanta residents, in that a given increase in favorability tends to more strongly increase the shares of the vehicle-shedding alternatives for them compared to the case for non-Atlanta residents. This is natural, in view of the fact that Atlanta has more and better options for *exercising* a preference for non-car modes. For example, on average, census block groups in the Atlanta region have higher transit scores and public transit commute mode shares (Table 6).

The two segments also present different sensitivities to the two activity change factor scores. In general, Atlanta residents react more strongly to both expectations of traveling longer distances by AVs, and expectations of gaining time flexibility. In particular, as the former expectations increase, there will be a greater increase for Atlanta residents in the shares of relocating home (whether closer or farther away). Perhaps this reflects the greater geographic spread of activities in a major metropolitan area, so that an increased tolerance of traveling longer distances makes relocation to a more desirable residence (whether that is considered to be

Table 6
Comparison of census block-group level descriptive statistics.

Variable	Statistics	Atlanta region	Non-Atlanta region
Population density	Mean	4.79	1.79
(pop/acre)	Standard deviation	5.26	3.08
	25th percentile	1.84	0.11
	75th percentile	5.98	2.57
Job density	Mean	2.45	0.81
(jobs/acre)	Standard deviation	9.26	3.28
	25th percentile	0.14	0.01
	75th percentile	1.71	0.59
Commuting by public transit	Mean	4.2%	2.2%
(mode share in ACS 2017)	Standard deviation	7.9%	5.1%
	25th percentile	0.0%	0.0%
	75th percentile	4.5%	1.6%
Transit score	Mean	2.96	2.23
[0,1]	Standard deviation	3.26	2.25
	25th percentile	0.00	0.00
	75th percentile	5.80	3.90

Note: Population density, job density, and commuting by public transit are based on American Community Survey (ACS) 2017 5-year estimates and Longitudinal Employer-Household Dynamics data. Transit score is from AllTransit; it measures a general performance score for public transit based on several indicators (e.g. number of stops, headways).

closer in or farther away) appear more feasible. In smaller regions, by contrast, an increased tolerance for longer distances may not meaningfully change the residential options for as many people, short of moving out of the region altogether.

Turning to Fig. 6, we also see some substantive differences between the two segments with respect to impacts of income and age. In Atlanta, increases in income increase the share of the “same and reducing” alternative, while elsewhere they diminish it. Conversely, in smaller regions, increases in income increase the share of the “same and *not* reducing” alternative, while in Atlanta they leave it relatively unaffected. In other words, while effects on the alternatives involving *moving* are (at least more) similar across segments, effects on the two choices *not* to move are quite different, where higher incomes make staying put but shedding vehicles more attractive in Atlanta, and staying put but not shedding vehicles more attractive elsewhere. This is, again, likely to be a consequence of the richer diversity of transportation modes that a major metropolitan area like Atlanta can support. For example, based on other questions in the survey, 85% and 48% of Atlanta residents reported that ridehailing (e.g. Uber/Lyft) and shared ridehailing (e.g. UberPOOL) are available where they live, whereas only 50% and 14% of non-Atlanta residents did[5]. The fact that higher incomes increase the shares of one of the “staying put” alternatives for each segment (although a different one for each) may indicate that wealthier people have already been able to move to their “ideal” location, and thus have greater residential location inertia.

Regarding age, as a general tendency we see a greater sensitivity in Atlanta than elsewhere. A striking specific difference is that in the Atlanta region, being younger or older *increases* the share of the “status quo” (“same and not reducing”) alternative relative to the 35–64-year-old group, whereas elsewhere it *reduces* the share. We are unsure of the reasons for this, but the presence of coefficients for the same variable (associated with the same alternative) that are both significant but of opposite signs between the two segments reflects taste heterogeneity of the most extreme kind.

6. Concluding remarks

Many scholars have discussed potential shifts in long-term decisions resulting from the benefits of AVs. Based on a survey of Georgia residents (2017–2018), this study investigated respondents’ expectations regarding two long-term decisions in a hypothetical fully-AV era: for *residential location*, whether to move closer to places visited often, move farther away to find a more attractive location, or not move; and for *vehicle ownership*, whether to reduce the number of household vehicles or not. It is unsurprising that a majority of people are expecting “no change” in these two decisions, because long-term decisions are relatively stable, the ramifications of AVs may still be difficult for many people to imagine, and the nature of the AV era remains profoundly uncertain for everyone. Nevertheless, sizable shares of people can already imagine AVs prompting change along at least one of these dimensions.

We used pooled and segmented cross-nested logit (CNL) models to appropriately reflect the shared unobserved variables influencing common elements of a residential location/vehicle ownership choice bundle. Key factors that affected the choice of bundle were identified, including some conventional factors (e.g. socio-demographics and attitudes), and some novel measurements of expectations regarding activity changes prompted by AVs. We found that those who are young, lower-income, pro-suburban, and/or pro-non-car-modes were more likely to prefer a change. In addition, some likely activity pattern effects (more distant travel, more time use flexibility) triggered by AVs were motives to change the longer-term residential location/vehicle ownership decisions – a key

[5] It is not easy to obtain objective data about the geographical coverage of ridehailing services. Hence, in the survey, we asked respondents to indicate whether the services are available. Some people said “I don’t know” and some indications (yes/no) may not be accurate. However, we believe this information can serve as a reasonable approximation.

finding. Current choices also mattered: for example, those with fewer vehicles than driving-age people in the household were more likely than others to want to move closer to frequently-visited locations, while those with more vehicles than driving-age members were more likely than others to expect to shed vehicles. Overall, we found evidence to support our hypotheses that AVs could work in concert with attitudinal preferences to stimulate change in these long-term decisions, and that some effects on daily activities that are triggered by AVs could also motivate people to relocate home and/or shed household vehicles.

We also speculated that these long-term decisions would reflect taste heterogeneity, and employed deterministic segmentation to uncover one source of it. In particular, by segmenting on geography (Atlanta region versus non-Atlanta region, or major metro area versus smaller region), the model performed significantly better. However, as aforementioned, finite segmentation schemes are parameter-greedy, and there is thus a tradeoff between model realism and parsimony with respect to adding more segments or variables. We found meaningful heterogeneity across geography, suggesting that residents in major metropolitan areas will react differently from those in smaller regions as AVs become available. Generally speaking, we saw greater sensitivity to (i.e. larger changes in share with respect to changes in) a number of factors among Atlanta residents compared to non-Atlanta residents. There were also cases in which significant coefficients for the same variable and associated with the same alternative had the opposite signs for the two segments. We presume that many of the observed differences in taste stem from the divergent land use and transportation infrastructure environments between larger and smaller regions, with the former offering a broader areal spread, greater variability in residential neighborhoods, and a richer set of transportation options (including opportunities for walkable/bikeable accessibility). From the sustainability perspective, AVs are expected to have both positive effects (by motivating people to shed vehicles or move closer) and negative effects (by motivating people to move farther away and thus increase overall trip lengths), but our results hint at the possibility that providing options such as shared mobility (probably, in the future, an automated version of Uber-like ridehailing services), public transit, and micro-mobility will help people modify their long-term choices in more environmentally-sustainable directions.

Many questions still need to be addressed. First, because there are still huge uncertainties about the AV era (which is inherent in all AV studies), respondents' reactions at the present time are inevitably volatile. Especially, future regulatory and business models of shared mobility are unclear and they may significantly affect both decisions of residential location and vehicle ownership. For example, if SAVs were widely dominant and we explicitly had respondents picture such a future by assumption, the shares of people who would change residential location and vehicle ownership could have been higher than the ones we obtained. This uncertainty is also reflected in the sustainability perspective. Home relocation and reduction in household vehicles (whether by sharing fewer household-owned vehicles or using externally-provided shared mobility services, or both) has the potential to reduce a household's carbon footprint, but may generate different types of trips (e.g. deadheading).

Second, we identified some key factors affecting potential residential location and vehicle ownership in the AV era, but where people actually decide to live and how many vehicles they will have are still unclear. Models that reflect conventional tradeoffs (e.g. commute distance versus housing costs; car-owning costs versus inconvenience in sharing vehicles with other household members) will almost certainly need to be modified to reflect the impacts of AVs (particularly, the reduction of the burden imposed by travel time) on these tradeoffs. During this transition period, stated preference or combined stated preference/revealed preference studies offer a logical methodology for recalibrating conventional wisdom.

Third, and relatedly, the advent of AVs has highlighted the importance of the ways travel time is spent now, and will be spent in a hands-free travel future. A reduction in the disutility of time spent traveling could be a major driver of both residential location and vehicle ownership decisions. However, there is certainly variability in the ways that time is spent now, and in the desire to spend it in those or other ways, with accordingly diverse impacts on the valuation of travel time and thence the willingness to accept longer trips. For example, that willingness is likely to differ between people who do nothing special while traveling, those who do work, and those who watch videos while traveling. One of the explanatory variables in our models does, in fact, serve as a proxy for activities while traveling (namely the *gain time flexibility* factor), and many other studies have also begun to address this issue (see, e.g., Bouscasse and de Lapparent, 2019; Pudāne et al., 2018; Taiebat et al., 2019; Choi and Mokhtarian, 2020). But much is yet to be learned, particularly with respect to the diversity across the population in this regard.

Lastly, we pre-determined one source of taste heterogeneity for our model to be geographic. However, heterogeneity can also stem from other sources (e.g. household composition) and thus it will be further informative to planning if we can uncover some of those other sources. From a modeling perspective, it could be useful to explore other advanced approaches that can incorporate taste heterogeneity as well as flexible substitution patterns (e.g. mixed CNL, Hess et al., 2012; latent class CNL, Wen et al., 2013).

CRediT authorship contribution statement

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

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