

Investigating Autonomous Vehicle Impacts on Individual Activity-Travel Behavior

Katherine A. Dannemiller

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: kadannemiller@utexas.edu

Aupal Mondal

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: aupal.mondal@utexas.edu

Katherine E. Asmussen

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Email: kasmussen29@utexas.edu

Chandra R. Bhat (corresponding author)

The University of Texas at Austin
Department of Civil, Architectural and Environmental Engineering
301 E. Dean Keeton St. Stop C1761, Austin TX 78712, USA
Tel: 1-512-471-4535; Email: bhat@mail.utexas.edu
and
The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong

ABSTRACT

This paper develops an analytic system to investigate the effects of AV availability on multiple dimensions of activity-travel behavior at once, based on a direct survey-based modeling approach. In particular, the model uses individual socio-demographics, built environment variables, as well as psycho-social variables (in the form of latent psychological constructs) as determinant variables to explain likely AV impacts on five dimensions of short-term activity-travel choices: (1) Additional local area trips (that is, those that would not be characterized as long distance trips; a long distance trip was defined in the survey as a trip more than 75 miles one-way), (2) Trip distance to shop or eat-out activities in the local area, (3) Trip distance to leisure activities in the local area, (4) Additional long distance road trips beyond the local area, and (5) Commute travel time. The model system includes a confirmatory factor analysis step, a multivariate linear regression model for the latent constructs, and a multivariate ordered-response model for the five main outcomes just listed. Data from a 2019 Austin area survey of new mobility service adoption and use forms the basis for our empirical analysis. Our results, when aggregated across all respondents, does suggest that AVs may not after all have a substantial impact on overall trip-making levels, although local area trips are likely to become longer (for all purposes, including the commute). The highest impact of AVs will, it appears, be on the number of long distance trips (with such trips increasing). Our in-depth examination of the variations in AV activity-travel responses across population segments and geographies underscores the importance of modeling multiple activity-travel dimensions all at once. In addition, our results highlight the value of using psycho-social latent constructs in studies related to the adoption/use of current and emerging mobility services, both in terms of improved prediction fit as well as proactive strategies to design equitable, safe, and community-driven AV systems. There is likely to be considerable heterogeneity in how different population groups view and respond to AVs, and it is imperative that AV campaigns and AV design consider such heterogeneity so as to not “leave anyone behind”.

Keywords: Equity, autonomous vehicles (AVs), activity-travel, long distance travel, safety, design, policy.

1. INTRODUCTION

The transportation, technological, and media worlds have been recently abuzz with the concept of autonomous vehicles (AVs) – that is, motorized vehicles that are able to guide themselves from an origin point desired by an individual to the destination point desired by the individual. Fundamentally, humans yield full control to artificial intelligence technology for the purpose of transportation. As such, the network sensing, communication, data science, and predictive technologies, and associated considerations of privacy, security, equity, and ethics, are critical elements of an AV system. These issues have been discussed at length in the computer science and socio-technical literature (see, for example, Kim et al., 2020a; Ma et al., 2020). On the transportation side of things, the excitement of AVs is driven by the potential safety, accessibility, and traffic processing benefits. From a safety standpoint, taking driving control away from individuals is likely to reduce crashes, because human errors and drunk driving represent upwards of 90% of all crashes (Shinar, 2019; Arvin et al., 2021). From an enhanced accessibility standpoint, those unable to drive or restricted in their movement because of driving challenges (e.g., the elderly, disabled, and children) can be more mobile, reducing the social exclusion of such individuals and enhancing their quality of life. From a traffic processing capacity standpoint, driverless cars can increase the capacities of highways and intersections, thus reducing traffic delays and increasing travel time reliability. For example, driverless cars can reduce the distance between cars, allowing platooning and an increase in the capacity of travel lanes; they also can accurately position themselves within lanes, reducing lane widths and increasing carrying capacity without the physical expansion of highways. These, and other related potential benefits of AVs have been studied extensively in the literature, especially in the past three years (see, for example, Fraedrich et al., 2019; Hawkins and Nurul Habib, 2019; Soteropoulos et al., 2019).

While there is considerable literature on potential AV effects on safety, accessibility, and traffic processing ability, most such studies attempt to understand AV effects based on simulations using *a priori* assumptions related to AV adoption and use behavior. Some of these studies do use a scenario approach to acknowledge the wide bandwidth of possible user behavior responses, but the bandwidth used may still not adequately represent the range of behavior in the AV future. As a simple example, the AV adoption (ownership/penetration) rates over time in many of these simulations are based on AV fleet penetration forecasts, as developed by private consultants, academics, and Delphi surveys of transportation experts (Litman, 2020 and Kuhr et al., 2017 provide a useful overview of such methods). However, these prediction efforts are at a macro-level, and ignore individual-level variations in adoption propensity based on individual-level factors. Only more recently has there been an increased recognition of the need to rigorously study the demographic, attitudinal, and lifestyle factors influencing the adoption decision at an individual-level (see, for example, Zmud and Sener, 2017; Lavieri et al., 2017; Spurlock et al., 2019; Yap et al., 2016; Ashkrof et al., 2019; Moody et al., 2020). Similarly, from a user behavior standpoint (that is, the impact of AV access on activity-travel patterns), many studies assume a drop in the value of travel time (VTT) due to drive-free travel of the order of 50%-100% in simulations (relative to the time value placed by individuals currently in human-driven vehicles).

This reduction is based on the notion that the ability to pursue other activities during travel will reduce the opportunity cost of the time invested in the driving task itself. Indeed, car manufacturers are attempting to seize this “selling point” as they position concept-AVs as “new” and “luxury/eclectic” living areas designed for comfort and the meaningful use of travel time (see, for example, Volvo, 2019). However, some recent studies have questioned the assumed decreases in VTT used in earlier simulation studies of AV effects, suggesting a much more modest 30% or even smaller overall decrease in VTT because of the use of an AV (see Singleton, 2019 and Moore et al., 2020; a few recent papers have also estimated small increases in VTT because of an AV, as discussed in Rashidi et al., 2020). The use of a reasonable VTT in the simulations is important for the appropriate assessment of AV effects, especially because a VTT change can impact multiple activity-travel dimensions, including the number of trips made, trip distances within an urban area, and the frequency of long distance trips.

Motivated by the discussion above, the focus of this paper is on more directly understanding the effects of AV availability on multiple dimensions of activity-travel behavior, without resorting to making *a priori* assumptions about aspects of AV user behavior. The study does not differentiate between privately-owned AVs and shared AVs (SAVs) and does not investigate consumers’ acceptance (and the rate of acceptance over time) of AV technology, which has been the attention of the other recent studies listed earlier. We further restrict our analysis to mobility choices, conditional on longer term residential location and vehicle ownership impacts (see Fraedrich et al., 2019; Krueger et al., 2019; Moore et al., 2020; and Kim et al., 2020b for recent studies on these longer-term effects). Our emphasis here is on understanding variations across individuals in shorter-term activity-travel behavior responses, given AV adoption and residential/vehicle ownership choices. Specifically, we use individual socio-demographics, as well as psycho-social variables (in the form of latent psychological constructs), as determinant variables to directly explain likely AV impacts on five dimensions of short-term activity-travel choices: (1) Additional local area trips generated (local area trips are those that would not be characterized as long distance trips; a long distance trip was defined in the survey as a trip more than 75 miles one-way), (2) Trip distance to shop or eat-out activities in the local area, (3) Trip distance to social/recreational activities in the local area, (4) Additional long distance road trips beyond the local area, and (5) Commute travel time. A multivariate ordered-response model is estimated, using data from a 2019 Austin area survey of new mobility service adoption and use.

The rest of this paper is organized as follows. Section 2 provides a brief overview of the past relevant literature. Section 3 describes the data collection design, sample characteristics and the modeling methodology. Section 4 presents the model results and goodness of fit measures. Finally, Section 5 discusses the practical implications of our findings and concludes by summarizing the results and briefly identifying future research directions.

2. LITERATURE OVERVIEW

Understanding and predicting the potential impacts of AV technologies on activity-travel behavior, is critical to land use and transportation systems planning. Most studies examining AV adoption,

the paradigm of adoption (as a private AV or as shared AVs), and potential effects on activity-travel behaviors have been descriptive in nature (as Gkartzonikas and Gkritza, 2019, indicate in their review of AV studies, “more than half of the reviewed studies only reported a descriptive analysis of the survey results”). Most other studies use existing travel-demand frameworks to model AV effects, including methods within trip-based, activity-based, agent-based, and stochastic simulation modeling frameworks (see, for example, Childress et al., 2015; Davidson and Spinoulas, 2015; Bernardin et al., 2019; Kröger et al., 2019; Vyas et al., 2019; Dias et al., 2020; as Soteropoulos et al., 2019, indicate in another exhaustive review, “Most of the modeling studies mainly use existing travel demand models...”). Such frameworks typically start by identifying the many possible reasons for AV effects on different activity-travel dimensions, and then use scenario-based methods to add “factors” that modify specific aspects of existing frameworks to assess AV effects. For example, Dias et al. (2020) identify the potential for increased passenger vehicle miles of travel (VMT) because of latent demand (older individuals, individuals below the age of 16, and differently-abled citizens being able to travel alone), increased trip distances because of spending time more productively when traveling in an AV, and a higher single occupant mode share because of draw away from high-occupancy vehicle modes such as rail and bus. In their modification of the four-step trip model, they then proceed to apply factors such as an increase of trips by 5%-10% by AV-owning households and a decrease in the value of travel time by 25% when traveling in an AV to capture potentially increased trip distances and shifts away from high-occupancy vehicles to AVs. Similarly, Vyas et al. (2019) also identify potential reasons for changes in specific activity-travel dimensions in the presence of AVs, and apply, at different places in their activity-based framework, specific factors such as “Auto in-vehicle travel time productivity bonus” (to reflect a reduction in VTT in AVs, which they vary between 25-50%) and “no escort promotion” (to reflect the fact that children can now travel alone without the need for an escort to drive them). Some studies attempt to provide more justification for the use of specific factor values based on examining today’s activity-travel patterns and identifying travel needs not fulfilled today but that can be pursued using AVs tomorrow (see, for example, Truong et al., 2017).

The factor modification-based modeling approach discussed above has the advantage of being easily introduced into current travel demand modeling frameworks. Also, by using a scenario-based process, the approach recognizes the range of possible activity-travel effects, while utilizing the behavioral relationships already embedded in today’s activity-travel models (for example, once the VTT reduction factor is set for AV travel, current behavioral models can be used to examine trip distance and mode shift changes). As importantly, for a given scenario (that is, a given fixed set of modification factors), the approach is able to provide “precise” change estimates (that is, percentage change from today’s base case of no AVs) for individual activity-travel dimensions as well as at the macro-level of vehicle miles travel or vehicle hours of travel. However, the approach also has limitations. First, as discussed earlier in the context of assumed VTT values, the approach could be inaccurate even if precise, should the range of scenarios not include the “true” scenario that may play out (that is, the key modification factors considered do not capture the actual modification levels corresponding to the “true” scenario). Second, while the

approach can be conveniently embedded within existing modeling frameworks, in application, it typically uses a uniform (across individuals) modification level for the key parameters and assumes away heterogeneity (across individuals) in response to AVs (as, for example, the use of a fixed VTT reduction factor across all individuals). Such a single across-the-board assumption for the modification level for each attribute is imposed because it is not clear what the segments should even be (that is, how the segments should be defined) for any attribute (as, for example, what segments to use to apply different VTT values across segments). Besides, even if the segments are assumed, one has to make a second-level assumption about the vector of corresponding latent segment-specific modification factors for each attribute. This leads to a proliferation of factors and scenarios, pretty much negating the very notion of creating a limited set of scenarios in the first place. At the same time, however, studies in the human development area (see Martin and Park, 2003; Duhigg, 2012; Voinescu et al., 2020) indicate that there will be substantial heterogeneity in habits/behavior modification in response to changes in the external environment, which can, for example, lead to very different VTT shifts across individuals. While segments may be more easily defined in an activity-based modeling framework, there is still the problem of the need to assume a vector of values of segment-specific factors for each activity/travel component. Third, the modification-based studies focus on macro-level network changes in vehicle miles of travel over an entire region (such as a city or a state). These studies do not investigate individual activity-travel behavior, or purpose-specific variations in travel behavior, due to AV availability. This is clearly evidenced in the “main results” column in Table 1 of Soteropoulos et al. (2019) (which is a good review of studies examining AV impacts on travel behavior). As can be noted in the table, and also Table 4 of Gkartzonikas and Gkritza (2019), the final outcome indicators in most modeling studies relate to macro-level vehicle miles of travel (VMT) or vehicle kilometers of travel (VKT) changes, but not individual-level trip generation and trip length characteristics.¹ Fourth, it is well-established in the information science literature that attitudes, tech-savviness, lifestyle preferences, and affective attributes are critical determinants of behavioral response to new technologies (Mani and Chouk, 2017; Marikyan et al., 2019). Some recent AV-related studies have also demonstrated the importance of such psycho-social characteristics on AV response behavior (see, for example, Hohenberger et al., 2017; Lavieri and Bhat, 2019a; Moore et al., 2020; Nair and Bhat, 2021; Narayanan et al., 2020 and Rahimi et al., 2020 provide a good overview of such studies). Accommodating such psycho-social effects is important to increase the ecological validity of studies (see next section), and is also particularly important for proactive policy-making; service providers and public agencies need to be cognizant of not only demographic factors, but also lifestyle/affective emotion considerations shaping AV behavioral responses, to inform customized intervention strategies targeted toward specific demographic groups. But the factor-based modification approach does not incorporate such psycho-social determinants of AV

¹ Admittedly, there have been some individual-level survey-based models of the choice between private AVs and the use of shared AVs (SAVs), or the choice of egress mode to public transportation (with one of the choices being AVs), or the effect of AVs on current modes such as public transport and slow modes (see Section 3.1.2 of the Soteropoulos paper), but there has been little effort on examining trip-making and trip lengths at an individual-level (see also Kim et al., 2020c).

response behavior. As also stated by Gkartzonikas and Gkritza (2019), a research effort that is admittedly two year dated, “Interestingly, models of intention to use AVs based on the Theory of Reasoned Behavior (TRB) and the Theory of Planned Behavior (TBP), which can relate behavior with attitudes, have not been estimated to date”.

2.1 The Current Paper

In the current study, we adopt a direct survey-based modeling approach to examine potential AV effects on short-term activity-travel behavior patterns (as opposed to the factor modification-based approach discussed earlier). Specifically, a survey is used to elicit respondent perspectives on activity-travel behavior change in the presence of an AV.² The survey does not make a distinction between privately-owned AVs and shared AVs (SAVs), but asks respondents to provide their responses imagining that they had regular access to an AV “by owning, leasing, or using autonomous ride-hailing services” (most earlier studies discussed in the previous section consider only private AVs). Also, to be sure, our approach is different from a few studies that have used stated survey-based games to study potential VTT changes (for input to the factor modification-based modeling approach discussed above). For example, Kolarova et al. (2018) use stated preference responses of individuals in two gaming scenarios, one scenario corresponding to mode choice in today’s context (between the modes of walk, bicycle, car, and public transportation) and a second scenario corresponding to mode choice in an AV context. They derive a VTT for each mode (varying only by income) based on these experiments. Similar stated preference gaming studies of mode choice have been undertaken by others (see, for example, Krueger et al., 2019; de Almeida Correia et al., 2019; Lavieri and Bhat, 2019b) to obtain VTT estimates in the presence of AVs. Unlike these studies, we directly seek information on individuals about potential AV impacts on activity-travel dimensions (specifically, trip-making, trip lengths, and commute times) beyond AV adoption and mode choice.

Overall, our direct survey-based modeling approach examines multiple aspects of activity-travel behavior by eliciting consumer responses in broad ordinal or grouped response categories

² While the use of a survey to collect information about potential responses in a hypothetical environment may seem to be somewhat of a stretch, and one can legitimately harbor reservations regarding the reliability of the responses provided, there is considerable evidence in the social-psychology and information sciences literature that attitudes toward a new product or experience (such as safety concerns or interest in productive use of travel time), subjective norms and lifestyle preferences (including individual demographics and variety seeking preference), and perceived usefulness of a product (related to tech-savviness and ease of use) have a substantial bearing on behavioral intentions and actual behavioral action. In fact, these concepts are at the foundation of the Theory of Planned Behavior (TPB; Ajzen, 1991) and the traditional Technology Acceptance Model (TAM) (Davis, 1989; Venkatesh and Davis, 2000). Extensive studies in consumer behavior have validated the use of the above-mentioned psycho-social identities of individuals in explaining the use of, and response to, other automated technology developments (such as smart phone uptake, voice-controlled virtual assistants, and lane-keeping/automatic cruise control technologies in vehicles; see, for example, Astroza et al., 2017, Leung et al., 2018, Foroudi et al., 2018, and Marikyan et al., 2019). Thus, eliciting demographic characteristics, attitudes, lifestyle preferences, and potential behavioral responses, even if in a currently non-existing environment, and using them to predict future behavioral action in a new environment, as we pursue in the current paper, is a better approach than simply assuming things “from the air” (see also Ge et al., 2019 and Chee et al., 2020).

to a series of questions. These questions and response categories are as follows (in all questions, respondents were asked to assume that they have access to an AV)³:

For all first four dimensions below, the response was captured on a five-point Likert scale of very unlikely, unlikely, neutral, likely, and very likely. The question was “How likely would you change in each of the following ways”:

- (1) Make additional trips that I do not make now (Additional local area trips or ALT for short)
- (2) Travel farther to go shopping or eat out (Trip distance to shop or TDS for short)
- (3) Travel farther to go to social/recreational activities (Trip distance to leisure or TDL for short)
- (4) Make more long distance road trips (Additional long distance trips or ALDT for short).

For the fifth and final dimension, the question and response categories were as follows:

- (5) Commute travel time (CTT): How much longer would you be willing to commute (compared to current commute)? The response was captured in the five grouped categories of (a) Would not accept a longer commute, (b) Up to 5 additional minutes, (c) Between 5 and 15 minutes, (d) Between 15 and 30 minutes, and (e) More than 30 additional minutes).

Different from the factor modification-based approach, our approach cannot provide precise estimates of modified behavior. But we believe it can provide a more accurate reflection of how behaviors may change in the presence of an AV, tied to demographic groupings and residence geography. After all, because of the high degree of innovativeness of an AV, and the many policy, ethical, and regulatory “moving parts” leading up to AV access and use, the idea of what constitutes an AV can conjure up different images for different individuals. In such a setting, attempting to develop precise estimates of behavioral changes using factor-based modification approaches, even if under a suite of different scenarios, may have limited value. A similar issue of psychological distantness can also hinder reliable information from respondents in a stated survey-based gaming approach (Zmud et al., 2016). Indeed, the consumer research and survey methodology fields are clear that, when a product configuration and functionality is unclear to respondents, traditional approaches to elicit willingness to pay preferences will be of limited value (Dawid and Delli Gatti, 2018). In such cases, it is typical to elicit consumer responses in broad (and non-numerical) response categories rather than “box” respondents and force them to respond in fine numerical response categories.

In summary, there are four broad and salient aspects of the current effort. First, as also recently indicated by Kim et al. (2020c), while there has been substantial research on the higher level choice decisions of AV adoption (including paradigm of adoption and vehicle type/ownership choice), and on the relatively lower-level mode choice decision in an AV

³ In the survey, a description of an AV was provided as follows: “An Autonomous Vehicle (AV) is a vehicle that drives itself without human supervision or control. It picks up and drops off passengers including those who do not drive (e.g., children, elderly), goes and parks itself, and picks up and delivers laundry, groceries, or food orders on its own. When AVs become available, ride-hailing companies (e.g., Uber and Lyft) will use them to provide rides without a human driver in the vehicle. When answering the questions in this section, please assume a future in which autonomous vehicles (AVs) are widely adopted, but human-driven vehicles are still present.”

environment, there has been little effort in the field on studying the intermediate decisions of how AVs may affect travel distances and trip generation. This is true regardless of whether we are talking about factor-based modification studies or direct survey-based studies. As already discussed, the factor-based methods also focus, as their final output, almost exclusively on macro-level network VMT changes, rather than on individual responses. Also, unlike Kim et al. (2020c), who cluster individuals into one of six clusters (based on what aspects of their travel individuals are most likely to change, such as the clusters of no change, change unlikely, more leisure/long distance trips, longer trip for both local and long distance travel, etc.), we explicitly consider all possible changes a specific individual will make in each of five separate dimensions. The difference is that Kim et al.'s (2020c) exploratory study clusters individuals based on which singular dimension an individual is most likely change, while our analytic study has a specific model for each travel dimension. Our modeling, therefore, provides much more granularity at the individual-level regarding changes in the five travel dimensions and any combination of the dimensions. Besides, as our study reveals, individuals who are more likely to make more trips are also more likely to make longer trips for all purposes and make more long distance trips, and so it would be difficult to pigeonhole individuals into a very limited set of clusters. Second, we consider not only long distance trips and local area trips, but also focus expressly on trip lengths/times by the three purposes of commute, shopping, and leisure. We are not aware of any earlier study that focuses on purpose-specific trip lengths as an outcome when examining potential AV impacts. Third, we consider a suite of demographic, built environment, as well as psycho-social attitudinal variables in our analysis, unlike many earlier AV studies that primarily consider demographic variables. Also, our consideration of built environment (BE) variables goes beyond simple macro-level representations based on density and includes additional variables such as land-use mix, population density and retail employment density. As importantly, we introduce psycho-social constructs as determinants of the main travel outcomes of interest, and relate these to observed demographics, so that the proposed model can be employed in forecasting mode. Besides, we also demonstrate this forecasting capability by partitioning the influence of an exogenous variable into a direct effect and indirect mediating effects through the psycho-social constructs. This exercise provides important policy insights to identify effective targeting and positioning strategies, customized to each socio-demographic group of the population. We believe we are the first to apply such a partitioning strategy in the context of AV-induced trip generation and distance to activity location changes. Fourth, in addition to being the only survey-based study that we are aware of that explicitly addresses potential AV impacts on each of the five individual-level dimensions studied in this paper, we also model all the five dimensions jointly while simultaneously controlling for psycho-social, BE and demographic variables. Ignoring the jointness across activity-travel dimensions can lead to inefficiency in estimating covariate effects for each outcome because it fails to borrow information on other outcomes. Especially when working with relatively small samples, joint modeling provides important benefits. Also, recognizing jointness allows the ability to answer intrinsically multivariate questions such as the effect of a covariate on a multidimensional outcome (Teixeira-Pinto and Harezlak, 2013). This is

not simply an esoteric econometric issue, but has real-world repercussions for forecasting and policy analysis. For example, as we will demonstrate later in Section 4.3, ignoring the jointness in the five dimensions leads to a very poor data fit in terms of disaggregate and aggregate predictions. This is because of the strong (high magnitude and high statistical significance) positive correlation in unobserved factors across the travel dimensions (even after including a suite of psycho-social variables, BE attributes, and demographic variables). The net result is that the independent model grossly underpredicts, for example, the combination choice of individuals likely to make more trips and individuals likely to travel longer distances. Given that vehicle miles of travel and traffic congestion considerations are dependent on a combination of trip-making and trip lengths (along with other choices, of course), ignoring jointness would lead to underestimations in VMT changes due to AVs. Thus, considering the jointness among number of trips, and trip lengths/travel times for each of the shopping, leisure, and work activity purposes is critical.

3. METHODOLOGY

3.1 Analytic Framework and Sample Description

The analytic framework focuses on developing a joint model for the five main outcomes associated with the stated activity-travel responses of respondents (see Figure 1 for a diagrammatic representation of the overall framework). Individual-level variables (individuals demographic and household characteristics), BE variables, as well as attitudes/lifestyle factors (also referred to as psycho-social factors) are all considered as determinants of the five main outcomes (the specific exogenous variables shown in Figure 1 were the ones that showed moderate to strong effects in our model, and will be discussed in more detail in Section 3.1.1). Of these, the psycho-social factors are not directly observed, but are considered as latent stochastic constructs expressed through the responses to the suite of attitudinal statements (the responses to these statements are also referred to as indicators). In the current study, four latent constructs are used: (1) individual's technology-savviness (tech-savviness), (2) safety concern, (3) variety-seeking lifestyle, and (4) interest in productive use of travel time (IPTT).⁴ A traditional confirmatory factor analysis determined the most suitable indicators for each latent construct. Next, the identified group of indicators for each construct is collapsed to a single continuous "factor" (to conserve on space, the confirmatory factor analysis results and this methodology are presented in an online supplement to this paper; see <https://www.cae.utexas.edu/prof/bhat/ABSTRACTS/AVMultDimBeh/OnlineSupp.pdf>). Of course, these single continuous values are point values for a particular sample and are considered

⁴ These latent constructs are identified based on earlier studies in transportation (see, for example, Lavieri and Bhat, 2019a, Li and Kamargianni, 2020, and Gee et al., 2019), information science (see, for example, Marikyan et al., 2019 and Nwankwo et al., 2014), and the more general psychology/ethnography field (see, for example, Vianello et al., 2013 and Gifford and Nilsson, 2014). Also to be noted is that other latent constructs were also developed and considered, including those associated with security concern, green lifestyle propensity, and time sensitivity. However, these did not turn out to be statistically significant in explaining any of the five main outcomes, after considering the four constructs used in our model. In part, this is because of correlation between these other constructs and the four constructs considered in this paper. For example, the indicators for time sensitivity and interest in the productive use of travel time (IPTT), though loading on separate indicators in our analysis, also had a relatively high correlation.

as manifestations of the underlying stochastic latent construct. Thus, the single continuous values are used as dependent variables in a linear regression, with individual-level characteristics used as exogenous variables. Across the four latent constructs, we thus have four dependent variables in a multivariate linear regression. This multivariate linear regression (effectively mimicking the structural equations model or SEM component of Bhat's (2015) Generalized Heterogeneous Data Model (GHDM)) can be estimated simultaneously with the multivariate ordered-response probit (MORP) model for the five main outcomes (again, the latter MORP model uses the latent constructs as exogenous variables, in what constitutes the measurement equations model or MEM component of Bhat's GHDM model). However, for ease in estimation, we adopt a two-stage estimation approach. In the first step, we first estimate a multivariate regression model of the latent construct scores (with individual-level characteristics being the exogenous variables, with say a vector of parameters α on the exogenous variables x_q for individual q). This first SEM step falls in the category of the classic textbook treatment of the seemingly unrelated regression (SUR) model (see, for example, Greene, 2012), except with the restriction that the covariance matrix of the errors is actually a correlation matrix (because the continuous latent constructs are scale-less, and the single continuous values for these are constructed such that the variances of the errors are normalized to one; also note that the x_q vector does not include a constant for any (and all) latent constructs, because our construction of the single continuous values for these constructs is such that the values have a mean zero, another innocuous normalization because the latent constructs have no cardinal location interpretation). Next, in the second MEM step, estimates of the latent constructs are constructed as $\hat{\alpha}'x_q$, and used as exogenous variables, along with the individual-level characteristics and BE variables, in the MORP model (details of the structure and estimation of this MORP model are relegated to the online supplement). This applied estimator belongs to the class of two-step optimization estimators (2SOE), which ensures that, under general conditions, the estimator is consistent and asymptotically normal (CAN; see Newey and McFadden, 1994). However, the second step MORP asymptotic covariance matrix needs to be corrected. The procedure is presented in Terza (2016), and is applied in this paper.⁵

Overall, the individual-level characteristics and the BE attributes constitute the exogenous variables in our model system (see left side of Figure 1). On the other hand, the latent constructs, while also serving as determinant variables for the main outcomes, are affected themselves by the individual-level variables (so, these latent constructs are placed in the middle of Figure 1). Thus,

⁵ The full-information maximum likelihood (FIML) estimator for our application entails a 19-dimensional integral for the multivariate normal cumulative distribution (MVNCD) function. An alternative, more robust estimator (that is, an estimator that is more robust to the mis-specification of a 19-variate normal distribution assumption for the error terms underlying the 14 indicators and five outcomes) is the composite marginal likelihood (CML) estimator, even though the CML may lose some amount of efficiency if the true 19-variate distribution is indeed multivariate normal (see Bhat, 2014). The 2SOE, like the CML, also is more robust to mis-specification than the FIML estimator (even if potentially less efficient like the CML). In this study, we use the 2SOE approach because the computation of the standard-errors in the 2SOE (see Terza, 2016) for the specific application in this study is somewhat simpler relative to the computation of the standard errors for the CML estimator. A relative comparison of the CML and 2SOE estimators in different application contexts is an interesting direction for future research.

the individual-level variables have both a direct effect on the main outcomes of interest, as well as an indirect mediating effect through the latent constructs. The BE variables, the demographic variables, and the latent constructs are discussed next.

3.1.1 Exogenous Variables

3.1.1.1. BE Variables

In addition to information on the five main outcomes of interest discussed earlier, a separate section obtained respondents' individual and household socio-demographics, as well as their home locations. As part of data preparation, the home locations were geocoded, mapped to census block groups (CBG), and then bestowed with built environment (BE) attributes as obtained from the U.S. Environment Protection Agency (EPA) Smart Location Database (Ramsey and Bell, 2014). The BE attributes corresponding to each respondent's residential CBG included population density (people/acre), employment density (jobs/acre), retail density (retail jobs/acre), land use mix index based on five sectors of employment (retail, office, industrial, service, entertainment), street network density (links/acre), distance to nearest transit stop (meters from the centroid of CBG to the nearest transit stop), transit access (whether the distance to the nearest transit is less than/equal to 3/4 of a mile or over), and living environment (urban, suburban, or rural).^{6,7} All variables are continuous variables, except the transit access variable (dummy) and the living environment variable (categorical). Of these variables, only four turned out to have some (even if modest) impact on the main outcomes of interest in our empirical model system, all in a dummy variable form. These variables are living environment (urban versus non-urban), population density (high versus not-high; a population density value of more than 20 individuals per acre is characterized as high population density), land-use mix, and retail density (high versus not-high; a retail density value of more than 0.5 retail jobs per acre is characterized as high retail density).

3.1.1.2 Demographic Variables

Table 1 provides descriptive statistics for the demographic variables. Overall, the sample exhibits characteristics that render it suitable for a modeling exercise such as that undertaken in this paper. The sample does reveal an over-representation of women (65.7% in the sample relative to the 50% reflected in the census population of the Austin-Round Rock, TX Metro area, as per U.S. Census Bureau (2018)) and young individuals aged 18-29 years (58.2% in the sample relative to 23.7% from the U.S. Census Bureau). In terms of education levels, again, our sample shows a markedly lower percentage of individuals who have completed high school or less (13.7% compared to 29.0% from the Census) and a higher percentage of individuals who have completed some college or technical school (34.6% relative to 25.0% from the Census). However, the distributions of those

⁶ The land-use mix index is a continuous variable between 0 and 1, as obtained from the U.S. EPA Smart Location Database. This index is computed using an entropy approach (see Ramsey and Bell, 2014 for details).

⁷ The living environment characterization is determined based on activity density, which represents the total number of jobs and dwelling units per unprotected acre for each CBG. Based on Ramsey and Bell (2014), CBGs with an activity density less than 0.5 activity units per unprotected acre of land are classified as rural, while those with activity densities higher than 6 units per unprotected acre are classified as urban; all other CBGs are classified as suburban.

with an undergraduate degree or a graduate degree are very comparable to those from the Census). Finally, in view of the fact that a good percentage (51%) of survey respondents are students (though 38% of these students are also employed), the sample is more representative of low-income households.

The sample skewness relative to the population may be attributed to a number of factors, including the social media component of the recruitment campaign, the financial incentive scheme, and the survey topic (all of which may be the reason for the over-representation of young individuals). This sample skewness implies that any descriptive statistics on the endogenous variables from the current sample cannot be used to characterize the Austin area adult population. However, there is no reason to believe that the individual level causal relationships (how changes in exogenous demographics impact the five endogenous outcomes of interest) estimated here would not be applicable to the larger adult population, because we are controlling for the exogenous demographic variables in our model specification. For example, safety concerns are likely to be different among different age groups, but we have included the “age” category variables as exogenous variables for the latent construct regression model as well as the main outcomes model to account for such demographic heterogeneity. In addition, our sample displays adequate variation across the range of values of each demographic variable, allowing us to test a variety of functional forms for the effects of these variables. Importantly, if the sampling strategy itself is not based on the endogenous variables (that is the sample corresponds to the case of exogenous sampling, as is the case with our sampling approach), an unweighted estimation approach provides consistent estimates, as well as yields more efficient estimates relative to a weighted procedure (see Wooldridge, 1995 and Solon et al., 2015 for an extensive discussion of this point). Overall, the combination of our exogenous sampling approach, as well as the adequate variation in the sample to test demographic effects at a fine level of resolution, implies that there is no reason to believe that the individual level relationships estimated from disaggregate models developed in this paper are not applicable to the larger population.

3.1.2 Latent Constructs

Four latent constructs representing tech-savviness, safety concern, variety-seeking lifestyle, and IPTT are used in our model system to explain the main outcomes of interest. The indicators used to extract information on each of these latent constructs are listed and presented in Figure 2.

The first latent construct, technology savviness, is a measure of how educated, well-informed, and experienced an individual is with technology. Tech-savvy individuals are likely to be more fascinated than their peers with new gadgets, automation, and technological advancement; in fact, earlier research has clearly established the strong positive link between tech-savviness and a ‘pro-AV’ outlook (for example, see Lavieri et al., 2017). As can be observed from Figure 2, the sample is pretty tech-savvy, as evidenced by a majority of individuals who state that they would like to be among the first to acquire new technology. Also, over 70% of the sample feels that learning how to use new technology is not frustrating to them, and that ubiquitous internet connectivity is important.

The second latent construct, AV safety concern, is “a potential barrier” for AV adoption (Nazari et al., 2018). The public remains wary about trusting a machine to take over the job of a human, especially in the context of putting human life in the hands of the machine. A particular concern is the reliability of sensors, equipment, and overall AV technology, especially in complicated traffic situations or edge cases (that is, situations that are challenging and highly improbable but not impossible). Indeed, Figure 2 shows that over 75% of respondents are in somewhat or strong agreement that technology reliability is a concern, while just over 25% state they would be (somewhat or very) comfortable sleeping in a vehicle and less than 20% indicate that they would be (somewhat or very) comfortable with an AV picking up/dropping off a child. The high level of wariness with AV technology is rather remarkable, given that the sample is highly educated. Overall, one would expect individuals with higher levels of safety-concerns to be more cautious in the use of AVs, even after having access to an AV.

The third latent construct is Variety Seeking Lifestyle (VSL). This represents “the individual’s interest in exploration, and openness to new experiences and changes” (Lavieri and Bhat, 2019a). In terms of AVs, VSL is used to capture one’s sense of exploration and adventure, as well as a need for diversity in activity opportunities. This latent construct has been widely used in the field of psychology to capture differences in individuals’ tendencies toward mode inertia (Rieser-Schüssler and Axhausen, 2012), and also in the use of ride-hailing (Alemi et al., 2018; Lavieri and Bhat, 2019a). Figure 2 suggests that the sample self-reports as being high in VSL, with over 80% stating that they like to try new and different things and over 70% indicating that they like the idea of variety in activity opportunities around their residence. The expectation is that variety-seeking individuals would be likely to make more trips and travel farther distances when AVs become available for use.

The last latent construct is Interest in Productive use of Travel Time (in short, IPTT). AVs offer the rider the potential to use time in new ways, as opposed to being focused on the road. According to surveys by Lavieri and Bhat (2019b) and Sharda et al. (2019), over 60% of adults agree that they “like to make productive use of my time when I travel”. This latent construct essentially captures the opportunity cost of travel time. Figure 2 indicates an overall positive tendency for IPTT in the sample. One might expect that individuals with a high IPTT may be suppressing trips today and traveling shorter distances because of the time sunk in driving. In the presence of AVs, such individuals can be expected to feel more unshackled and may potentially pursue more (and longer) trips.

3.1.3 Main Outcome Variables

Descriptive statistics of the five main outcomes of this paper are presented in Figure 3. The statistics for ALT (making additional local area trips) reveal that the sample loads more toward not making additional local trips in the presence of AVs (only about 40% say they are (somewhat or very) likely to make additional trips, while 45% fall on the other side of the neutral response. However, proceeding to the other outcomes, the propensity to travel farther to go shopping, to pursue leisure, and to make more long distance trips definitively loads more on the positive side

of neutral rather than the negative, in particular, over 50% of the individuals are in agreement that they would make more long distance trips.

The final descriptive ordered outcome reflects “How much longer would you be willing to commute (one way) in an AV?” A little over 20% indicate that they would not be willing to accept a longer commute, while less than 5% at the other extreme indicate that they would be willing to accept a travel time of over 30 minutes in an AV. A vast majority (over 60%) appear to be willing to accept between 5 to 15 minutes of additional travel time. The acceptance of a longer commute time may be the result of a combination of a willingness to travel longer in exchange for a more desirable work/living environment as well as the possibility that the opportunity cost of travel time gets reduced when traveling in an AV (Moore et al., 2020).

Overall, while the descriptive statistics from our sample cannot be generalized to the population at large, Figure 3 reinforces the findings from Zmud and Sener (2017) that AVs may not after all have a substantial impact on overall trip-making, although local area trips are likely to become longer (for all purposes, including the commute). The highest impact of AVs will, it appears, be on the number of long distance trips (with such trips increasing). Of course, these observations are in the aggregate; the emphasis of this study is to examine variations in the AV responses across population segments and geographies.

4. MODEL RESULTS

We explored a whole range of alternative specifications for the explanatory variables. For the continuous variables of respondent age, respondent’s household income, and population/retail density, a number of functional forms were tested, including a linear form, a dummy variable categorization, as well as piecewise spline forms. But the dummy variable specification turned up to provide the best data fit in all cases, and is the one adopted in the final model specification. In this dummy variable form, we tested many different finer categories, and progressively combined categories based on statistical tests and intuitive reasoning to yield parsimonious specifications.

The final model specification was obtained based on a systematic process of testing alternative combinations of explanatory variables based on statistical fit, combined with a healthy dose of intuition and parsimony considerations. In this final model specification, not all the included variables are statistically significant at a 95% confidence level. This is to acknowledge the small size of our estimation that may have led to the marginal significance of some of the variables, which nonetheless can help inform future investigations with larger sample sizes. Also, the procedure to construct continuous values of the latent constructs is based on estimating the loadings of each construct on the indicators. These loadings are not of primary interest in this paper and are available in the online supplement.

In the following section, we discuss the results obtained from the multivariate regression analysis for the latent constructs, and, in the subsequent section, we discuss the results of the MEM MORP model.

4.1 Latent Constructs

The effects of socio-economic and household characteristics on the four latent constructs (psychosocial variables) are presented in Table 2. As we will see in the next section, the latent constructs themselves, in turn, have a strong impact on the main outcomes, implying that there is a substantial mediating impact of individual-level characteristics on AV activity-travel responses. Any cells marked "--" in Table 2 indicate that the corresponding row variable has no impact on the column latent construct.

The results in Table 2 indicate that women, relative to men, are less tech-savvy and are more concerned with safety. These results are well established in the ethnography and transportation literatures, attributed to the gender-gap in technology access in the digital age and the generally higher risk-averseness among women (see Mushtaq and Riyaz, 2020; Acheampong and Cugurullo, 2019; Asmussen et al., 2020). The latter result is based on the notion of "risk as feelings" (see also Loewenstein et al., 2001), which states that our instinctive and intuitive emotions dominate reasoned approaches when faced with risk (in our case, new AV technology constitutes a risk). Further, since women experience feelings of nervousness and fear more than men in anticipation of negative outcomes when confronted with risks, the net result may be a heightened AV safety concern among women.

In terms of age effects, younger individuals are generally more tech-savvy, less concerned about safety, predisposed toward a variety-seeking lifestyle, and more interested in the productive use of travel time, compared to their older peers. All these findings are intuitive and have support in earlier studies. Younger individuals (especially the so-called millennials and those of the Z-generation) have grown up in an era of "digital bloom" while older adults have had to adapt to the technological evolution at a time in their lives when the ability to 'learn' and adapt takes greater effort (Correa et al., 2010; Hamid and Cheng, 2013). The heightened safety concern in older individuals has been associated with nervousness and a lack of confidence, as well as a general cynicism with the functional capability and reliability of new gadgets (Peretti-Watel et al., 2009; Dohmen et al., 2011). In terms of variety-seeking, the psychology and personality literature identify that younger individuals are more open to new experiences and are more likely to ascribe high value to new sensation and stimulation, seeking variety in their daily lives (Milojev and Sibley, 2017). Additionally, younger individuals are more adept and familiar with ICT devices, enabling them to engage in a wider variety of activities while traveling, leading to a higher IPTT.

The level of education and employment status are also found to be significant determinants of the latent constructs. Highly educated individuals (with at least a Graduate degree) are more likely to use their travel time productively, while employed individuals are less concerned about AV safety and are observed to have higher IPTT levels of interest in the productive use of travel time. The lower safety concern with AVs among employed individuals is presumably because these individuals experience or witness unexpected incidents on a more regular basis in human-driven traffic during their daily commutes, increasing their trust in machine-driven technology. The results in Table 2 also suggest that students exhibit lower propensity for variety-seeking behavior compared to non-students, an intriguing result that needs further investigation.

Finally, household income and presence of children (less than 16 years of age) are also key determinants of the latent constructs. Individuals belonging to a high income household exhibit higher levels of tech-savviness, lower levels of concerns about AV safety and a higher degree of variety-seeking lifestyle (for the highest income group), while individuals in households with children have a heightened safety concern and a lower IPTT. The finding on safety concern is logical; after all, one of the indicators in our safety concern construct is the statement “I would feel comfortable having an AV pick up/drop off children without adult supervision”.

The correlations in the unobserved factors across the latent constructs are presented toward the bottom of Table 2 and are not very statistically significant. The only significant correlation beyond the 95% confidence level is the negative correlation between safety concern and IPTT. Intrinsically safety-concerned individuals are associated with a lower IPTT, presumably because their mistrust of AV technology would lead them to pay attention to the road even if in an AV.

4.2 Main Outcomes

Table 3 presents the coefficients estimated for the main outcomes (ALT, TDS, TDL, ALDT and CTT). These coefficients refer to the impact on the underlying propensities characterizing the outcomes (in the usual ordered-response fashion). These propensities get mapped to the actual observed ordinal category responses through the threshold values (presented toward the bottom of Table 3; the thresholds do not have any substantive interpretations). Any cells marked “--” in Table 3 indicate that the corresponding row variable has no impact on the column outcome variable.

4.2.1 Effects of Latent Constructs

The latent constructs have a highly significant impact on all the main outcomes, underscoring the importance of considering psycho-social factors when studying potential activity-travel behavior changes in response to AVs. Higher tech-savviness is associated with a lower proclivity for traveling farther for leisure in the presence of an AV, perhaps a reflection of the notion that technological advancement has brought us “digitally close but physically apart”. In fact, Downey and Gibbs (2020) suggest in their study that there is an inverse relationship between face-to-face social skills and time-expenditure on online gaming and social networking. While these gaming and virtual networking activities can enhance tech-savviness, it also can lead to a lower inclination for in-person leisure in general, with no motivation to travel farther simply because of a hands-free means to get to the leisure location.

Other results pertaining to the latent construct effects are in line with expectations. Unsurprisingly, the latent construct related to AV safety-concern significantly diminishes trip-making propensity across all five dimensions, while variety-seeking lifestyle (VSL) is positively related to all the ordered outcomes except for increase in commute travel time or CTT (for which there is no significant effect). This latter result is to be expected, because the commute location is fixed in the short term, and thus there is no reason that VSL should impact CTT in any way. However, for discretionary purposes (such as shopping, eat-out, social, recreational, and road trips), a variety-seeking individual, unshackled from the need to drive, is likely to be willing to

travel more and travel farther to enjoy and seek new and varied experiences. Finally, in the group of latent construct effects, higher levels of IPTT have a positive effect on all activity-travel dimensions. In the case of commute travel time, the impact of IPTT is through an interaction with the “employed” variable suggesting that IPTT is a key determinant for willingness to increase commute times for employed individuals, but not students (as discussed earlier, commute was defined as travel to the workplace for employed individuals and travel to the study place for students; for a person who is both a student and employed, travel to the study place constitutes the commute). A plausible reason for this last result is that employed individuals may be more time-poor than students, especially in the context of their lifecycle and familial responsibilities.

It is possible to evaluate the relative effects of the latent variables on the propensities for each main outcome. To do so, we consider the standard deviations of each of the latent constructs (computed across individuals). Then, by multiplying this standard deviation by the coefficients on the latent constructs in Table 3, we obtain the relative magnitude effects of the latent variables. The standard deviations are 0.236, 0.304, 0.095, and 0.109 for the tech-savviness, safety-concern, variety-seeking, and IPTT constructs, respectively. Examining these standard deviations along with the coefficients in Table 3 clearly indicates that safety concern is the psycho-social variable that dominates the other psycho-social variables on how individuals will respond to AVs in terms of activity-travel pattern changes. IPTT is a relatively distant second, while variety-seeking is third and tech-savviness has the lowest impact.

4.2.2 Effects of Individual-Level Characteristics

The individual-level effects in Table 3 provide the direct effects of socio-demographics on the underlying propensities of the main outcomes, after controlling for their indirect (mediated) effects through the latent constructs. As may be observed from the table, gender and age dominate in terms of direct effects. For a man and woman with the same latent construct values, the woman is more inclined to make more trips and travel farther for non-commute purposes. This gender difference is consistent with the notion that women are more time-poor than men, with much of the familial responsibilities continuing to rest squarely on the shoulder of the woman (see Bernardo et al., 2015; Cerrato and Cifre, 2018). Indeed, Donner (2020) suggests that any increasing support for women in the workforce among men may not necessarily be tied solely to progressive thinking, but may be at least as much due to the notion of “money buffering” for economic “rainy days”. Overall, this continued traditional gender asymmetry in task allocation can lead to social exclusion among women, who are unable to undertake the leisure activities they might want to pursue. However, in the presence of AVs, women may seize the opportunity to pursue some of these currently suppressed desires. Besides, women generally tend to be more wary of online shopping and are more likely to travel to the store to do their shopping compared to men (Kraljević and Filipović, 2017), as well as tend to place more value on community and social connections (see Fraikue, 2016). An important issue to keep in mind is that the gender effect discussed above is based purely on the direct effect. The indirect mediating effect of gender comes into play in affecting the main outcomes through the tech-savviness and safety concern effects of Table 2. For

example, the net effect of being a woman on the propensity to make additional local trips (ALT) is 0.332 (direct effect) $-0.904 \times 0.586 = -0.198$. Thus, overall, women have a lower propensity for ALT than men; that is, the negative safety concern indirect effect for women dominates the direct additional trip-making desire effect. In fact, the negative safety concern among women dominates the direct effect for all the activity-travel dimensions.

The effect of age in Table 3 indicates that, after controlling for the latent constructs, younger individuals (especially those in the 18-29 year age group), have a higher propensity to make more trips, travel farther for non-commute purposes, as well as be willing to incur a higher commute time. At least three reasons may explain these results. First, younger adults (especially those below the age of 30 years) generally participate less and allocate relatively limited time to household responsibilities compared to older individuals (Craig and Powell, 2018). Second, the human development and family sciences literature (see, for example, Green et al., 2001; Kim and Shen, 2020) indicates that younger adults desire and maintain more expansive and geographically dispersed social networks as a vehicle to pursue leisure outside the home, while older adults prefer small-sized social networks in close proximity to their residence as a means to alleviate feelings of loneliness. Third, the time-use literature (see Paillard-Borg et al., 2009; Bhat et al., 2020) has established that, because of physical mobility challenges and other reasons, reading and other activities at home dominate the time-use of older adults. These three current tendencies, in combination, can get heightened in an AV-scenario, resulting in the estimated age effect on the non-commute dimensions in Table 3. For the commute dimension (CTT), the results reveal that younger adults are more willing to commute longer if they have access to an AV. Younger adults are typically more willing to move residences to act on any residential location cognitive dissonance issues they perceive with their current living conditions, as well as are more prepared to changes jobs compared to middle and older aged populations (Lu and Gursoy, 2016; U.S. Bureau of Labor Statistics, 2018). These tendencies perhaps are getting accentuated when they do not have to drive. Interestingly, the direct effects just discussed for age are substantially reinforced by the indirect mediated effects of age through the latent constructs for all the activity-travel dimensions. That is, in the overall, because of both direct and indirect effects, younger individuals have a higher propensity for all the five activity-travel dimensions in Table 3, relative to their older peers.

Household income has a direct negative effect on the trip distance to shop (TDS) dimension. That is, individuals from higher income households (with annual income greater than \$100,000) indicate a lower propensity to travel farther for shopping activities if an AV were available to them. Another interpretation of this result is that lower income households (with annual incomes less than or equal to \$100,000) have a higher propensity to travel farther for shopping activities, presumably because such individuals are among the most time-poor as well as actively comparison-shop for the most affordable option. An AV would contribute to alleviating the former time-poverty issue for individuals from lower income households, while facilitating the latter. However, when taken in combination with the indirect mediating effects of household income, the overall effect of household income on TDS does turn positive.

4.2.3 Built-Environment Factors

The effects of the BE factors are all direct effects on the activity-travel dimensions. The results for these variables mirror the setting in the current non-AV setting, with (a) urban living leading to more local area trip-making, (b) residence in higher population density, richer land-use mix, and higher retail density areas resulting in shorter local trips (Naess, 2012; Singh et al., 2018). All these effects get reinforced with AV access. The increased AV-based trip-making in urban areas may be a cause for concern, because it can further increase traffic congestion in these areas. However, Lavieri et al. (2017) find that AV adoption is more likely to gravitate toward a sharing model in dense urban areas, which can lead to a more efficient fulfillment of trip desires with a smaller VMT footprint (because a sharing model obviates the need for to-and-fro movements associated with travel in private AVs). Besides, dense areas are also more conducive to pooling multiple riders, both from a customer standpoint (lower delays due to pooling) as well as a provider perspective (because of the density of demand). In the survey used for the current study, AV access was presented in an agnostic way in eliciting activity-travel responses, but future studies can emphasize the use paradigm (private car use, or private shared AV use, or pooled shared AV use) some more. Overall, the BE effects from this study and other related studies suggest that, independent of AV introduction, there is continued value in moving toward the consideration of neo-urbanist policies, such as densification of neighborhoods and mixed land-use planning, that can promote pooling as well as short distance trips.

4.2.4 Unobserved Correlation

All the error correlations (across the propensities of the five main outcome variables) are highly statistically significant (see bottom of Table 3). That is, unobserved individual-level factors that increase the propensity along any one dimension also increase the propensity along the other four dimensions. As one would expect, the positive correlations are particularly high among the propensities of local area trip-making and trip-lengths (that is, between the ALT, TDS, and TDL dimensions), with substantial correlations also between these non-commute activity dimensions and the additional long distance road trips. The correlations with the commute travel time dimension are also positive, though smaller in magnitude.

4.3 Model Goodness of Fit

The performance of the proposed model may be compared with a traditional model that does not consider latent constructs and also ignores any type of dependency between the outcomes. To estimate this traditional model, we do not consider the latent constructs in the ordered outcome models; however, to put things on an equal footing for comparison, we include all the determinants of the latent constructs as explanatory variables in the ordered outcomes (that is, we do not only include all the exogenous variables appearing in Table 3, but also all the exogenous variables appearing in Table 2). We then compute the log-likelihood of this traditional model and compare this to that of our proposed model. We also compute the log-likelihood for the constants-only

model (considering only the thresholds) for the five ordered outcomes. Our proposed model and the traditional model (being non-nested) may be compared using a predictive Bayesian Information Criterion (BIC) statistic [= $-\mathcal{L}(\hat{\theta}) + 0.5(\# \text{ of model parameters}) \log(\text{sample size})$] ($\mathcal{L}(\hat{\theta})$ is the predictive log-likelihood at convergence). The model with a higher BIC statistic is the preferred model. In addition to the comparison using the BIC value, an informal predictive non-nested likelihood ratio test may be used to compare the models. The adjusted likelihood ratio index of each model of the models is first computed with respect to the log-likelihood with only the constants in the ordered outcome models.

$$\bar{\rho}^2 = 1 - \frac{L(\hat{\theta}) - M}{L(c)} \quad (1)$$

where $L(\hat{\theta})$ and $L(c)$ are the predictive log-likelihood functions at convergence and at constants, respectively, and M is the number of parameters (excluding the constants) estimated in the model. If the difference in the indices is $(\bar{\rho}_2^2 - \bar{\rho}_1^2) = \tau$, then the probability that this difference could have occurred by chance is no larger than $\Phi\{-[-2\tau L(c) + (M_2 - M_1)]^{0.5}\}$, with a small value for the probability of chance occurrence suggesting that the difference is statistically significant and the model with the higher value for the adjusted likelihood ratio index is preferred.

We also evaluate the data fit of the two models intuitively and informally at both the disaggregate and aggregate levels. To compare the accuracy in predictions between the two models, we compute the average probability of correct prediction for both the models at the observed ordered levels. At an aggregate level, to facilitate a more tractable comparison between the two models, the five-point rating scale is converted to a binary scale (by combining ratings of 0 through 3 into one level, and 4 and 5 into another level) and only bivariate pairings of the five outcomes are considered in the comparison (e.g., ALT-TDS; ALT-TDL; ALT-ALDT; and so on). Predictions from the two models are compared to observed numbers of observations falling into each of the bivariate combinations. The absolute percent error (APE) in prediction is computed for each bivariate combination category and compared between the joint and independent models.

The disaggregate fit measures are provided in Table 4. The proposed model has a substantially higher log-likelihood value at convergence compared to the traditional model, indicating a superior fit; additionally, the BIC values also favor the proposed model over the traditional model. From the informal non-nested likelihood ratio statistics value provided in the penultimate row of Table 4, it can be inferred that the probability of the adjusted likelihood ratio index difference between the proposed and the traditional model occurring by chance is literally zero. The average probability of correct prediction (see the last row of Table 4) for our model is significantly higher (by more than 10 times) than that of the independent model. This probability value for our proposed model may still appear to be low, however, given that the five ordered outcomes with five levels each can produce a total of $5^5 = 3125$ combinations of possible outcomes, the value of 0.0205 is about 64 times the probability of correct prediction based on a random choice assignment ($1/3125 = 0.00032$).

The aggregate data fit measures are presented in Table 5. At the aggregate level, the predicted shares from the proposed model for each of the combinations presented in the table is superior to the traditional model in terms of the absolute percentage error (APE). The weighted average APE considering all the combinations in the table is presented in the last row of Table 5. Once again, the proposed model convincingly outperforms the traditional model, with a weighted APE of just over 3% compared to the weighted APE of more than 30% for the independent model.

Overall, the disaggregate and aggregate data fit measures clearly highlight the importance of incorporating psycho-social variables, as well as modeling multiple activity-travel dimensions all at once, when investigating AV effects (rather than, as is commonly done, ignoring psycho-social variables and modeling different dimensions of activity-travel as isolated and disjointed choices).

4.4 Average Treatment Effects (ATEs)

The results in Table 2 and 3 may be translated to ATEs of the effects of each of the individual-level and BE variables on the activity-travel dimension outcomes. ATE is a metric that computes the impact on a downstream posterior variable of interest due to a treatment that changes the state of an antecedent variable from A to B . For example, if the intent is to estimate the “treatment” effect of age on ALT choice, A can be the state where an individual is older than 64 years, and B can be the state where the individual is 29 years or below. The impact of this change in state is measured in terms of the change in the shares of the outcomes of interest between the case where all individuals in the dataset are in state A and the case where all the individuals in the dataset are in state B . Direct as well as mediating effects of age through the psycho-social variables are considered.

For presentation ease, in this paper, we only report the ATEs for a change from the lowest extreme to the highest extreme for the antecedent variable (for example, we focus only on the change from the base age category of 65+ to 18-29 years). For the land-use continuous variable, we change from the base value of the 25th percentile to the 75th percentile. Also, we compute the change in shares for the combined “somewhat likely” and “very likely” categories for the ALT, TDS, TDL, and ALDT outcomes (we will refer to this combined category as the “likely” category), and only for a combined “between 15-30 additional minutes” and “more than 30 minutes” category for the CTT dimension (we will refer to this combined category as the “more than 15 minutes” category).

The overall ATE effects for all the dimensions are presented in Table 6. Consider the ATE effect of age on the ALT dimension in Table 6, which shows a value of 0.290. This implies that if 100 older individuals were replaced by 100 younger individuals, 29 additional individuals (of the 100) would likely make additional local trips with AV access. Other entries may be similarly interpreted. Overall, gender, age, and income have the highest magnitude of effects, with women, older individuals, and low-income individuals less likely to increase their activity-travel intensity across all five dimensions. In particular, individuals in the youngest age group of 18-29 years are the most likely to increase their activity-travel if they have access to AVs, and this is particularly

so for long distance trip-making. Not surprisingly, individuals from high income households are most likely to increase their trip distance for leisure activities, relative to other demographic groups. BE effects are also quite substantial; urban living contributes to a likely increase in local area trips in an AV environment, while higher density and land-use mix all lead to a decrease in trip lengths and the commute.

Table 6 provides insights into the total effect of the individual-level characteristics. However, for policy analysis purposes, it is more insightful to understand the conduit (pathway) of this total effect through a partitioning into a direct effect and the following four psycho-social size sub-effects: tech-savviness effect, safety concern effect, variety-seeking effect, IPTT effect, and the remaining direct effect. To conserve on space, we provide these partitioned ATE effects for only the ALT dimension in Table 7, and relegate the tables corresponding to the TDS, TDL, ALDT and CTT dimensions to the online supplement. The last column of Table 7 is identical to the column entitled “ALT Additional Local Trips” in Table 6, corresponding to the total effect. The sub-effect categories are labeled in a way that a positive change in the sub-effect would generally lead to a positive increase in the propensity of trip-making in an AV environment. Thus, the sub-effects are labeled as “Tech-savviness increase”, “Safety concern decrease”, “Variety-Seeking Lifestyle increase” and “IPTT increase”. The “% contribution by mediation through...” columns are then to be interpreted as follows. The value of 34% in the column for “Safety Concern decrease” for the age variable in Table 7 indicates that, in terms of magnitude, 34% of the sum of the magnitude contributions of each sub-effect (ignoring directionality) to the ATE change along the ALT dimension is due to the safety concern sub-effect. A positive percentage value of 34% suggests that the change from the base category (age greater than equal to 65 years) to the “treatment” category (age 18-29 years) would lead to an increase in the “Safety Concern decrease” effect (that is, this change leads to an increase in AV trip-making propensity because individuals in the 18-29 years age category are likely to be less concerned about the safety aspect of AVs). The other entries in the same row of “age treatment” indicate that “Variety-Seeking lifestyle increase” contributes 3%, “IPTT increase” contributes 16%, and the direct effect contributes the remainder of the 47% of the ATE change (all are positive percentages indicating that these sub-effects lead to an increase in the AV trip-making propensity along the ALT dimension; the sum of all sub-effects will total 100% for each row). Other entries may be similarly interpreted.

The results in Table 7 indicate that the effects of gender, age, and income, which, as discussed earlier, have the highest overall magnitude of effect on ALT, are dominated by the safety concern latent construct (besides the direct effect of the age treatment). As we discuss more in the next section, this suggests that the best way to position AV benefits to women, older individuals, and low income individuals is to allay their safety concern, rather than investing in tech-savviness efforts or highlighting productivity benefits in an AV. This is also true for employed individuals and parents, as highlighted by the 52% and 59% magnitude contributions of the safety concern sub-effect for these variables. But, for these two latter groups of individuals (and, to a lesser extent, for older individuals), highlighting the productivity benefits in an AV should also produce tangible results. Interestingly, our results suggest that interventions aimed at increasing tech-savviness

considerations will not have an impact on ALT (in fact, other than for a marginal effect associated with travel distance for Leisure (TDL), as may be observed from Table 3 in the online supplement, tech-savviness has little bearing on the travel dimensions).

5. CONCLUSIONS AND POLICY IMPLICATIONS

The current paper develops an analytic system to investigate the effects of AV availability on multiple dimensions of activity-travel behavior, based on a direct survey-based modeling approach. In particular, the model uses individual socio-demographics, BE variables, as well as psycho-social variables (in the form of latent psychological constructs) as determinant variables to directly explain likely AV impacts on five dimensions of short-term activity-travel choices: (1) Additional local area trips (ALT) generated, (2) Trip distance to shop or eat-out activities in the local area (TDS), (3) Trip distance to leisure activities in the local area (TDL), (4) Additional long distance road trips (>75 miles one-way) beyond the local area (ALDT), and (5) Commute travel time (CTT). The model system includes a confirmatory factor analysis step, a multivariate linear regression model for the latent constructs, and a multivariate ordered-response model for the five main outcomes just listed. Data from a 2019 Austin area survey of new mobility service adoption and use forms the basis for the current study, which focuses on investigating variations in the AV responses across population segments and geographies rather than on aggregate macro-level descriptive statistics of the stated AV responses. In this regard, while aggregate sample statistics will not, in general, represent population response characteristics because of the convenience sample used, there is no reason to believe that characterizing and quantifying the effects of individual-level differences in response behavior to AVs from a convenience sample will provide inappropriate results, as long as exogenous demographic variables are controlled for in the model specification and there is adequate variation in the sample in these demographic variables (as in the case of the current study).

Our individual-level results underscore the importance of considering psycho-social variables (latent constructs) in models of mobility and activity participation, in addition to typical socio-demographic and built environment characteristics. While a host of psycho-social variables were considered, the four that turned out to be significant determinants of the five activity-travel outcomes included tech-savviness, safety concern, variety-seeking lifestyle, and IPTT. Of these psycho-social variables, safety concern appears to be the single most important determinant of stated activity-travel responses in the presence of an AV, with IPTT coming in a distant second. Additionally, the results clearly indicate substantial heterogeneity in the activity-travel responses to AVs across demographic groups and geographic areas. From a broader perspective, our investigation raises three specific issues that need more attention as we plan for an age of AVs.

Planning for Equitable Transportation: AVs have been touted as opening up new mobility opportunities for older adults in particular, who may have limited driving ability. However, based on the overall ATE of the age variable in Table 6, our analysis suggests that, in terms of mobility enhancements, it will be the younger adults who will harness the full potential of a drive-free travel environment by pursuing their desires for out-of-home activity participation, even if far away.

While some of the general reticence to travel among older adults may simply be based on personal preferences, there is evidence of social exclusion among older adults (Levitas et al., 2007; Walsh et al., 2017). That is, desires of older adults to go places gets suppressed, because of a lack of affordable and/or convenient options to “get there”, leading to feelings of loneliness and exclusion. In this context, AVs have been looked upon as mobility and quality of life enhancers for these older adults. But, our analysis suggests that, unless appropriate actions are taken, AVs will not deliver this much-touted mobility benefits to older adults and will likely widen the relative schism between the young and the old in terms of accessibility to activity opportunities. Further, the partitioning of the overall ATE effect for the age variable suggests that this reluctance for AV use among older adults has a substantial direct effect that is not related to tech-savviness or safety concern, or variety-seeking or IPTT. Rather, this direct effect may be associated with the sensory, cognitive, and physiological uniqueness of older adults. For instance, it is well established in the gerontology and psychology literature that ageing is typically associated with a decline in cognitive ability (such as memory, attention, and verbal and visual/spatial information retention; see Deary et al., 2009; Boot et al., 2013). This suggests that for AVs to be designed with older adults in mind, the human-machine interface (HMI) needs to be simple, uncluttered, voice-activated, and with multi-modal audio/visual interfaces for high priority HMI instructions (see Morgan et al., 2017). Similar to the asymmetric benefits to younger adults, our results related to the total effect in Table 6 and magnitude of the direct effect in Table 7 also suggest that women and low-income individuals may be less positively impacted by AVs, at least in terms of pursuing trips of their desire to places of their desire. In the context of the result related to income, the suggestion in our results is a growing divide between the “haves” and the “have-nots” (Creger et al., 2019). For example, the “haves” may purchase luxurious recreation vehicles as AVs, given the amount of time they anyway will spend inside without driving. Thus, the vehicles of high-income individuals may occupy more roadway space and contribute more to delays than the smaller vehicles of low-income individuals. This uneven externality of travel implies that the lower income individuals will bear more cost per mile, unless per mile use charges based on vehicle size, or regulations regarding vehicle size, are introduced in the AV market.

Addressing Safety Concerns: Safety concern is a dominant reason for the lower stated use of AVs among older individuals, women, low income individuals, unemployed individuals, and those with children. These are exactly the same groups who also are rather marginalized in terms of being mobility-poor, time-poor, or money-poor. In this regard, our study is perhaps the first study that explicitly connects the need to address AV-related safety concerns to addressing AV transportation equity issues. This highlights the value of considering psycho-social variables in AV response models. Policy actions to reduce safety concerns among marginalized groups as well as AV design to quell some of these concerns are important. For example, Lee and Mirman (2018) suggest that women, in particular, are more concerned about child safety, including whether their child would be buckled up securely. Women also are averse to giving up their driving control to a machine because of concerns associated with the ability of AVs to navigate environments with aggressive

drivers. Successful demonstrations of AV ability at women-dominated professional and social locations, as well as design features that automate the buckling-up of children in a safe manner, may be avenues to allay the safety concerns of women. As with women, older adults are also not trusting of technology to act reliably, especially in life-critical situations. As a result, and also because of habit formation and reluctance to change, older adults are less likely to use AVs that, ironically, could benefit them the most. By underscoring the safety features, demonstrating the reliability of these safety features, as well as appealing to older adults' need for keeping the "spark" going in their lives by continuing to go places and seeing the world (Levy, 2020), AV benefits in terms of mobility enhancement can be brought to them. Importantly, if older adults are to perceive AVs as a means to better their mobility opportunities, their distrust of technology needs to be dispelled through safety awareness campaigns as well as customized HMI design features. The ATE effects related to "presence of children" further underscore the importance of addressing safety concerns. Parents (regardless of gender) are another group who tend to be socially excluded and time poor (see, for example, Bernardo et al., 2015), and their mobility may be enhanced through AVs by addressing their safety concerns.

Managing Urban Congestion: While the manufacturing and marketing sectors focus on the uptake of AVs, transportation planners and land-use authorities need to find a way to sustainably control the use of AVs. Our results suggest that urban dwellers are likely to increase their trip-making propensity (locally) in an AV-accessible future. Due to the framing of the question in our survey, we are unable to distinguish between private AV use or shared AV (SAV) use or pooled SAV use (PSAV) (since the question only asked the respondents to imagine having access to an AV either by "owning, hiring or sharing"). However, there is the real possibility of a substantial increase in trip-making and urban congestion levels, unless current trips as well as future additional trips in urban areas gravitate toward a PSAV use paradigm. Another issue with AVs (especially with the privately owned ones) is the generation of empty trips, especially if the trips are within reasonable short distances within an urban region. These empty trips are generated when AVs return home after a drop, either to avoid parking charges or to serve other members of a household. Road use pricing charges, with subsidies or waivers if PSAV is used, may be an approach to curb traffic congestion. To restrict AV use over shorter distances in the case of SAVs (to avoid draw away from non-motorized modes of transportation), a non-linear-in-distance fare policy may be implemented. Supplementing such policies with residential densification, a good land use-mix, and high retail density can lead to containing the number of trips made, while also "compacting" the geographic footprint of trips (and vehicle miles of travel). This result is encouraging and reinforces the notion that neo-urbanist design of communities and the built environment should remain as an important transportation demand management instrument in the toolbox of transportation and community planners. Also, to avoid cross-substitution effects between pooled SAV (PSAV) and transit, cities may consider an integrated (both in terms of service as well as payment) PSAV and transit service, with PSAV serving as the "first-last" mile connector. This

kind of an integrated service may be promoted through deep subsidies for pooled rides, tied to the resulting reduction in overall externality costs.

Overall, our results underscore the importance of modeling multiple activity-travel dimensions all at once, when investigating AV effects. In addition, our results highlight the value of using psycho-social latent constructs in studies related to the use of current and emerging mobility services, both in terms of improved prediction fit as well as proactive strategies to design equitable, safe, and community-driven AV systems. There is likely to be considerable heterogeneity in how different population groups view and respond to AVs, and it is imperative that AV campaigns and AV design consider such heterogeneity so as to not “leave anyone behind”.

As with any study, this study too has limitations. For one, like all other survey-based studies of AV behavior, the reliability of the responses provided by individuals (and, therefore, the ecological validity of our analysis) may be in question. This is because AVs continue to remain abstract and psychologically distant, conjuring up different images for different people. Future research would certainly benefit from introducing more realism in the response elicitation mechanism, such as the use of virtual reality experiments within stated preference elicitations (see Voinescu et al., 2020). Also, the questions used in the modeling effort did not incorporate considerations related to the costs of owning, maintaining, and operating AVs, which may have led some respondents to believe that the costs associated with owning AVs are similar to that associated with owning regular vehicles, thus influencing their stated level of use of AVs in terms of trip-making and trip distances.

ACKNOWLEDGMENTS

This research was partially supported by the U.S. Department of Transportation (USDOT) under Grant DTRT13GUTC58 for the Data-Supported Transportation Operations and Planning (D-STOP) University Transportation Center and Grant 69A3552047138 for the Center for Automated Vehicles Research with Multimodal AssurEd Navigation (CARMEN) University Transportation Center, and the UT Good Systems Grand Challenge. The authors are grateful to Lisa Macias for her help in formatting this document, and to two anonymous reviewers who provided useful comments on an earlier version of this paper.

REFERENCES

- Acheampong, R.A., and Cugurullo, F., 2019. Capturing the behavioural determinants behind the adoption of autonomous vehicles: Conceptual frameworks and measurement models to predict public transport, sharing and ownership trends of self-driving cars. *Transportation Research Part F*, 62, 349-375.
- Ajzen, I., 1991. The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, 50(2), 179-211.
- Alemi, F., Circella, G., Mokhtarian, P., and Handy, S., 2018. On-demand ride services in California: Investigating the factors affecting the frequency of use of Uber/Lyft. Presented at the *97th Annual Meeting of the Transportation Research Board*, Washington D.C.
- Arvin, R., Khattak, A.J., and Qi, H., 2021. Safety critical event prediction through unified analysis of driver and vehicle volatilities: Application of deep learning methods. *Accident Analysis & Prevention*, 151, 105949.
- Ashkrof, P., Homem de Almeida Correia, G., Cats, O., and van Arem, B., 2019. Impact of automated vehicles on travel mode preference for different trip purposes and distances. *Transportation Research Record*, 2673(5), 607-616.
- Asmussen, K.E., Mondal, A., and Bhat, C.R., 2020. A socio-technical model of autonomous vehicle adoption using ranked choice stated preference data. *Transportation Research Part C*, 121, 102835.
- Astroza, S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Lavieri, P.S., and Dias, F.F., 2017. Analysis of the impact of technology use on multimodality and activity travel characteristics. *Transportation Research Record: Journal of the Transportation Research Board*, 2666(1), 19-28.
- Bernardin Jr, V.L., Mansfield, T., Swanson, B., Sadrsadat, H., and Bindra, S., 2019. Scenario modeling of autonomous vehicles with trip-based models. *Transportation Research Record: Journal of the Transportation Research Board*, 2673(10), 261-270.
- Bernardo, C., Paleti, R., Hoklas, M., and Bhat, C.R., 2015. An empirical investigation into the time-use and activity patterns of dual-earner couples with and without young children. *Transportation Research Part A*, 76, 71-91.
- Bhat, C.R., 2014. The composite marginal likelihood (CML) inference approach with applications to discrete and mixed dependent variable models. *Foundations and Trends in Econometrics*, 7(1), 1-117.
- Bhat, C.R., 2015. A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. *Transportation Research Part B*, 79, 50-77.
- Bhat, C.R., Mondal, A., Asmussen, K.E., and Bhat, A.C., 2020. A multiple discrete extreme value choice model with grouped consumption data and unobserved budgets. *Transportation Research Part B*, 141, 196-222.
- Boot, W.R., Champion, M., Blakely, D.P., Wright, T., Souders, D.J., and Charness, N., 2013. Video games as a means to reduce age-related cognitive decline: Attitudes, compliance, and effectiveness. *Frontiers in Psychology*, 4, 31.
- Cerrato, J., and Cifre, E., 2018. Gender inequality in household chores and work-family conflict. *Frontiers in Psychology*, 9, 1330.
- Chee, P.N.E., Susilo, Y.O., and Wong, Y.D., 2020. Determinants of intention-to-use first-/last-mile automated bus service. *Transportation Research Part A*, 139, 350-375.

- Childress, S., Nichols, B., Charlton, B., and 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.
- Correa, T., Hinsley, A.W., and De Zuniga, H.G., 2010. Who interacts on the web?: The intersection of users' personality and social media use. *Computers in Human Behavior*, 26(2), 247-253.
- Craig, L., and Powell, A., 2018. Shares of housework between mothers, fathers and young people: Routine and non-routine housework, doing housework for oneself and others. *Social Indicators Research*, 136(1), 269-281.
- Creger, H., Espino, J., and Sanchez, A.S., 2019. Autonomous vehicle heaven or hell? Creating a transportation revolution that benefits all. The Greenlining Institute. http://greenlining.org/wp-content/uploads/2019/01/R4_AutonomousVehiclesReportSingle_2019_2.pdf. Accessed July 30, 2020.
- Davidson, P., and Spinoulas, A., 2015. Autonomous vehicles: what could this mean for the future of transport. Australian Institute of Traffic Planning and Management (AITPM) National Conference, Brisbane, Queensland.
- Davis, F.D., 1989. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319-340.
- Dawid, H., and Delli Gatti, D., 2018. Chapter 2 - Agent-based macroeconomics. *Handbook of Computational Economics*, 4, 63-156.
- de Almeida Correia, G.H., Loeff, E., van Cranenburgh, S., Snelder, M., and 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*, 119, 359-382.
- Deary, I.J., Corley, J., Gow, A.J., Harris, S. E., Houlihan, L.M., Marioni, R.E., Penke, L., Rafnsson, S.B., and Starr, J.M., 2009. Age-associated cognitive decline. *British Medical Bulletin*, 92(1), 135-152.
- Dias, F.F., Nair, G.S., Ruiz-Juri, N., Bhat, C.R., and Mirzaei, A., 2020. Incorporating autonomous vehicles in the traditional four-step model. *Transportation Research Record: Journal of the Transportation Research Board*, 2674(7), 348-360.
- Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3), 522-550.
- Donner, F., 2020. The household work men and women do, and why. *The New York Times*, <https://www.nytimes.com/2020/02/12/us/the-household-work-men-and-women-do-and-why.html>. Accessed June 14, 2020.
- Downey, D.B., and Gibbs, B.G., 2020. Kids these days: Are face-to-face social skills among American children declining?. *American Journal of Sociology*, 125(4), 1030-1083.
- Duhigg, C., 2012. *The Power of Habit: Why we do what we do in life and business*. Random House, New York.
- Foroudi, P., Gupta, S., Sivaram, U., and Broderick, A., 2018. Investigating the effects of smart technology on customer dynamics and customer experience. *Computers in Human Behavior*, 80, 271-282.
- Fraedrich, E., Heinrichs, D., Bahamonde-Birke, F.J., and Cyganski, R., 2019. Autonomous driving, the built environment and policy implications. *Transportation Research Part A*, 122, 162-172.

- Fraikue, F.B., 2016. Reasons for eating out and socio-demographic characteristics of customers. *Proceedings of INCEDI 2016 Conference*, Accra, Ghana, August 29-31, 2016.
- Ge, Y., Ranjbari, A., Lewis, E.O.C., Barber, E., and MacKenzie, D., 2019. Defining psychometric variables related to use of autonomous vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, 2673(12), 655-669.
- Gifford, R., and Nilsson, A., 2014. Personal and social factors that influence pro-environmental concern and behaviour: A review. *International Journal of Psychology*, 49(3), 141-157.
- Gkartzonikas, C. and Gkritza, K., 2019. What have we learned? A review of stated preference and choice studies on autonomous vehicles. *Transportation Research Part C*, 98, 323-337.
- Green, L.R., Richardson, D.S., Lago, T., and Schatten-Jones, E.C., 2001. Network correlates of social and emotional loneliness in young and older adults. *Personality and Social Psychology Bulletin*, 27(3), 281-288.
- Greene, W.H. 2012. *Econometric Analysis* (Seventh ed.). Pearson Prentice-Hall, Upper Saddle River, 332-344.
- Hamid, N.R.A., and Cheng, A.Y., 2013. A risk perception analysis on the use of electronic payment systems by young adult. *WSEAS Transactions on Information Science and Applications*, 10(1), 26-35.
- Hawkins, J., and Nurul Habib, K., 2019. Integrated models of land use and transportation for the autonomous vehicle revolution. *Transport Reviews*, 39, 66-83.
- Hohenberger, C., Spörrle, M., and Welp, I.M., 2017. Not fearless, but self-enhanced: The effects of anxiety on the willingness to use autonomous cars depend on individual levels of self-enhancement. *Technological Forecasting and Social Change*, 116, 40-52.
- Kim, C., and Shen, C., 2020. Connecting activities on social network sites and life satisfaction: A comparison of older and younger users. *Computers in Human Behavior*, 105, 106222.
- Kim, M., Kim, H.K., and Lee, S.H., 2020a. A distributed cooperative localization strategy in vehicular-to-vehicular networks. *Sensors*, 20(5), 1413.
- Kim, S.H., Mokhtarian, P.L., and Circella, G., 2020b. Will autonomous vehicles change residential location and vehicle ownership? Glimpses from Georgia. *Transportation Research Part D*, 82, 102291. <https://doi.org/10.1016/j.trd.2020.102291>.
- Kim, S.H., Mokhtarian, P.L., and Circella, G., 2020c. How, and for whom, will activity patterns be modified by self-driving cars? Expectations from the state of Georgia. *Transportation Research Part F*, 70, 68-80.
- Kolarova, V., Steck, F., Cyganski, R., and Trommer, S., 2018. Estimation of the value of time for automated driving using revealed and stated preference methods. *Transportation Research Procedia*, 31, 35-46.
- Kraljević, R., and Filipović, Z., 2017. Gender differences and consumer behavior of millennials. *Acta Economica Et Turistica*, 3(1), 5-13.
- Kröger, L., Kuhnimhof, T., and Trommer, S., 2019. Does context matter? A comparative study modelling autonomous vehicle impact on travel behaviour for Germany and the USA. *Transportation Research Part A*, 122, 146-161.
- Krueger, R., Rashidi, T.H., and Dixit, V.V., 2019. Autonomous driving and residential location preferences: Evidence from a stated choice survey. *Transportation Research Part C*, 108, 255-268.

- Kuhr, J., Ruiz-Juri, N., Bhat, C.R., Archer, J., Duthie, J.C., Varela, E., Zalawadia, M., Bamonte, T., Mirzaei, A., and Zheng, H., 2017. Travel modeling in an era of connected and automated transportation systems: An investigation in the Dallas-Fort Worth area. Technical Report D-STOP/2017/122, prepared for the Data-Supported Transportation Operations and Planning Center (D-STOP) of the U.S. Department of Transportation.
- Lavieri, P.S., and Bhat, C.R., 2019a. Investigating objective and subjective factors influencing the adoption, frequency, and characteristics of ride-hailing trips. *Transportation Research Part C*, 105, 100-125.
- Lavieri, P.S., and Bhat, C.R., 2019b. Modeling individuals' willingness to share trips with strangers in an autonomous vehicle future. *Transportation Research Part A*, 124, 242-261.
- Lavieri, P.S., Garikapati, V.M., Bhat, C.R., Pendyala, R.M., Astroza, S., and Dias, F.F., 2017. Modeling individual preferences for ownership and sharing of autonomous vehicle technologies. *Transportation Research Record: Journal of the Transportation Research Board*, 2665, 1-10.
- Lee, Y.C., and Mirman, J.H., 2018. Parents' perspectives on using autonomous vehicles to enhance children's mobility. *Transportation Research Part C*, 96, 415-431.
- Leung, E., Paolacci, G., and Puntoni, S., 2018. Man versus machine: Resisting automation in identity-based consumer behavior. *Journal of Marketing Research*, 55(6), 818-831.
- Levitas, R., Pantazis, C., Fahmy, E., Gordon, D., Lloyd-Reichling, E., and Patsios, D., 2007. The multi-dimensional analysis of social exclusion. Department for Communities and Local Government, University of Bristol, Bristol, UK.
- Levy, V., 2020. 2020 Travel Trends. *AARP Research*. https://www.aarp.org/content/dam/aarp/research/surveys_statistics/life-leisure/2019/2020-travel-trends.doi.10.26419-2Fres.00359.001.pdf. Accessed July 20, 2020.
- Li, W., and Kamargianni, M., 2020. An integrated choice and latent variable model to explore the influence of attitudinal and perceptual factors on shared mobility choices and their value of time estimation. *Transportation Science*, 54(1), 62-83.
- Litman, T., 2020. Autonomous vehicle implementation predictions: Implications for transport planning. Victoria Transport Policy Institute. Available at: <https://www.vtpi.org/avip.pdf>.
- Loewenstein, G.F., Weber, E.U., Hsee, C.K., and Welch, N., 2001. Risk as feelings. *Psychological Bulletin*, 127(2), 267-286.
- Lu, A.C.C., and Gursoy, D., 2016. Impact of job burnout on satisfaction and turnover intention: do generational differences matter?. *Journal of Hospitality & Tourism Research*, 40(2), 210-235.
- Ma, Y., Wang, Z., Yang, H., and Yang, L., 2020. Artificial intelligence applications in the development of autonomous vehicles: A survey. *IEEE/CAA Journal of Automatica Sinica*, 7(2), 315-329.
- Mani, Z., and Chouk, I., 2017. Drivers of consumers' resistance to smart products. *Journal of Marketing Management*, 33(1-2), 76-97.
- Marikyan, D., Papagiannidis, S., and Alamanos, E., 2019. A systematic review of the smart home literature: A user perspective. *Technological Forecasting and Social Change*, 138, 139-154.
- Martin M. and Park D.C., 2003. The Martin and Park Environmental Demands (MPED) questionnaire: Psychometric properties of a brief instrument to measure self-reported environmental demands. *Aging, Clinical and Experimental Research*, 15(1), 77-82.

- Milojevic, P., and Sibley, C.G., 2017. Normative personality trait development in adulthood: A 6-year cohort-sequential growth model. *Journal of Personality and Social Psychology*, 112(3), 510-526.
- Moody, J., Bailey, N., and Zhao, J., 2020. Public perceptions of autonomous vehicle safety: An international comparison. *Safety Science*, 121, 634-650.
- Moore, M. A., Lavieri, P. S., Dias, F. F., and Bhat, C. R., 2020. On investigating the potential effects of private autonomous vehicle use on home/work relocations and commute times. *Transportation Research Part C*, 110, 166-185.
- Morgan, P.L., Voinescu, A., Williams, C., Caleb-Solly, P., Alford, C., Shergold, I., Parkhurst, G., and Pipe, A., 2017. An emerging framework to inform effective design of human-machine interfaces for older adults using connected autonomous vehicles. In: Stanton N. (eds) *Advances in Human Aspects of Transportation. AHFE 2017*. Advances in Intelligent Systems and Computing, vol. 597, 325-334. Springer, Cham.
- Mushtaq, T., and Riyaz, S., 2020. The gender digital divide: An exploratory research of University of Kashmir. *Global Academic Journal of Humanities and Social Sciences*, 2(2), 18-21.
- Naess, P., 2012. Urban form and travel behavior: Experience from a Nordic context. *Journal of Transport and Land Use*, 5(2), 21-45.
- Nair, G.S. and Bhat, C.R., 2021. Sharing the road with autonomous vehicles: Perceived safety and regulatory preferences. *Transportation Research Part C*, 122, 102885.
- Narayanan, S., Chaniotakis, E., and Antoniou, C., 2020. Shared autonomous vehicle services: A comprehensive review. *Transportation Research Part C*, 111, 255-293.
- Nazari, F., Noruzoliaee, M., and Mohammadian, A.K., 2018. Shared versus private mobility: Modeling public interest in autonomous vehicles accounting for latent attitudes. *Transportation Research Part C*, 97, 456-477.
- Newey, K.W., and McFadden, D., 1994. Large sample estimation and hypothesis. *Handbook of Econometrics Volume 4*, Engle, R.F. and McFadden, D.L. (Eds), 36, 2111-2245.
- Nwankwo, S., Hamelin, N., and Khaled, M., 2014. Consumer values, motivation and purchase intention for luxury goods. *Journal of Retailing and Consumer Services*, 21(5), 735-744.
- Paillard-Borg, S., Wang, H., Winblad, B., and Fratiglioni, L., 2009. Pattern of participation in leisure activities among older people in relation to their health conditions and contextual factors: A survey in a Swedish urban area. *Ageing and Society*, 29(5), 803-821.
- Peretti-Watel, P., Legleye, S., Baumann, M., Choquet, M., Falissard, B., Chau, N., and Lorhandicap Group, 2009. Fatigue, insomnia and nervousness: gender disparities and roles of individual characteristics and lifestyle factors among economically active people. *Social Psychiatry and Psychiatric Epidemiology*, 44(9), 703-709.
- Rahimi, A., Azimi, G., Asgari, H., and Jin, X., 2020. Adoption and willingness to pay for autonomous vehicles: attitudes and latent classes. *Transportation Research Part D*, 89, 102611.
- Ramsey, K., and Bell, A., 2014. *Smart Location Database Version 2.0 User Guide*. U.S. Environmental Protection Agency. https://www.epa.gov/sites/production/files/2014-03/documents/sld_userguide.pdf.
- Rashidi, T.H., Waller, T., and Axhausen, K., 2020. Reduced value of time for autonomous vehicle users: Myth or reality? *Transport Policy*, 95, 30-36.
- Rieser-Schüssler, N., and Axhausen, K.W., 2012. Investigating the influence of environmentalism and variety seeking on mode choice. *Transportation Research Record: Journal of the Transportation Research Board*, 2322(1), 31-41.

- Sharda, S., Astroza, S., Khoeini, S., Batur, I., Pendyala, R.M. and Bhat, C.R., 2019. Do attitudes affect behavioral choices or vice-versa: Uncovering latent segments within a heterogeneous population. Technical paper, Department of Civil, Architectural and Environmental Engineering, The University of Texas at Austin. https://www.cae.utexas.edu/prof/bhat/ABSTRACTS/AttitudesBehavior_Latent_Seg.pdf
- Shinar, D., 2019. Crash causes, countermeasures, and safety policy implications. *Accident Analysis & Prevention*, 125, 224-231.
- Singh, P., Sinha, V.S.P., Vijhani, A., and Pahuja, N., 2018. Vulnerability assessment of urban road network from urban flood. *International Journal of Disaster Risk Reduction*, 28, 237-250.
- Singleton, P.A., 2019. Discussing the “positive utilities” of autonomous vehicles: will travelers really use their time productively? *Transport Reviews*, 39(1), 50-65.
- Solon, G., Haider, S.J., and Wooldridge, J.M., 2015. What are we weighting for? *Journal of Human Resources*, 50(2), 301-316.
- Soteropoulos, A., Berger, M., and Ciari, F., 2019. Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. *Transport Reviews*, 39(1), 29-49.
- Spurlock, C.A., Sears, J., Wong-Parodi, G., Walker, V., Jin, L., Taylor, M., Duvall, A., Gopal, A., and Todd, A., 2019. Describing the users: Understanding adoption of and interest in shared, electrified, and automated transportation in the San Francisco Bay Area. *Transportation Research Part D*, 71, 283-301.
- Teixeira-Pinto, A., and Harezlak, J., 2013. Factorization and latent variable models for joint analysis of binary and continuous outcomes. In de Leon, A.R., & Chough, K.C. (Eds.) *Analysis of Mixed Data: Methods & Applications* (1st ed.), pp. 81-91, Chapman and Hall/CRC, Boca Raton, FL.
- Terza, J.V., 2016. Simpler standard errors for two-stage optimization estimators. *The Stata Journal*, 16(2), 368-385. <https://doi.org/10.1177/1536867X1601600206>.
- Truong, L.T., De Gruyter, C., Currie, G., and Delbosc, A., 2017. Estimating the trip generation impacts of autonomous vehicles on car travel in Victoria, Australia. *Transportation*, 44(6), 1279-1292.
- U.S. Bureau of Labor Statistics, 2018. Consumer Expenditures - 2018. U.S. Department of Labor. <https://www.bls.gov/news.release/pdf/cesan.pdf>. Accessed July 12, 2020.
- U.S. Census Bureau, 2018. American Community Survey 1-year estimates. *Census Reporter Profile page for Austin-Round Rock, TX Metro Area*. <https://censusreporter.org/profiles/31000US12420-austin-round-rock-tx-metro-area/>. Accessed July 20, 2020.
- Venkatesh, V. and Davis, F.D., 2000. A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science*, 46(2), 186-204.
- Vianello, M., Schnabel, K., Sriram, N., and Nosek, B., 2013. Gender differences in implicit and explicit personality traits. *Personality and Individual Differences*, 55(8), 994-999.
- Voinescu, A., Morgan, P.L., Alford, C., and Caleb-Solly, P., 2020. The utility of psychological measures in evaluating perceived usability of automated vehicle interfaces—A study with older adults. *Transportation Research Part F*, 72, 244-263.
- Volvo, 2019. 360C, A new way to travel. The future is electric, autonomous and connected. <https://www.volvocars.com/intl/cars/concepts/360c.?redirect=true>. Accessed June 30 2020.

- Vyas, G., Famili, P., Vovsha, P., Fay, D., Kulshrestha, A., Giaimo, G., and Anderson, R., 2019. Incorporating features of autonomous vehicles in activity-based travel demand model for Columbus, OH. *Transportation*, 46(6), 2081-2102.
- Walsh, K., Scharf, T., and Keating, N., 2017. Social exclusion of older persons: A scoping review and conceptual framework. *European Journal of Ageing*, 14(1), 81-98.
- Wooldridge, J.M., 1995. Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics*, 68, 115-132.
- Yap, M.D., Correia, G., and Van Arem, B., 2016. Preferences of travellers for using automated vehicles as last mile public transport of multimodal train trips. *Transportation Research Part A*, 94, 1-16.
- Zmud, J.P., and Sener, I.N., 2017. Towards an understanding of the travel behavior impact of autonomous vehicles. *Transportation Research Procedia*, 25, 2500-2519.
- Zmud, J.P., Sener, I.N., and Wagner, J., 2016. Consumer acceptance and travel behavior impacts of automated vehicles. Report PRC 15-49 F, Transportation Policy Research Center, Texas A&M Transportation Institute.

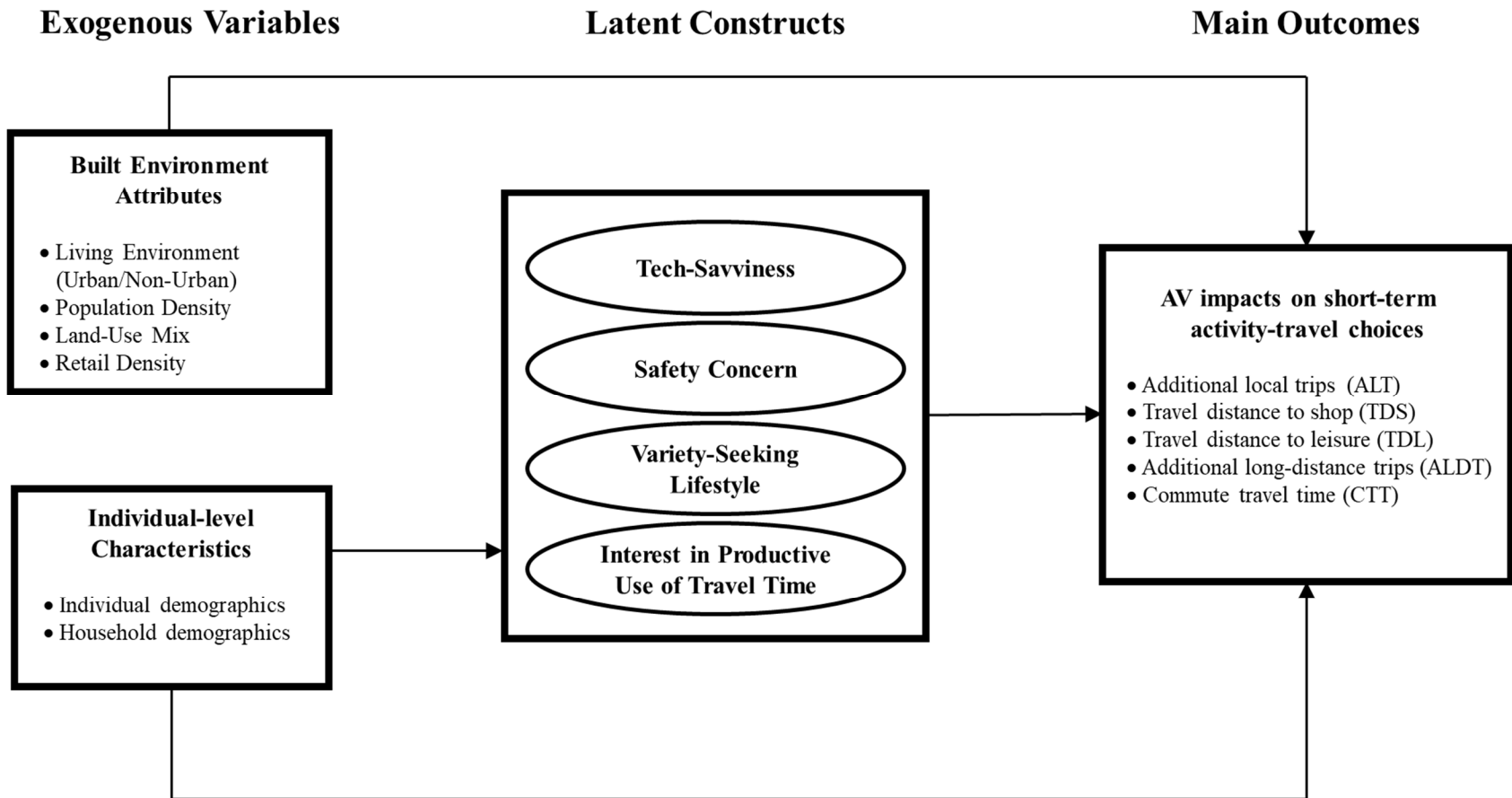


Figure 1. Analytic Framework

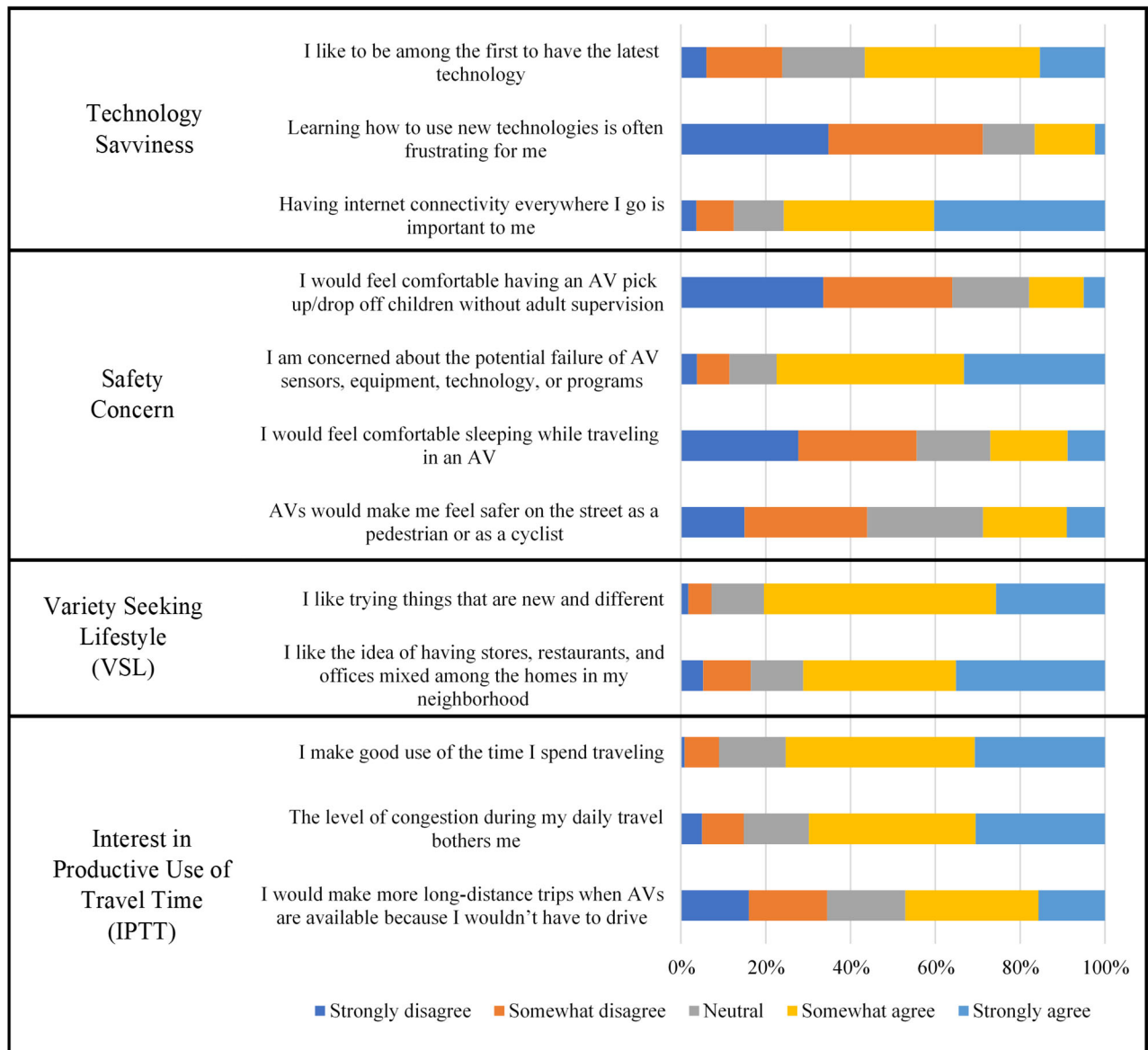


Figure 2. Distribution of Attitudinal Indicators

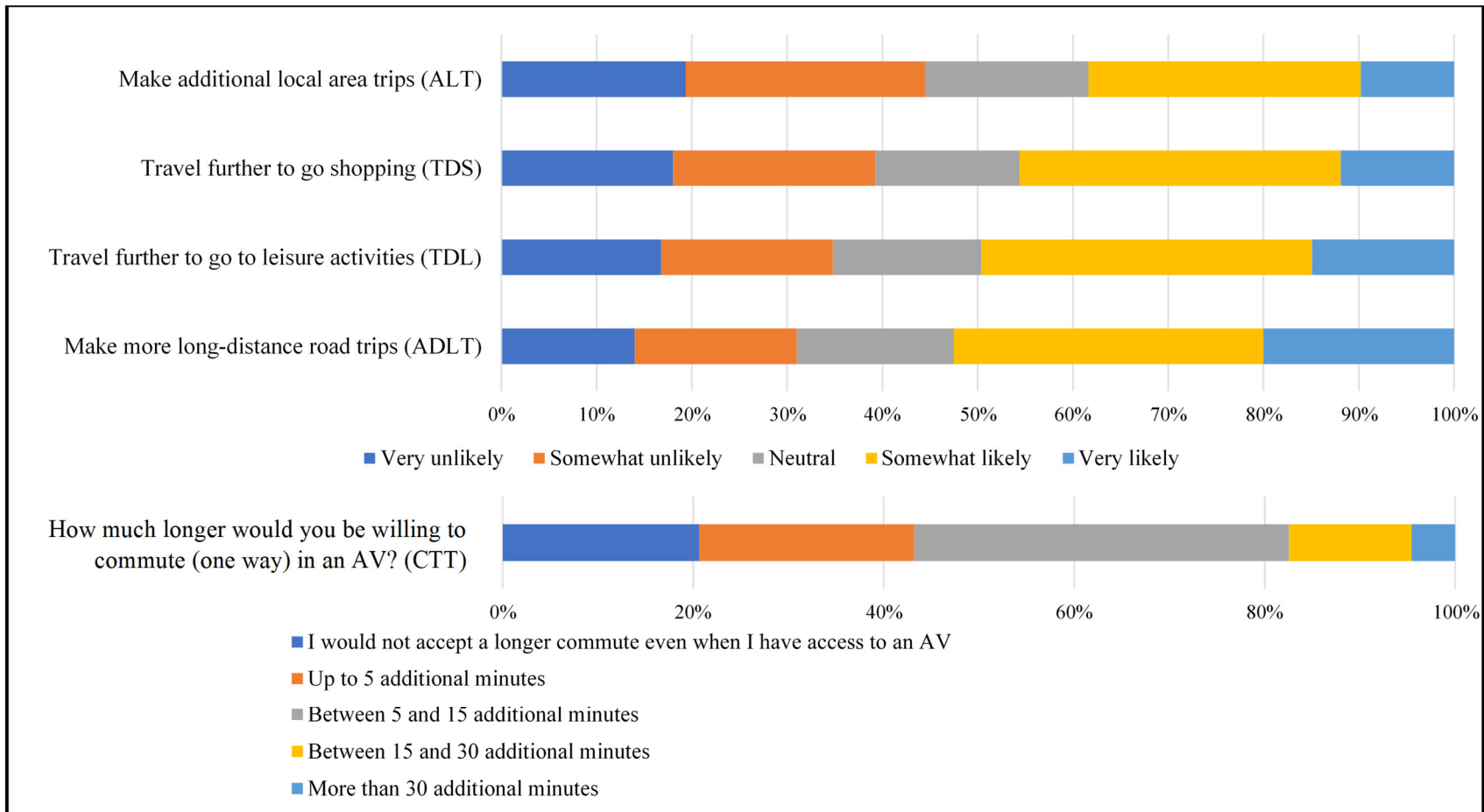


Figure 3. Distribution of Outcome Variables

Table 1. Sample Distribution of Exogenous Variables: Socio-Demographic and Household Related Characteristics

Variable	Count	%	Variable	Count	%	Variable	Count	%
Individual Demographics			Household Characteristics			Residence Built-Environment Characteristics¹		
Gender			Household Annual Income			Living Environment		
Female	591	65.7	Less than \$25,000	220	24.5	Urban	334	37.1
Male	308	34.3	\$25,000 to \$49,999	153	17.0	Suburban	453	50.4
Age			\$50,000 to \$74,999	145	16.1	Rural	112	12.5
18 to 29	523	58.2	\$75,000 to \$99,999	118	13.1	Population Density**		
30 to 39	102	11.4	\$100,000 to \$149,999	143	15.9	Medium-to-low	674	75.0
40 to 49	97	10.8	\$150,000 to \$249,999	83	9.3	High	225	25.0
50 to 64	85	9.4	\$250,000 or more	37	4.1	Retail Employment Density***		
65 or older	92	10.2	Household Size			Medium-to-low	704	78.3
Licensed			Live alone	226	25.2	High	195	21.7
Yes	788	87.7	2 people	252	28.0			
No	111	12.3	3 people	135	15.0			
Employment Type			4 or more people	286	31.8			
Student	459*	51.1	Children (<18 years) in Household					
Employed	546*	60.7	Yes	129	14.3			
Unemployed and not a student	105	11.7	No	770	85.7			
Education			Vehicles per Household					
Completed high-school or less	123	13.7	No vehicles	71	7.9			
Completed some college or technical school	311	34.6	1 vehicle	223	24.8			
Completed undergraduate degree	307	34.1	2 vehicles	296	32.9			
Completed graduate degree	158	17.6	3 vehicles	184	20.5			
			4 or more vehicles	125	13.9			

¹ Land-use mix, another built environment variable, is used as a continuous variable between 0 and 1. The mean of the mix variable was 0.607, with a median of 0.703. The lowest value is 0 and the highest is 0.971.

* 211 respondents were both employed and students. Of the 794 respondents who either worked or studied or worked and studied, 72 individuals did so from home and did not have a commute. Thus, only 722 respondents in the sample had a commute and responded in the survey on the commute travel time increase question.

** This continuous variable ranges from 0 to 72.3 people per acre; a Census Block Group with a population density above 20 ppl/acre is characterized as high population density.

*** This continuous variable ranges from 0 to 5.86 retail jobs per acre; a Census Block Group with a retail density above 0.5 jobs/acre is characterized as high retail density.

Table 2. Latent Construct Regression Result

Variables (base category)	Latent Construct Model									
	Tech-Savviness		Safety Concern		Variety-Seeking Lifestyle		IPTT			
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat		
<i>Individual-level Characteristics</i>										
Gender (male)										
Female	-0.401	-11.13	0.586	35.95	--		--			
Age (older than 64)										
18 to 29	0.366	7.31	-0.312	-7.11	0.135	5.38	0.195	8.73		
30 to 64	0.103	1.89	-0.159	-4.19	0.096	4.60	0.195	8.73		
Education (less than a graduate degree)										
Graduate degree	--		--		--		0.123	8.49		
Employment Type (unemployed, non-student)										
Employed	--		-0.103	-7.53	--		0.127	3.27		
Student	--		--		-0.174	-7.05	--			
<i>Household Characteristics</i>										
Income (<\$100,000)										
\$100,000 to \$249,999	0.177	3.95	-0.125	-6.57	--		--			
≥ \$250,000	0.211	1.74	-0.148	-1.75	0.314	6.36	--			
Presence of Children (no children)										
Presence	--		0.097	7.29	--		-0.090	-6.15		
Correlation among Latent Constructs	Tech-Savviness	1.000			-0.126	-1.19	0.217	1.53	0.210	1.29
	Safety Concern				1.000		-0.086	-1.34	-0.219	-2.41
	Variety-Seeking Lifestyle						1.000		0.387	11.80
	IPTT								1.000	
Likelihood at convergence = -4895.95; Likelihood at constants = -5845.83; Adjusted likelihood ratio index = 0.159										

Table 3. Main Outcome Multivariate Ordered Model

Exogenous Variables (base category)	ALT		TDS		TDL		ALDT		CTT	
	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat	Coeff.	t-stat
<u>Latent Constructs</u>										
Tech-Savviness	--		--		-0.106	-1.98	--		--	
Safety Concern	-0.904	-10.52	-0.954	-11.30	-0.915	-10.84	-1.015	-11.39	-0.598	-7.40
Variety-Seeking Lifestyle	0.198	2.00	0.218	2.26	0.189	1.97	0.222	2.21	--	
IPTT	0.680	5.12	0.713	5.18	0.844	6.19	0.984	7.18	--	
<u>Latent Construct Interactions</u>										
IPTT*Employed	--		--		--		--		0.365	3.63
<u>Individual-level Characteristics</u>										
Gender (male)										
Female	0.332	3.72	0.412	4.57	0.309	3.41	0.480	5.07	--	
Age (older than 64)										
18 to 29	0.393	3.18	0.275	3.47	0.417	3.32	0.543	4.38	0.223	2.63
30 to 64	0.156	1.38	--		0.156	1.40	0.286	2.30	--	
Income (≥ \$100,000)										
< \$100,000	--		0.092	1.90	--		--		--	
<u>Built Environment Factors</u>										
Land Use (rural or suburban)										
Urban	0.114	2.06	--		--		--		--	
Population Density (medium-to-low)										
High	--		--		-0.123	-2.27	--		--	
Land Use Mix										
High	--		--		-0.101	-1.35	--		-0.205	-1.59
Retail Density (medium-to-low)										
High	--		-0.082	-1.51	--		--		--	
Thresholds										
1 2	-0.399	-3.28	-0.504	-5.42	-0.646	-4.78	-0.546	-4.28	-0.818	-7.32
2 3	0.433	3.56	0.237	2.67	0.045	0.34	0.219	1.83	-0.121	-1.09
3 4	0.904	7.23	0.651	7.38	0.473	3.54	0.710	5.87	1.050	9.33
4 5	2.004	14.62	1.794	17.40	1.542	10.88	1.733	13.29	1.835	14.64
Correlations										
ALT	1.000	NA	0.785	53.70	0.784	48.90	0.603	24.09	0.340	8.90
TDS			1.000	NA	0.887	96.02	0.661	31.83	0.346	9.37
TDL					1.000	NA	0.690	36.76	0.349	9.55
ALDT							1.000	NA	0.283	7.38
CTT									1.000	NA

Table 4. Disaggregate Data Fit Measures

Summary Statistics	Model	
	Proposed Model	Trad. Model
Log-likelihood at convergence	-4983.84	-6498.77
Number of parameters	63	62
Bayesian Information Criterion (BIC)	5198.08	6716.41
Constants-only predictive log-likelihood	-6612.86	
Predictive adjusted likelihood ratio index	0.237	0.008
Informal non-nested adjusted likelihood ratio test: Joint model versus Indep. model	$\Phi [-55.04] \ll 0.001$	
Average probability of correct prediction	0.0205	0.0017

Table 5. Aggregate Data Fit Measures

Bivariate combinations	Observed				Proposed model prediction (APE)				Traditional model prediction (APE)			
	(0,0)*	(0,1)	(1,0)	(1,1)	(0,0)	(0,1)	(1,0)	(1,1)	(0,0)	(0,1)	(1,0)	(1,1)
ALT, TDS	441	113	48	297	443 (0.5)	114 (0.9)	56 (16.7)	286 (3.7)	347 (21.3)	207 (83.2)	145 (202.0)	200 (32.7)
ALT, TDL	416	138	37	308	423 (1.7)	133 (3.6)	47 (27.0)	296 (3.9)	326 (21.6)	228 (65.2)	132 (256.8)	213 (30.8)
ALT, ALDT	368	186	59	286	379 (3.0)	178 (4.3)	61 (3.4)	281 (1.7)	303 (17.7)	251 (34.9)	129 (118.6)	216 (24.5)
ALT, CTT	389	41	207	85	394 (1.3)	39 (4.9)	202 (2.4)	87 (2.4)	405 (4.1)	49 (19.5)	233 (12.6)	35 (58.8)
TDS, TDL	424	65	29	381	426 (0.5)	73 (12.3)	43 (48.3)	357 (6.3)	304 (28.3)	188 (189.2)	154 (431.0)	253 (33.6)
TDS, ALDT	355	134	72	338	367 (3.4)	131 (2.2)	73 (1.4)	328 (3.0)	278 (21.7)	215 (60.4)	153 (112.5)	253 (25.1)
TDS, CTT	347	36	250	89	360 (3.7)	32 (11.1)	242 (3.2)	88 (1.1)	387 (11.5)	18 (50.0)	274 (9.6)	43 (51.7)
TDL, ALDT	344	109	83	363	361 (4.9)	108 (0.9)	79 (4.8)	351 (3.3)	264 (23.3)	194 (78.0)	167 (101.2)	274 (24.5)
TDL, CTT	318	27	278	99	333 (4.7)	26 (3.7)	259 (6.8)	104 (5.1)	295 (7.2)	54 (100.0)	319 (14.7)	54 (45.5)
ALDT, CTT	298	29	298	97	303 (1.7)	27 (6.9)	289 (3.0)	103 (6.2)	271 (9.1)	50 (72.4)	320 (7.4)	81 (16.5)
Weighted mean absolute percentage error (MAPE)					3.25%				31.75%			

*Category 0 corresponds to the combined ordered outcome levels of 1, 2 and 3, while category 1 corresponds to the combined ordered outcome levels of 4 and 5.

Table 6. Average Treatment Effects (ATEs)

Variable	Base Level	Treatment Level	ALT Additional Local Trips “likely”	TDS Travel Farther for Shop “likely”	TDL Travel Farther for Leisure “likely”	ALDT Additional Long distance Trips “likely”	CTT “Increase commute travel time by more than 15 mins”
<i>Socio-demographic</i>							
Gender	Male	Female	-0.196	-0.202	-0.207	-0.062	-0.023
Age	≥65	18-29 years	0.290	0.229	0.269	0.416	0.083
Employment Status	Unemployed	Employed	0.112	0.090	0.143	0.155	0.012
Student status	Non-student	Student	-0.004	-0.021	-0.048	-0.021	-
Education	Less than graduate degree	Graduate degree	0.106	0.091	0.112	0.133	0.013
Income	<\$100,000	≥\$250,000	0.234	0.151	0.274	0.170	0.027
Presence of children	Not present	Present	-0.092	-0.065	-0.021	-0.076	-0.012
<i>Built-environment effects</i>							
Land use	Rural/suburban	Urban	0.289	-	-	-	-
Population density	Low/Medium	High	-	-	-0.200	-	-
Land-use mix	25 th percentile	75 th percentile	-	-	-0.047	-	-0.001
Retail density	Low/Medium	High	-	-0.160	-	-	-

Table 7. Average Treatment Effect (ATE) for the ALT Dimension

Variable	Base Level	Treatment Level	% Contribution by mediation through				% Direct Effect	Overall ATE
			Tech-Savviness increase	Safety Concern decrease	Variety-Seeking Lifestyle increase	IPTT increase		
Gender	Male	Female	0	-61	0	0	39	-0.196
Age	≥65	18-29 years	0	34	3	16	47	0.290
Employment Status	Unemployed	Employed	0	52	0	48	0	0.112
Student status	Non-student	Student	0	0	-100	0	0	-0.004
Education	Less than graduate degree	Graduate degree	0	0	0	100	0	0.106
Income	<\$100,000	≥\$250,000	0	68	32	0	0	0.234
Presence of children	Not present	Present	0	-59	0	-41	0	-0.092