The Induced Demand Implications of Alternative Adoption Modalities of Automated Vehicles

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ABSTRACT

There is considerable interest in understanding the potential induced demand implications of the advent of automated vehicles. In an automated vehicle future, drivers and passengers are relieved of the driving task, thus rendering car travel more convenient and less onerous. As such, there is the possibility that people will undertake more trips in an automated vehicle future, raising the specter of induced demand. Induced demand may also arise from mode shifts, changes in trip lengths, and residential relocations. This study posits that induced demand resulting from the adoption of automated vehicles is inter-related to the adoption modality. Automated vehicles may be purchased and owned personally or used as a mobility-on-demand service (or both). This study aims to shed light on the relationship between automated vehicle adoption modality and likelihood of making additional trips in an automated vehicle future. A joint model of these two outcome variables, wherein automated vehicle adoption modality affects likelihood of making additional trips, is estimated and presented in this paper. The results show that, regardless of the adoption modality, the likelihood of making additional trips increases, with private ownership contributing more to induced demand than a service-based adoption modality. This finding suggests that efforts should be aimed at curbing private ownership of automated vehicles to limit unintended consequences.

Keywords: automated vehicles, adoption modalities, induced demand, automated vehicle impacts, planning and policy implications, joint model system

1. INTRODUCTION

Progress in the development of automated vehicles has ushered in a new era of excitement about the future of mobility. Scenarios describing a future in which automated vehicles whisk people between locations offer a glimpse into the hopes and aspirations that these advanced transportation technologies are intended to fulfill (Fagnant and Kockelman, 2015). Travelers will be relieved of the driving task, thus rendering travel less onerous, conducive to multitasking, and more convenient for all – including the disabled (Malokin et al., 2019; Faber and Lierop, 2020; Emory et al., 2022). Although the availability and deployment of automated vehicles has been slower than originally expected, they are beginning to appear in several cities in the US and elsewhere. In San Francisco and Phoenix, companies such as Cruise and Waymo are offering rides to passengers in well-defined Operational Design Domains (ODD) (Stopher et al., 2021; Hu et al., 2022). Although these deployments of automated mobility-on-demand services are few and far between and have experienced some challenges, they serve as a harbinger of what is on the horizon in the mobility arena.

There are undoubtedly many benefits that could come about through transportation automation. Not only does automation provide relief from the driving task, but it creates opportunities for providing affordable mobility-on-demand services thus reducing the need for personal car ownership (Galich and Stark, 2021; Menon et al., 2018). Reduced car ownership and greater use of shared mobility-on-demand services can help advance sustainability goals in the transportation ecosystem (Hasan and Hentenryck, 2021; Davidson and Spinoulas, 2016), reduce and repurpose the land dedicated to parking (Nourinejad et al., 2018; Chai et al., 2023), and enhance mobility for the transportation disadvantaged (Harper et al., 2016). Transportation automation may also provide safety benefits by eliminating crashes that result from human driver error (which purportedly contributes to more than 90 percent of all crashes) (Papadoulis et al., 2019). If mobility service providers operate fleets of automated vehicles to offer mobility-on-demand, there may be greater opportunities to rapidly electrify personal transportation and increase the share of pooled trips (Weis et al., 2017). Automated mobility may also facilitate greater access to goods and services through reduced dependence on human drivers to perform deliveries (Batur et al., 2023); and automated vehicles may help fill the gap of first-mile/last-mile connectivity that is often needed for utilization of mass transit services (Huang et al., 2021).

Despite these many benefits, there are concerns that the reduced burden of travel engendered by automated transportation systems may induce new travel demand (Zhang et al., 2018; Das et al., 2017). Induced travel demand is a phenomenon that is consistent with the economic notion that demand for a good increases when the price of consuming that good drops (Goodwin, 1996; Mokhtarian et al., 2002; Noland and Lem, 2002; Duranton and Turner, 2011). With the reduced cost of transportation (both monetary cost and "effort" cost) afforded by automated mobility technologies, it is conceivable that people will travel farther distances to access a greater variety of desirable destinations, make additional new trips that they did not make previously, and/or shift away from the use of alternative modes of transportation as they embrace the convenience of personal automated vehicles (Dannemiller et al., 2023; Harb et al., 2022; Moreno et al., 2018). The ability to multitask while traveling (Hamadneh and Esztergár-Kiss, 2021) and the elimination of the driving task itself may inspire (some) households to locate farther away from work, stores, amenities, and other activity destinations (Moore et al., 2020). These potential changes in travel demand, attributable to the convenience and reduced cost/burden of travel when using automated vehicles, could negate the potential benefits of transportation automation and result in unintended consequences that do not advance a low carbon transportation future (Kröger et al., 2019; Narayanan et al., 2020; Polzin, 2022).

This paper aims to provide some key insights on the potential induced demand implications of the adoption of automated vehicles. It is conceivable and widely recognized that automated vehicles may be adopted in a number of modalities. Households may choose to purchase automated vehicles for their private use, similar to the personal car ownership paradigm that has prevailed for the past century. Alternatively, households may use automated mobility-on-demand services to meet their transportation needs without relying on personally owned vehicles (Vosooghi et al., 2019; Magassy et al., 2023). Some may be averse to using automated transportation and continue to use their current modes of transportation and conventional personal vehicles. Others may choose to transition to the use of automated vehicles in a blended or mixed modality, i.e., acquire personally owned automated vehicles *and* use automated mobility-on-demand services. The adoption modality may influence the extent to which induced demand occurs as a result of transportation automation. Those who are averse to automated vehicles (and not likely to adopt them) may not necessarily change their demand patterns. Those who purchase and acquire personally owned automated vehicles may exhibit greater levels of induced demand than those who subscribe and pay for automated mobility-on-demand services by the trip. When a vehicle is purchased for private use, the marginal cost of each trip is (perceived to be) low – thus resulting in a less cautious approach to using personal vehicles for making trips (Volker et al., 2020; Litman, 2024). On the other hand, when paying for transportation on a per-trip basis, the (perceived) cost of each additional trip may deter travelers from undertaking net new additional trips (Asgari and Jin, 2020).

It should be noted that the directionality of the relationship between these choice dimensions remains rather ambiguous. As explained above, the adoption modality may affect the likelihood of making additional trips. On the other hand, it is entirely plausible that the adoption modality is affected by the likelihood of induced demand, i.e., aspirations of leveraging the technology to make additional trips (induced demand) may affect the adoption modality. For example, if an individual would like to engage in more out-of-home activities by leveraging the convenience of automated vehicle technology, then they may choose to purchase an automated vehicle for personal use. On the other hand, an individual who does not aspire to make any additional trips may eschew personal ownership in favor of using a mobility-on-demand service. Although both directional effects are plausible, the model system estimated in this study assumes a structure in which adoption modality affects the likelihood of induced demand. This structure is adopted to recognize that adoption modality is a longer-term choice while trip-making is a short term choice, and most model frameworks generally adopt the structure where the longer term choices affect shorter term travel choices.

This research is essentially motivated by the recognition that the amount of induced demand engendered by automated transportation is inextricably linked to the modality in which automated vehicles are adopted and used. It is therefore of value and importance to model the likelihood of induced demand (arising from transportation automation) jointly with the modality in which automated transportation may be adopted. By modeling the two behavioral choices jointly, it will be possible to recognize the endogeneity inherent to these inter-related choice dimensions through the incorporation of error covariances that account for correlated unobserved attributes that may simultaneously affect both choices.

The model system is estimated using a survey data set that focused on eliciting information about intentions, preferences, and attitudes surrounding automated vehicles and mobility services. The survey, conducted in 2019 (pre-COVID era), provides rich information for a sample of more than 3000 respondents drawn from the four car-centric metropolitan areas of Phoenix, Austin, Atlanta, and Tampa. A joint simultaneous equations model of automated vehicle (AV) adoption modality and likelihood of making additional trips (induced demand) is estimated using the generalized heterogeneous data model (GHDM) developed by Bhat (2015). The model system accounts for the direct effect of adoption modality on induced demand while also reflecting the presence of correlated unobserved attributes affecting both choice dimensions.

The next section presents a detailed description of the data set and the survey sample used for model estimation. The third section presents the model structure and the modeling methodology. The fourth section presents model estimation results, while the fifth section presents a discussion of the implications of the results. Concluding remarks and directions for future research are offered in the sixth and final section.

2. DATA DESCRIPTION

This section summarizes the survey and data set used in this study. The survey and sample characteristics are described first. A more detailed descriptive analysis of endogenous variables and attitudinal indicators is provided second.

2.1. Survey Overview and Sample Characteristics

The data used in this study is derived from a survey conducted in 2019 in four large car-centric metropolitan areas of the United States. The four metropolitan areas include Phoenix (Arizona), Austin (Texas), Atlanta (Georgia), and Tampa (Florida). The survey, dubbed the Transformative Technologies in Transportation Survey, gathered detailed information on respondent attitudes, personality traits, lifestyle preferences, and mobility choices. In particular, the survey included very comprehensive sections that elicited information about respondent perceptions of and attitudes toward automated vehicles, emerging mobility services and technologies, and transportation options. The survey also collected comprehensive socio-economic and demographic data. The resulting data set was augmented with secondary land use and built environment attributes based on the zip code of respondent residence. A total of 3,465 individuals responded to the survey across the four metropolitan areas. Although the same survey instrument was used in all four regions, slight variations in recruitment and sampling strategies were adopted to enhance response rates and obtain a large sample size. Complete details about the survey and sample characteristics may be found elsewhere (Khoeini et al, 2020).

This study focuses on analyzing the relationship between (intended/likely) AV adoption modality and the likelihood of making additional trips in an AV future. As such, the analysis is performed only on the subset of individuals who indicated that they have some level of familiarity with automated vehicles (AVs). Those who indicated that they have no familiarity at all with AVs were omitted from the analysis subsample. After extensive data cleaning and filtering, the final analysis sample includes 3,032 respondents.

Table 1 presents detailed sample characteristics, including distributions for the endogenous variables of interest in this study. The sample characteristics depict rich variability, thus rendering the sample suitable for the type of model development and estimation effort undertaken in this paper. Females are slightly over-represented in the sample, accounting for about 55 percent of the sample. About one-quarter of the sample belongs to the lowest age group of 18-30 years, while around 11 percent fall within the 31-40 year range. Other age groups are represented in roughly similar proportions. Nearly 94 percent of respondents have a driver's license, 53 percent are either full- or part-time workers, and nearly 28 percent are neither workers nor students. The sample is skewed towards individuals with a higher level of education; nearly 38 percent have a Bachelor's degree and approximately 25 percent have a graduate degree. Those with a high school diploma or less comprise only eight percent of the sample. About three-quarters of the sample is comprised of Whites or Caucasians. Eight percent of the sample identifies as Asian and nearly seven percent identify as Black or African American.

TABLE 1 Socio-Economic and Demographic Characteristics of the Sample

Individual Demographics (N=3,032)		***Household Characteristics (N=3,032)***	
Variable	%	**Variable**	%
Gender		**Household annual income**	
Female	55.4	Less than $25,000	9.4
Male	44.6	$25,000 to $49,999	15.0
Age category		$50,000 to $99,999	34.6
18-30 years	24.2	$100,000 to $149,999	21.6
31-40 years	11.1	$150,000 to $249,999	13.1
41-50 years	15.1	$250,000 or more	6.3
51-60 years	16.9	**Household size**	
61-70 years	17.1	One	21.5
71+ years	15.6	Two	39.8
Driver's license possession		Three or more	38.6
Yes	94.1	**Housing unit type**	
No	5.9	Stand-alone home	71.2
Employment status		Condo/apartment	20.1
A student (part-time or full-time)	9.3	Other	8.7
A worker (part-time or full-time)	53.1	**Home ownership**	
Both a worker and a student	9.9	Own	69.7
Neither a worker nor a student	27.7	Rent	24.8
Education attainment		Other	5.5
Completed high school or less	8.0	**Vehicle ownership**	
Some college or technical school	28.4	Zero	3.7
Bachelor's degree(s)	38.1	One	23.8
Graduate degree(s)	25.5	Two	40.5
Race		Three or more	31.9
Asian or Pacific Islander	8.0	**Location**	
Black or African American	6.8	Atlanta, GA	29.8
Native American	0.4	Austin, TX	30.7
White or Caucasian	73.4	Phoenix, AZ	32.4
Other	11.3	Tampa, FL	7.1
Main Outcome Variables			
AV adoption modality		**Likelihood of making additional trips**	
Averse	28.0	Very unlikely	28.3
Service only	7.4	Somewhat unlikely	26.8
Ownership only	20.8	Neutral	18.0
Ownership and service	43.8	Somewhat likely	21.4
---	---	Very likely	5.4

The income distribution is quite rich, with a strong representation of individuals in every household income bracket. Approximately one-quarter of the sample resides in households within the low-income category (earning less than $50,000 per year), while another 35 percent reside in households within the middle income category (earning $50,000-$99,999 per year). The remainder are from households making $100,000 or more per year. Approximately 40 percent of individuals live in households with three or more members, another 40 percent reside in two-person households, and one-fifth of the sample is comprised of single-person households. Approximately 70 percent of respondents live in stand-alone homes and about 20 percent reside in condos or apartments. Home ownership stands at about 68 percent in the sample, with another 26 percent identifying as renters. The majority of the sample resides in households with multiple vehicles; about one-third reside in households with three or more vehicles and 40 percent live in households with two vehicles. Only four percent report living in households with zero vehicles. The sample is rather evenly divided between Phoenix, Atlanta and Austin, with Tampa representing a smaller proportion of the sample.

2.2. Endogenous Variables and Attitudinal Indicators

This study aims to investigate the relationship between two key endogenous variables:

- AV adoption modality (AVAM)
- Likelihood of making additional trips (LMAT)

The AVAM variable is a multinomial variable consisting of four levels, derived from the following combination of survey questions:

- "When do you expect to buy an AV?"
    - This question offers a three-level response ranging from "among the first to buy" to "never buy"
- Two five-level likert scale questions that elicit level of agreement with the following statements:
    - "I will use AV ridehailing services alone or with coworkers, friends, or family" (five response levels ranging from strongly disagree to strongly agree)
    - I will use AV ridehailing services with other passengers I don't know (five response levels ranging from strongly disagree to strongly agree)

By combining responses across these questions, it is possible to categorize respondents based on their AV adoption modality. First, those who indicated that they would never buy an AV and strongly disagree with both likert statements were categorized as AV-averse or simply *Averse*. The second category of respondents is labeled *Service-Only*. These individuals are those who indicated that they would never buy an AV but agreed (at any level) to ride in an AV ridehailing service, either in a private or shared mode. The third category of respondents is labeled *Ownership-Only*. These individuals are those who expressed an intent to buy an AV, but disagreed (at any level) with the statements on riding in an AV-based ridehailing service, either in a private or shared mode. The final category is a dual modality category called *Ownership-Service*. This category includes all other individuals, and essentially encompasses respondents who indicated plans to purchase an AV *and* also agreed (at any level) that they would ride in an AV ridehailing service (in either private or shared mode). Thus, the AVAM variable is a four-category multinomial variable: Averse, Ownership-Only, Service-Only, Ownership-Service.

The LMAT variable is directly tied to a single question in the survey: "Imagine a future when you can access an AV (by owning, leasing, or using automated ridehailing services). How likely would you make additional trips that you do not make now?". This question is answered via a five-level likert scale ranging from *very unlikely* to *very likely*. It should be noted that respondents were provided a detailed description of automated vehicles in the introduction portion of the survey. This description essentially characterized AVs as vehicles capable of chauffeuring passengers, running errands, picking up and dropping off children, and parking themselves autonomously with no human in the vehicle. The description went on to note that ridehailing companies (such as Uber and Lyft) would deploy AVs to provide rides on-demand without a human driver in the vehicle. The description concluded with a request, asking respondents to answer the questions assuming a future in which AVs are widely adopted (regardless of modality), but human driven vehicles are still available and present.

Distributions for these two endogenous variables (AVAM and LMAT) are shown at the bottom of Table 1. The majority of the sample (55 percent) indicated that they are very unlikely or unlikely to make (net new) additional trips in an AV future. Eighteen percent indicated a neutral stance, suggesting that they are unsure whether they would make additional trips. About 26 percent of the respondents indicated that they are likely or very likely to make net new additional trips in an AV future. This suggests that there is a sizeable portion of the sample exhibiting a propensity for additional trip making in an AV future. The AVAM variable distribution shows that 28 percent of respondents are AV averse, with no intention to adopt or use AVs in ownership or service modality. Only eight percent of the sample indicated a preference for using AVs solely in ridehailing/service mode. About one-quarter of the sample indicated that they would buy an AV for personal ownership, but not use AVs in service mode. The largest proportion – 44 percent of the sample – appears inclined to embrace an AV future, expressing an intent to *both* buy/own an AV *and* use AVs in ridehailing service mode.

The bivariate relationship between these two outcome variables is depicted in Figure 1. There is a rather clearly discernible pattern depicted by the graph. Within the AV-averse group, more than one-half (54.4 percent) are very unlikely to make additional trips by AVs in an AV future. This percentage progressively decreases as one moves from left to right on the x-axis of the graph. That is, as the degree to which AV technologies are embraced increases, the percent of individuals very unlikely to make additional trips progressively decreases (from 54.4 percent for AV-averse group to 15.1 percent for Ownership-and-Service group). Likewise, the percent of individuals who indicate that they are very likely to make additional trips in an AV future increases from a low of 0.4 percent for the AV-averse group to a high of nearly 10 percent for the Ownership-and-Service group. Overall, it can be seen that AVAM and LMAT show a relationship pattern consistent with expectations, with a higher likelihood of additional trip making when there is a greater propensity to embrace and adopt AV technologies in multiple modalities. It is this relationship that motivates the current study; if certain adoption modalities contribute to a greater likelihood of additional trip making in an AV future, then policy interventions and strategies can and need to be devised to help mitigate any unintended consequences of AV deployment in communities.

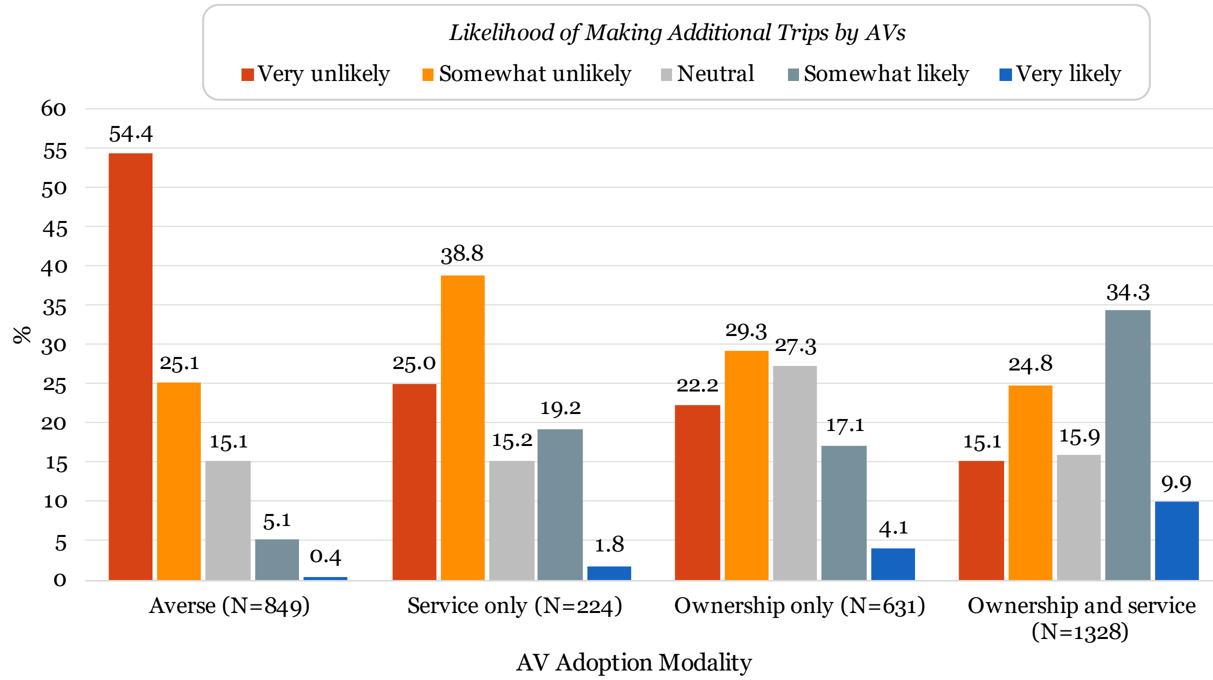

Figure 1 Likelihood of Making Additional Trips by AV Adoption Modality (N=3,032)

In order to capture the influence of AVAM on LMAT accurately, the modeling framework adopted in this paper needs to estimate the effect between these two outcome variables while controlling for socio-economic and demographic characteristics, built environment attributes, and any other influential factors. Among the influential factors of interest are attitudes and perceptions. Unlike many studies that assume unobserved attitudinal factors are reflected in random error terms, this study explicitly accounts for attitudes, perceptions, and preferences. The survey data set includes a host of attitudes and perceptions that can serve as the foundation for developing latent attitudinal constructs.

In this study, three latent attitudinal constructs are developed and included in the model specification. These constructs have been defined and selected based on prior research and behavioral reasonableness. For example, AVAM is likely to be highly related to the amount of trust that people place in AV technology and perceptions of emerging mobility services. On the other hand, the likelihood of making additional trips in an AV future is not only related to the amount of trust that people place in AV technology, but also to the third latent factor reflecting a pro-environment attitude. Presumably those who are pro-environment would be less likely to pursue net new additional trips in an AV future, most likely due to the deleterious environmental effects of additional vehicular travel.

Each latent construct is represented by three attitudinal variables (i.e., indicators) in the data set. These indicators are highly correlated with one another and contribute substantially to the definition of the latent constructs in this study. Figure 2 depicts the three latent constructs and the attitudinal statements that define them. The graph shows the percent of respondents indicating their level of agreement with various attitudinal statements. In the interest of brevity, each and every attitudinal statement and the associated respondent distribution is not described in detail here. The graph is quite self-explanatory, depicting the three attitudinal statements that comprise each factor. The AV Technology Trust factor is defined by the extent to which respondents are comfortable sleeping in an AV (during a ride), are concerned about the failure of AV technology (during a ride), and feel safer on the street as a pedestrian or cyclist. The Mobility Service Perception factor is defined by the extent to which respondents feel that AV services are reliable, are affordable, and enable saving time and money for parking. Finally, the Pro-Environment Attitude factor is defined by the extent to which respondents are committed to an environmentally friendly lifestyle, are committed to using a less polluting means of transportation, and feel that gas taxes should be raised to help combat the negative effects of transportation on the environment. Overall, the distributions of respondents for each of the attitudinal statements are consistent with expectations and demonstrate the suitability of the data for constructing latent attitudinal factors that may be incorporated in an econometric model specification.

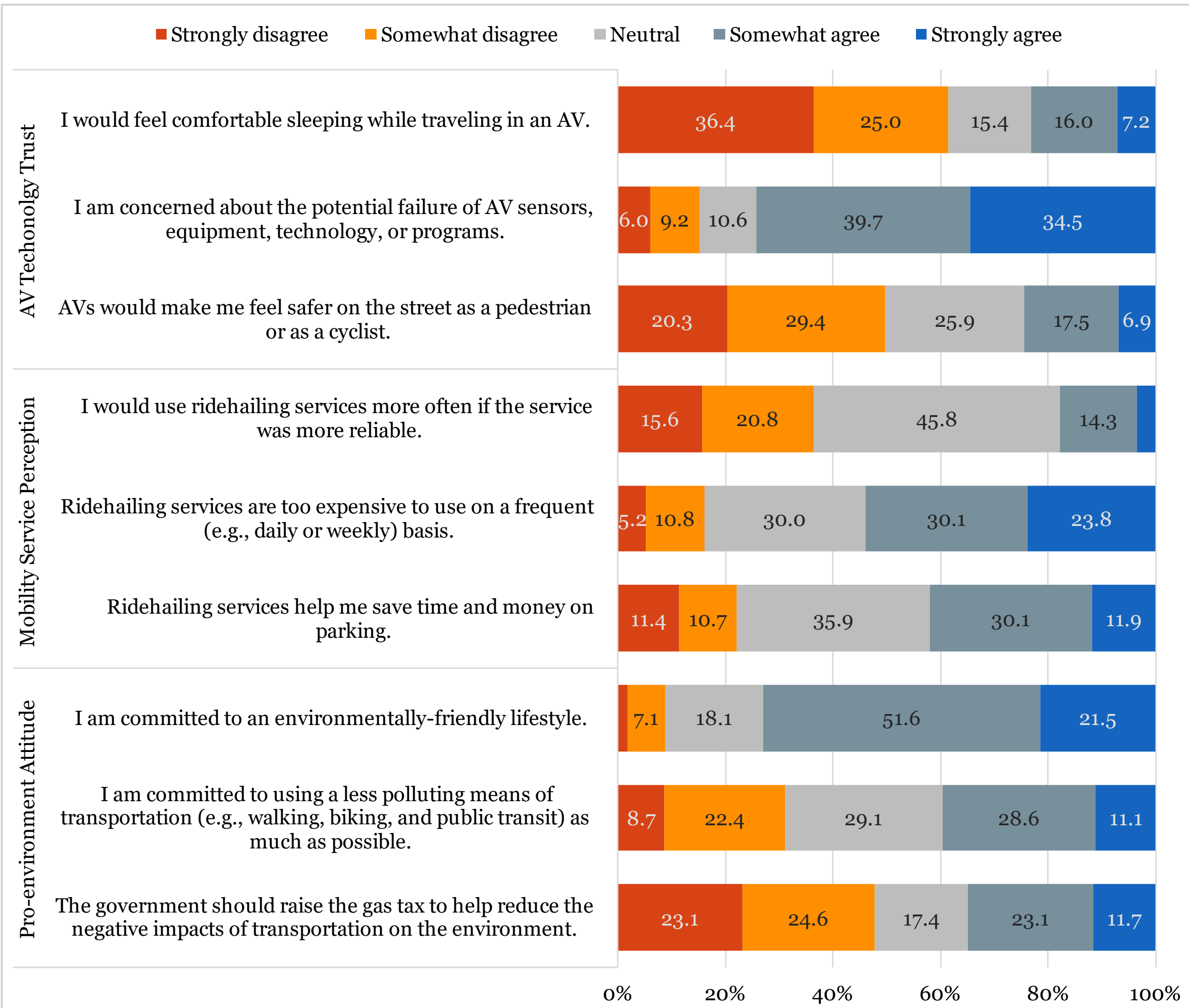

Figure 2 Agreement with Attitudinal Indicators Defining Latent Constructs (N=3,032)

3. MODELING FRAMEWORK

This section presents the model structure and framework adopted in this study. A qualitative depiction of the modeling methodology is presented first, followed by the details of the formulation and estimation methodology.

3.1. Model Structure

A simplified representation of the model structure adopted in this study is offered in Figure 3. The two main outcome variables, AV Adoption Modality (AVAM) and Likelihood of Making Additional Trips (LMAT), appear on the right-hand side of the figure. While AVAM constitutes an unordered multinomial choice variable, LMAT is an ordered response variable with multiple levels. As noted in the introductory section, the bivariate relationship between these two endogenous outcome variables may occur in either direction. A bidirectional relationship cannot be estimated due to identification issues (Bhat, 2015). Hence, in this study, it is assumed that AVAM influences LMAT; this directionality is assumed to reflect that longer term adoption modality choices may influence shorter term trip making choices (which is the directionality generally adopted in travel forecasting model systems). Future research efforts may further explore the directionality of the relationship between these two variables.

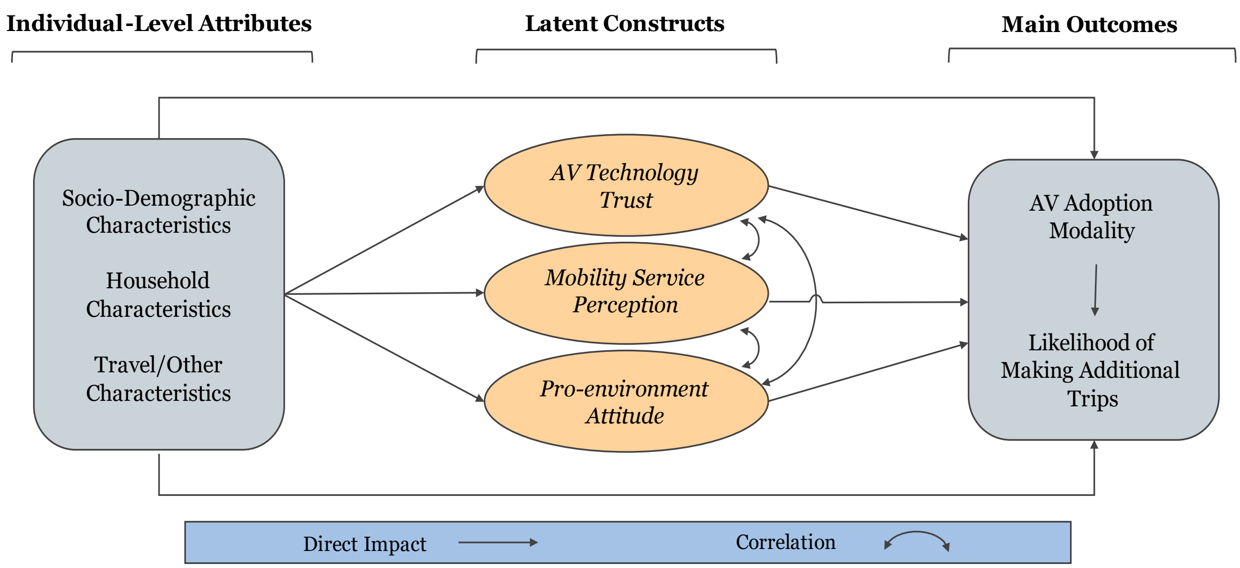

Figure 3 Model Framework

On the left-hand side of Figure 3 are various exogenous variables comprised of socio-economic and demographic attributes of the individual, household characteristics, and mobility characteristics that may be treated as exogenous for purposes of this study. These variables are assumed to influence both the latent attitudinal constructs and the main outcome variables (AVAM and LMAT).

The three latent constructs, positioned in the middle of the figure, serve as mediating variables. They are influenced by the exogenous variables on the one hand and, in turn, influence the main outcome variables. These latent attitudinal factors are derived by mapping them to their measured attitudinal indicator variables (as shown in Figure 2). For ease of representation, this mapping of attitudinal variables is not explicitly depicted in Figure 3. To account for the potential presence of correlated unobserved factors simultaneously affecting multiple behavioral outcomes and attitudinal factors, correlations between the latent attitudinal constructs are explicitly accommodated in the model specification. This is possible because the latent attitudinal constructs are treated as stochastic variables with a random error component. As error correlations between the latent constructs are explicitly incorporated in the model structure, separate error correlations between the behavioral outcome variables do not need to be specified. The error correlations between the latent constructs engender error correlations between the main outcome variables through the joint model specification and formulation. As the simultaneous equations model system involves jointly estimating a mix of discrete choice variables (multinomial choice and ordered choice), the estimation of all model parameters is performed jointly in a single step using the Generalized Heterogeneous Data Model (GHDM) methodology developed by Bhat (2015).

Overall, the model structure and formulation explicitly address endogeneity in the outcome variables and attitudinal factors, considers the stochastic nature of latent attitudinal constructs, and accommodates error correlations between the latent constructs and between the main endogenous outcome variables.

3.2. Model Estimation Methodology

The methodology employed in the current study represents a special case of the GHDM, involving both ordinal and multinomial outcomes. The corresponding mathematical formulations are detailed below.

For ease of presentation, the index for decision-makers in the exposition below is suppressed, and all error terms are assumed to be independent and identically distributed across decision-makers. Following Bhat's (2015) GHDM formulation, let l be an index for latent variables (l=1,2,…,L). Consider the latent variable z_l^* and write it as a linear function of covariates:

$$z_l^* = \boldsymbol{\alpha}_l'\boldsymbol{w} + \eta_l, \tag{1}$$

where $\boldsymbol{w}$ is a $(\tilde{D}\times 1)$ vector of observed covariates (excluding a constant), $\boldsymbol{\alpha}_l$ is a corresponding $(\tilde{D}\times 1)$ vector of coefficients, and η_l is a random error term assumed to be standard normally distributed for identification purpose. Next, define the $(L\times\tilde{D})$ matrix $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, ..., \boldsymbol{\alpha}_L)'$, and the $(L\times 1)$ vectors $\boldsymbol{z}^* = (z_1^*, z_2^*, ..., z_L^*)'$ and $\boldsymbol{\eta} = (\eta_1, \eta_2, \eta_3, \dots, \eta_L)'$. A multivariate normal (MVN) correlation structure is allowed for $\boldsymbol{\eta}$ to accommodate interactions among the unobserved latent variables: $\boldsymbol{\eta} \sim MVN_L[\boldsymbol{0}_L, \boldsymbol{\Gamma}]$, where $\boldsymbol{0}_L$ is an $(L\times 1)$ column vector of zeros, and $\boldsymbol{\Gamma}$ is an $(L\times L)$ correlation matrix. In matrix form, we may write Equation (1) as:

$$\boldsymbol{z}^* = \boldsymbol{\alpha}\boldsymbol{w} + \boldsymbol{\eta}. \tag{2}$$

Now consider N ordinal outcomes (indicator variables as well as main outcomes) for the individual, and let n be the index for the ordinal outcomes $(n = 1, 2, ..., N)$. Also, let J_n be the number of categories for the n^{th} ordinal outcome $(J_n \geq 2)$ and let the corresponding index be j_n $(j_n = 1, 2, ..., J_n)$. The current empirical case has N = 10, which consists of 9 indicator variables and one main outcome variable. Each of these variables has $J_n = 5$, representing the number of ordered categories. Let $\tilde{y}_n^*$ be the latent underlying variable whose horizontal partitioning leads to the observed outcome for the n^{th} ordinal variable. Assume that the individual under consideration chooses the a_n^{th} ordinal category. Then, in the usual ordered response formulation, for the individual, the following may be written:

$$\tilde{y}_n^* = \tilde{\boldsymbol{\gamma}}_n'\boldsymbol{x} + \tilde{\boldsymbol{d}}_n'\boldsymbol{z}^* + \tilde{\varepsilon}_n, \text{ and } \tilde{\psi}_{n,a_n-1} < \tilde{y}_n^* < \tilde{\psi}_{n,a_n}, \tag{3}$$

where $\boldsymbol{x}$ is an $(A\times 1)$ vector of exogenous variables (including a constant) as well as possibly the observed values of other endogenous ordinal variables, and other endogenous multinomial choice variables introduced as dummy variables (though only in a recursive fashion and not in a cyclic manner) , $\tilde{\boldsymbol{\gamma}}_{\boldsymbol{n}}$ is a corresponding vector of coefficients to be estimated, $\tilde{\boldsymbol{d}}_{\boldsymbol{n}}$ is an $(L \times 1)$ vector of latent variable loadings on the n^{th} ordinal outcome, the $\tilde{\psi}$ terms represent thresholds, and $\tilde{\varepsilon}_n$ is the standard normal random error for the n^{th} ordinal outcome. Note, however, that for the indicators (but not the main outcomes), typically the $\boldsymbol{x}$ vector will not appear on the right side of Equation (3); also, there are specific identification conditions for the number of non-zero elements of $\tilde{\boldsymbol{d}}_{\boldsymbol{n}}$ that can be present in each indicator equation and across all indicator equations. For further details, please refer to Bhat (2015).

Continuing with the formulation, for each ordinal outcome, $\tilde{\psi}_{n,0} < \tilde{\psi}_{n,1} < \tilde{\psi}_{n,2} ... < \tilde{\psi}_{n,J_n-1} < \tilde{\psi}_{n,J_n}$; $\tilde{\psi}_{n,0} = -\infty$, $\tilde{\psi}_{n,1} = 0$, and $\tilde{\psi}_{n,J_n} = +\infty$. For later use, let $\tilde{\boldsymbol{\psi}}_{\boldsymbol{n}} = (\tilde{\psi}_{n,2}, \tilde{\psi}_{n,3} ..., \tilde{\psi}_{n,J_n-1})'$ and $\tilde{\boldsymbol{\psi}} = (\tilde{\boldsymbol{\psi}}_{\boldsymbol{1}}', \tilde{\boldsymbol{\psi}}_{\boldsymbol{2}}', ..., \tilde{\boldsymbol{\psi}}_{N})'$. Stack the N underlying continuous variables $\tilde{y}_n^*$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{y}}^*$, and the N error terms $\tilde{\varepsilon}_n$ into another $(N \times 1)$ vector $\tilde{\boldsymbol{\varepsilon}}$. Define $\tilde{\boldsymbol{\gamma}} = (\tilde{\boldsymbol{\gamma}}_1, \tilde{\boldsymbol{\gamma}}_2, ..., \tilde{\boldsymbol{\gamma}}_H)'$ as an $(N \times A)$ matrix and $\tilde{\boldsymbol{d}} = \left(\tilde{\boldsymbol{d}}_{\boldsymbol{1}}, \tilde{\boldsymbol{d}}_{\boldsymbol{2}}, ..., \tilde{\boldsymbol{d}}_{N}\right)$ as an $(N \times L)$ matrix. Additionaly, let $\mathbf{IDEN}_N$ be the identity matrix of dimension N representing the correlation matrix of $\tilde{\boldsymbol{\varepsilon}}$ (the unit diagonals are needed for identification; for convergence stability and parsimony, it is assumed that the elements of the $\tilde{\boldsymbol{\varepsilon}}$ vector are uncorrelated with each other, though specific elements of the $\tilde{\boldsymbol{y}}^*$ vector can still be correlated through the stochatic latent constructs). Finally, stack the lower thresholds for the decision-maker $\tilde{\psi}_{n,a_n-1}(n = 1, 2, ..., N)$ into an $(N \times 1)$ vector $\tilde{\boldsymbol{\psi}}_{\boldsymbol{low}}$ and the upper thresholds $\tilde{\psi}_{n,a_n}(n = 1, 2, ..., N)$ into another vector $\tilde{\boldsymbol{\psi}}_{up}$. Then, in matrix form, the measurement equation for the ordinal outcomes (indicators) for the decision-maker may be written as:

$$\tilde{\boldsymbol{y}}^* = \tilde{\boldsymbol{\gamma}}\boldsymbol{x} + \tilde{\boldsymbol{d}}\boldsymbol{z}^* + \tilde{\boldsymbol{\varepsilon}}, \quad \tilde{\boldsymbol{\psi}}_{\boldsymbol{low}} < \tilde{\boldsymbol{y}}^* < \tilde{\boldsymbol{\psi}}_{\boldsymbol{up}}. \tag{4}$$

Now let there be G multionomial outcome variables for an individual, and let g be the index for the each multinomial variable $(g = 1, 2, 3, ..., G)$. Also, let I_g be the number of alternatives corresponding to the g^{th} multinomial variable ($I_g \geq 3$) and let i_g be the corresponding index $(i_g = 1, 2, 3, ..., I_g)$. In the curent case, G=1 and I_1 =4; however, the framework presented here can apply to any number of multinomial otcomes. Consider the g^{th} multinomial variable and assume the usual random utility structure for each alternative i_g.

$$U_{gi_g} = \boldsymbol{b}_{gi_g}' \boldsymbol{x} + \boldsymbol{\vartheta}_{gi_g}' (\boldsymbol{\beta}_{gi_g} \boldsymbol{z}^*) + \varsigma_{gi_g}, \tag{5}$$

where $\boldsymbol{x}$ is an $(A \times 1)$ vector of exogenous variables (including a constant) as well as possibly the observed values of other endogenous ordinal variables (introduced in a recursive fashion), as defined earlier, $\boldsymbol{b}_{gi_g}$ is an $(A \times 1)$ column vector of corresponding coefficients, and ς_{gi_g} is normal error term. $\boldsymbol{\beta}_{gi_g}$ is an $(N_{gi_g} \times L)$-matrix of variables interacting with latent variables to influence the utility of alternative i_g, and $\boldsymbol{\vartheta}_{gi_g}$ is an $(N_{gi_g} \times 1)$-column vector of coefficients capturing the effects of latent variables and their interaction effects with other exogenous variables. If each of the latent variables impacts the utility of the alternatives for each multinomial variable purely through a constant shift in the utility function, $\boldsymbol{\beta}_{gi_g}$ will be an identity matrix of size L, and each element of $\boldsymbol{\vartheta}_{gi_g}$ will capture the effect of a latent variable on the constant specific to alternative i_g

of nominal variable g. Let $\boldsymbol{\varsigma_g} = (\varsigma_{g1}, \varsigma_{g2}, \ldots \varsigma_{gI_g})'$ $(I_g \times 1$ vector), and $\boldsymbol{\varsigma_g} \sim MVN_{I_g}(\mathbf{0}, \mathbf{\Lambda_g})$. Taking the difference with respect to the first alternative, the only estimable elements are found in the covariance matrix $\breve{\mathbf{\Lambda}}_g$ of the error differences, $\boldsymbol{\breve{\varsigma}_g} = (\breve{\varsigma}_{g2}, \breve{\varsigma}_{g3}, \ldots, \breve{\varsigma}_{gI_g})$ (where $\breve{\varsigma}_{gi} = \varsigma_{gi} - \varsigma_{g1}, i \neq 1)$. Further, the variance term at the top left diagonal of $\breve{\mathbf{\Lambda}}_g$ $(g = 1, 2, \ldots, G)$ is set to 1 to account for scale invariance. $\mathbf{\Lambda_g}$ is constructed from $\breve{\mathbf{\Lambda}}_\mathbf{g}$ by adding a row on top and a column to the left. All elements of this additional row and column are filled with values of zero. In addition, the usual identification restriction is imposed such that one of the alternatives serves as the base when introducing alternative-specific constants and variables that do not vary across alternatives (that is, whenever an element of $\boldsymbol{x}$ is individual-specific and not alternative-specific, the corresponding element in $\boldsymbol{b}_{gi_g}$ is set to zero for at least one alternative i_g). To proceed, define $\boldsymbol{U}_g = (U_{g1}, U_{g2}, \ldots, U_{gI_g})'$ $(I_g \times 1$ vector), $\boldsymbol{b}_g = (\boldsymbol{b}_{g1}, \boldsymbol{b}_{g2}, \boldsymbol{b}_{g3}, \ldots, \boldsymbol{b}_{gI_g})'$ $(I_g \times A$ matrix), and $\boldsymbol{\beta}_g = (\boldsymbol{\beta}'_{g1}, \boldsymbol{\beta}'_{g2}, \ldots, \boldsymbol{\beta}'_{gI_g})'$ $\left(\sum_{i_g=1}^{I_g} N_{gi_g} \times L\right)$ matrix. Also, define the $\left(I_g \times \sum_{i_g=1}^{I_g} N_{gi_g}\right)$ matrix $\boldsymbol{\vartheta_g}$, which is initially filled with all zero values. Then, position the $(1 \times N_{g1})$ row vector $\boldsymbol{\vartheta}'_{g1}$ in the first row to occupy columns 1 to N_{g1}, position the $(1 \times N_{g2})$ row vector $\boldsymbol{\vartheta}'_{g2}$ in the second row to occupy columns $N_{g1}+1$ to $N_{g1} + N_{g2}$, and so on until the $(1 \times N_{gI_g})$ row vector $\boldsymbol{\vartheta}'_{gI_g}$ is appropriately positioned. Further, define $\boldsymbol{\varpi}_g = (\boldsymbol{\vartheta}_g \boldsymbol{\beta}_g)$ $(I_g \times L$ matrix), $\ddot{G} = \sum_{g=1}^{G} I_g$, $\tilde{G} = \sum_{g=1}^{G} (I_g - 1)$, $\boldsymbol{U} = \left(\boldsymbol{U}'_1, \boldsymbol{U}'_2, \ldots, \boldsymbol{U}'_G\right)'$ $(\ddot{G} \times 1$ vector), $\boldsymbol{\varsigma} = (\varsigma_1, \varsigma_2, \ldots \varsigma_G)'$ $(\ddot{G} \times 1$ vector), $\boldsymbol{b} = (\boldsymbol{b}'_1, \boldsymbol{b}'_2, \ldots, \boldsymbol{b}'_G)'$ $(\ddot{G} \times A$ matrix), $\boldsymbol{\varpi} = (\boldsymbol{\varpi}'_1, \boldsymbol{\varpi}'_2, \ldots, \boldsymbol{\varpi}'_G)'$ $(\ddot{G} \times L$ matrix), and $\boldsymbol{\vartheta} = \text{Vech}(\boldsymbol{\vartheta}_1, \boldsymbol{\vartheta}_2, \ldots, \boldsymbol{\vartheta}_G)$ (that is, $\boldsymbol{\vartheta}$ is a column vector that includes all elements of the matrices $\boldsymbol{\vartheta}_1, \boldsymbol{\vartheta}_2, \ldots, \boldsymbol{\vartheta}_G$). Then, in matrix form, Equation (5) may be written as:

$$\boldsymbol{U} = \boldsymbol{bx} + \boldsymbol{\varpi}\, \boldsymbol{z}^* + \boldsymbol{\varsigma}, \tag{6}$$

where $\boldsymbol{\varsigma} \sim MVN_{\ddot{G}}(\mathbf{0}_{\ddot{G}}, \mathbf{\Lambda})$. As earlier, to ensure identification, $\mathbf{\Lambda}$ is specified as follows:

$$\mathbf{\Lambda} = \begin{bmatrix} \mathbf{\Lambda}_1 & \mathbf{0} & \mathbf{0} & \mathbf{0} \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{\Lambda}_2 & \mathbf{0} & \mathbf{0} \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{\Lambda}_3 & \mathbf{0} \cdots & \mathbf{0} \\ \vdots & \vdots & \vdots & \vdots \ldots & \vdots \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \ldots & \mathbf{\Lambda}_G \end{bmatrix} (\ddot{G} \times \ddot{G} \text{ matrix}). \tag{7}$$

In the general case, this allows the estimation of $\sum_{g=1}^{G}\left(\frac{I_g*(I_g-1)}{2}-1\right)$ terms across all the G nominal variables, as originating from $\left(\frac{I_g*(I_g-1)}{2}-1\right)$ terms embedded in each $\breve{\mathbf{\Lambda}}_g$ matrix; (g=1,2,…,G) .

Let $\boldsymbol{\delta}$ be the collection of parameters to be estimated: $\boldsymbol{\delta}=[\text{Vech}(\boldsymbol{\alpha}), \text{Vechup}(\boldsymbol{\Gamma}), \text{Vech}(\tilde{\boldsymbol{\gamma}}), \text{Vech}(\tilde{\boldsymbol{d}}), \tilde{\boldsymbol{\psi}}, \text{Vech}(\boldsymbol{b}), \boldsymbol{\vartheta}, \text{Vech}(\boldsymbol{\Lambda})]$, where the operator "Vech(.)" vectorizes all the non-zero elements of the matrix/vector on which it operates and "Vechup(.)" indicates strictly upper diagonal elemenets.

With the matrix definitions above, the continuous components of the model system may be written compactly as:

$$\boldsymbol{z}^*=\boldsymbol{\alpha w}+\boldsymbol{\eta}, \tag{8}$$

$$\tilde{\boldsymbol{y}}^*=\tilde{\boldsymbol{\gamma}}\boldsymbol{x}+\tilde{\boldsymbol{d}}\boldsymbol{z}^*+\tilde{\boldsymbol{\varepsilon}}, \text{with Var}(\tilde{\boldsymbol{\varepsilon}})=\mathbf{IDEN}_N \;\; (N\times N\text{ matrix}) \;, \tag{9}$$

$$\boldsymbol{U}=\boldsymbol{bx}+\boldsymbol{\varpi}\,\boldsymbol{z}^*+\boldsymbol{\varsigma}. \tag{10}$$

To develop the reduced form equations, replace the right side of Equation (8) for $\boldsymbol{z}^*$ in Equations (9) and (10) to obtain the following system:

$$\tilde{\boldsymbol{y}}^*=\tilde{\boldsymbol{\gamma}}\boldsymbol{x}+\tilde{\boldsymbol{d}}\boldsymbol{z}^*+\tilde{\boldsymbol{\varepsilon}}=\tilde{\boldsymbol{\gamma}}\boldsymbol{x}+\tilde{\boldsymbol{d}}(\boldsymbol{\alpha w}+\boldsymbol{\eta})+\tilde{\boldsymbol{\varepsilon}}=\tilde{\boldsymbol{\gamma}}\boldsymbol{x}+\tilde{\boldsymbol{d}}\boldsymbol{\alpha w}+\tilde{\boldsymbol{d}}\boldsymbol{\eta}+\tilde{\boldsymbol{\varepsilon}}\;, \tag{11}$$

$$\boldsymbol{U}=\boldsymbol{bx}+\boldsymbol{\varpi}\,\boldsymbol{z}^*+\boldsymbol{\varsigma}=\boldsymbol{bx}+\boldsymbol{\varpi}\,(\boldsymbol{\alpha w}+\boldsymbol{\eta})+\boldsymbol{\varsigma}=\boldsymbol{bx}+\boldsymbol{\varpi}\,\boldsymbol{\alpha w}+\boldsymbol{\varpi}\,\boldsymbol{\eta}+\boldsymbol{\varsigma}\,.$$

Now, consider the $[(N+\vec{G})\times 1)]$ vector $\boldsymbol{yU}=\left[[\tilde{\boldsymbol{y}}^*]',\boldsymbol{U}'\right]'$. Define

$$\boldsymbol{B}=\begin{bmatrix}\boldsymbol{B_1}\\ \boldsymbol{B_2}\end{bmatrix}=\begin{bmatrix}\tilde{\boldsymbol{\gamma}}\boldsymbol{x}+\tilde{\boldsymbol{d}}\boldsymbol{\alpha w}\\ \boldsymbol{bx}+\boldsymbol{\varpi}\,\boldsymbol{\alpha w}\end{bmatrix}\text{and}\,\boldsymbol{\Omega}=\begin{bmatrix}\boldsymbol{\Omega_1} & \boldsymbol{\Omega}'_{12}\\ \boldsymbol{\Omega}_{12} & \boldsymbol{\Omega_2}\end{bmatrix}=\begin{bmatrix}\tilde{\boldsymbol{d}}\boldsymbol{\Gamma}\tilde{\boldsymbol{d}}'+\mathbf{IDEN_N} & \tilde{\boldsymbol{d}}\boldsymbol{\Gamma}\boldsymbol{\varpi}'\\ \boldsymbol{\varpi}\,\boldsymbol{\Gamma}\tilde{\boldsymbol{d}}' & \boldsymbol{\varpi}\,\boldsymbol{\Gamma}\boldsymbol{\varpi}'+\boldsymbol{\Lambda}\end{bmatrix}. \tag{12}$$

Then $\boldsymbol{yU}\sim \boldsymbol{MVN}_{N+\vec{G}}(\boldsymbol{B},\boldsymbol{\Omega})$.

Now the focus is on the estimation of the model. To estimate the model, note that, under the utility maximization paradigm, $U_{gi_g}-U_{gm_g}$ must be less than zero for all $i_g\neq m_g$ corresponding to the gth nominal variable, since the individual chose alternative m_g. Let $u_{gi_gm_g}=U_{gi_g}-U_{gm_g}\,(i_g\neq m_g)$, and stack the latent utility differentials into a vector $\boldsymbol{u_g}=\left[\left(u_{g1m_g},u_{g2m_g},...,u_{gI_gm_g}\right)';i_g\neq m_g\right]$. Also, define $\boldsymbol{u}=\left(\left[\boldsymbol{u}_1\right]',\left[\boldsymbol{u}_2\right]',...,\left[\boldsymbol{u_G}\right]'\right)'$. Now the distribution of the vector $\boldsymbol{yu}=\left(\vec{\boldsymbol{y}}',\boldsymbol{u}'\right)'$ needs to be developed from that of $\boldsymbol{yU}=\left[\vec{\boldsymbol{y}}',\boldsymbol{U}'\right]'$. To do so, define a matrix $\mathbf{M}$ of size $\left[N+\tilde{G}\right]\times\left[N+\vec{G}\right]$. Fill this matrix with values of zero. Then, insert an identity matrix of size N into the first N rows and N columns of the matrix $\mathbf{M}$. Next, consider the rows from $N+1$ to $N+I_1-1$, and columns from $N+1$ to $N+I_1$. These rows and columns correspond to the first nominal variable. Insert an identity matrix of size (I_1-1) after supplementing with a column of '-1' values in the column corresponding to the chosen alternative.

Next, rows $N+I_1$ through $N+I_1+I_2-2$ and columns $N+I_1+1$ through $N+I_1+I_2$ correspond to the second nominal variable. Continue this procedure for all G nominal variables. With the matrix $\mathbf{M}$ as defined, we can write $\boldsymbol{yu} \sim \boldsymbol{MVN}_{N+\tilde{\boldsymbol{G}}}(\tilde{\boldsymbol{B}}, \tilde{\boldsymbol{\Omega}})$, where $\tilde{\boldsymbol{B}} = \mathbf{M}\boldsymbol{B}$ and $\tilde{\boldsymbol{\Omega}} = \mathbf{M\Omega M}'$.

Next, define threshold vectors as follows:

$\breve{\boldsymbol{\psi}}_{\boldsymbol{low}} = \left[\tilde{\boldsymbol{\psi}}'_{\boldsymbol{low}}, \left(-\boldsymbol{\infty}_{\tilde{G}}\right)'\right]'$ ($[(N+\tilde{G})\times 1]$ vector) and $\breve{\boldsymbol{\psi}}_{\boldsymbol{up}} = \left[\tilde{\boldsymbol{\psi}}'_{up}, \left(\mathbf{0}_{\tilde{G}}\right)'\right]'$ ($[(N+\tilde{G})\times 1]$ vector), where $-\boldsymbol{\infty}_{\tilde{G}}$ is a $\tilde{G}\times 1$-column vector of negative infinities, and $\mathbf{0}_{\tilde{G}}$ is another $\tilde{G}\times 1$-column vector of zeros. Then the likelihood function may be written as:

$$
\begin{aligned}
L(\boldsymbol{\delta}) &= \Pr\left[\breve{\boldsymbol{\psi}}_{low} \le \boldsymbol{yu} \le \breve{\boldsymbol{\psi}}_{up}\right], \\
&= \int_{D_r} f_{N+\tilde{G}}(\boldsymbol{r} \mid \tilde{\boldsymbol{B}}, \tilde{\boldsymbol{\Omega}})dr,
\end{aligned}
\tag{13}
$$

where the integration domain $D_r = \{\boldsymbol{r} : \breve{\boldsymbol{\psi}}_{low} \le \boldsymbol{r} \le \breve{\boldsymbol{\psi}}_{up}\}$ is simply the multivariate region of the elements of the $\boldsymbol{yu}$ vector determined by the observed ordinal outcomes, and the range $(-\boldsymbol{\infty}_{\tilde{\boldsymbol{G}}}, \mathbf{0}_{\tilde{G}})$ for the utility differences taken with respect to the utility of the chosen alternative for the multinomial outcome. The likelihood function for a sample of Q decision-makers is obtained as the product of the individual-level likelihood functions.

Since a closed-form expression does not exist for this integral and evaluation using simulation techniques can be time-consuming, the One-variate Univariate Screening technique proposed by Bhat (2018) was used for approximating this integral. The estimation of parameters was carried out using the *maxlik* library in the GAUSS matrix programming language.

4. MODEL ESTIMATION RESULTS

This section presents the model estimation results. The results for the latent construct model component are discussed first, while the results for the bivariate model of behavioral outcomes are discussed second.

4.1. Latent Construct Model Component

The results for the latent construct model component are shown in Table 2. The table is comprised of two parts. The top half of the table shows the effects of explanatory variables on the three latent constructs, whereas the bottom half presents the factor loadings of the attitudinal indicators used to define the latent constructs. A quick review of the factor loadings suggests that the attitudinal variables considered are quite appropriate and strong indicators of the latent constructs. The factor loadings all exhibit expected signs and are statistically significant at any significance level.

Several socio-economic and demographic variables are found to influence the latent constructs. Consistent with expectations, females exhibit a lower trust in AV technology (also reported by Sener et al., 2019) but a more positive perception of mobility services. Females may consider ridehailing services as a safe and reliable mode of transportation (Smith, 2016), especially when compared with riding public transportation or walking alone. Among different age groups, younger individuals - who tend to be more technologically savvy – exhibit higher levels of AV technology trust and a more positive perception of mobility services (when compared with older segments). These findings are consistent with those reported in the literature (e.g., Hulse et al., 2018; Nielsen et al., 2018).

TABLE 2 Determinants of Latent Variables and Loadings on Indicators (N = 3,032)

Explanatory Variables (base category)		**Structural Equations Model Component**					
		AV Technology Trust		Mobility Service Perception		Pro-environment Attitude	
		Coef	t-stat	Coef	t-stat	Coef	t-stat
Individual characteristics							
Gender (not female)	Female	-0.56	-13.09	0.49	4.63	na	na
Age (*)	18-30 years	na	na	1.58	8.56	na	na
	18-40 years	0.36	7.58	na	na	na	na
	65 years or older	na	na	-0.57	-4.26	na	na
Race (*)	Asian	na	na	1.00	5.19	0.22	2.14
	Black	-0.31	-4.10	na	na	na	na
Education (*)	Bachelor's or higher	na	na	na	na	0.43	8.35
Occupation (*)	Both worker and student	0.17	2.13	na	na	na	na
	Student	na	na	na	na	0.56	7.83
Household characteristics							
Household income (*)	$25,000 or less	na	na	na	na	0.20	2.33
	$100,000 or more	0.21	4.86	na	na	na	na
	$150,000 or more	na	na	-0.35	-2.75	na	na
Household size (1 or 3+)	Two	na	na	na	na	0.13	2.71
Correlations between latent constructs							
AV Technology Trust		1	na	0.08	—	0.29	6.55
Mobility Service Perception				1	na	0.18	2.05
Pro-environment Attitude						1	na
Attitudinal Indicators		**Loadings of Latent Variables on Indicators (Measurement Equations Model Component)**					
AVs would make me feel safer on the street as a pedestrian or as a cyclist.		0.96	33.17				
I am concerned about the potential failure of AV sensors, equipment, technology, or programs.		-0.80	-34.44				
I would feel comfortable sleeping while traveling in an AV.		1.32	32.23				
Ridehailing services help me save time and money on parking.				0.07	3.68		
Ridehailing services are too expensive to use on a frequent (e.g., daily or weekly) basis.				0.34	8.56		
I would use ridehailing services more often if the service was more reliable.				0.21	7.93		
The government should raise the gas tax to help reduce the negative impacts of transportation on the environment.						0.78	17.69
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.						0.73	16.11
I am committed to an environmentally-friendly lifestyle.						0.44	14.11

Note: Coef = coefficient; "na" = not applicable; "—" = not statistically significant at the 90% confidence level.
*Base category is not identical across the model equations and corresponds to all omitted categories.

When it comes to the pro-environment attitude, however, no significant gender or age effects were found. This finding is not all that inconsistent with what has been documented in the literature, with prior research reporting mixed results on the effects of gender and age on pro-environment attitudes. It appears that gender and age effects are largely dependent upon the location, context, time period, and situational awareness (Weaver, 2002; Levine and Strube, 2012; Gifford and Nilsson, 2014).

Asians display a more positive perception of mobility services and stronger pro-environment attitudes compared to other racial groups; these findings are respectively aligned with results reported by Conway et al. (2018) and Head et al. (2019). Moreover, Blacks depict a lower level of AV technology trust, possibly due to the digital divide experienced by minority communities (Wu et al., 2021) and concerns about possible biases that often creep into emerging technologies (Hill, 2020).

Those with a higher education level (Bachelor's degree or higher) depict a stronger pro-environment attitude, similar to that found by Lavieri et al. (2017), and consistent with the greater awareness that such individuals may have regarding environmental issues. Students are also more pro-environment than other groups, once again due to heightened awareness among younger cohorts and the educated. Those who are both workers and students are likely exposed to a greater array of technological tools, resulting in a higher level of AV technology trust; this finding is also reported by Dannemiller et al. (2021). Income is an important determinant of latent constructs. Low-income individuals depict stronger pro-environment attitudes while high-income individuals depict a higher level of AV technology trust. Higher income individuals also exhibit a lower perception of mobility services. These findings are all consistent with expectations. Lower income individuals are more likely to experience the deleterious effects of environmental degradation and hence have heightened sensitivity to environmental issues. Higher income individuals enjoy greater exposure to technology (thus contributing to higher AV trust) and higher levels of personal car ownership and use, thus contributing to lower support for raising gas taxes and less favorable perception of mobility services (they do not see a need for such services). These findings align with those reported by Kyriakidis et al. (2015), Ejelöv and Nilsson (2020), and Dannemiller et al. (2021).

The model estimation results show two instances of significant error correlations, even after controlling for a host of socio-economic and demographic variables. A significant positive correlation is observed for AV technology trust and pro-environment attitude, as well as between pro-environment attitude and mobility service perception. These findings underscore the jointness of the latent constructs and the presence of shared unobserved underlying factors (e.g., personality traits, such as whether a person is a technophile) that simultaneously influence the latent constructs – thus justifying the simultaneous equations modeling methodology adopted in this study.

4.2. Bivariate Model of Behavioral Outcomes

Table 3 presents estimation results for the bivariate model of behavioral outcomes – AV Adoption Modality (AVAM) and Likelihood of Making Additional Trips (LMAT). The key finding is that, even after accounting for a host of socio-economic, demographic, and attitudinal factors within a joint behavioral modeling framework, the likelihood of making additional trips (LMAT) increases with the introduction of AVs regardless of the modality in which AVs are adopted. Model results depict a very intuitive increasing (positive) pattern for coefficients associated with alternative adoption modalities. Compared to AV-averse, all other adoption modalities contribute positively to the likelihood of making additional trips, with the modality corresponding to a full embrace of the technology (i.e., both ownership and service) depicting the largest positive coefficient. Even the modality where AVs are adopted in service-only mode contributes positively to the likelihood of making additional trips. This clearly suggests, and one can reasonably conclude, that the convenience and increased accessibility provided by AVs will most likely result in net new additional trips (induced demand); cities and communities need to plan for such an AV future and integrate AV technologies in their transportation ecosystems in ways that maximize benefits and minimize unintended negative consequences. It should be noted that the effects of AV adoption modalities on the likelihood of making additional trips (reported in the table) constitute "true, cleansed" effects because the model formulation fully accounts for spurious unobserved correlations between the two outcome variables (through the correlations across stochastic latent constructs). In this particular study, it is found that the error correlations between levels of the outcome variables are statistically insignificant (correlations are reported at the end of Table 3 in the section just above the Data Fit Measures). Nevertheless, the ability to account for such correlations enables the accurate identification of effects between the outcome variables of interest.

The model estimation results are quite intuitive and consistent with expectations and prior literature. The latent constructs significantly influence AV adoption modality and likelihood of making additional trips. Trust in AV technology is positively influencing all adoption modalities (also found by Lavieri et al., 2017 and Dannemiller et al., 2021), with a progressively increasing series of coefficients from service-only to ownership-and-service modality. A positive mobility service perception is associated with a higher probability of adopting AVs in ownership mode or ownership-and-service mode. It should be noted that AVs essentially provide the same type and level of service as an on-demand mobility service; both relieve the individual of the driving task. Hence, a positive perception of mobility services is associated with a higher likelihood of owning AVs, because that would provide the benefits of ownership and on-demand mobility service (no driving task, ability to multitask, etc.). Those with a more pro-environment attitude, however, are likely to be more sensitive about the ill-effects of ownership and hence show a greater tendency to adopt AVs in service-only mode. Both AV technology trust and positive mobility service perception contribute to an increased likelihood of making additional trips; these findings are intuitive as individuals who trust the technology and are more positive about on-demand mobility services are likely to take advantage of AV technology to the fullest and make more trips than they do currently. The findings also suggest that the environmental sensitivity of the individual (represented by the pro-environment attitude) has no influence on the likelihood of making additional trips in an AV future.

The next set of results in the table correspond to socio-economic and demographic variables. Females are more likely to adopt in service-only mode, consistent with their stronger perception of mobility services and lower levels of AV technology trust. There is no gender effect on likelihood of making additional trips. With respect to age, those in the peak travel years (41-50 years) are less likely to adopt service-only mode, presumably because they need the flexibility of ownership. Those in the 31-40 years of age who are possibly constrained by work and family obligations depict a higher likelihood of making additional trips in an AV future (they can use the vehicles to run errands autonomously). Older age groups, as expected (Krueger et al., 2016), embrace ownership-based modalities to a lesser degree, suggesting that they have a lower need for ownership and are ready to be relieved of the hassles of car ownership (e.g., maintenance).

TABLE 3 Estimation Results of AV Adoption Modality (AVAM) and Likelihood of Making Additional Trips (LMAT) Model Components (N = 3,032)

Explanatory Variables (base category)		Service only Coef	Service only t-stat	Ownership only Coef	Ownership only t-stat	Ownership and service Coef	Ownership and service t-stat	LMAT Coef	LMAT t-stat
		Main Outcome Variables							
		AVAM *(base: Averse)*						LMAT *5-level: strongly disagree (1) to strongly agree (5)*	
		Service only		Ownership only		Ownership and service			
		Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Endogenous variable									
AVAM (Averse)	Service only	na	na	na	na	na	na	0.62	6.62
	Ownership only	na	na	na	na	na	na	0.75	11.16
	Ownership and service	na	na	na	na	na	na	1.15	17.29
Latent constructs									
AV technology trust		0.43	8.43	0.57	15.11	0.97	23.17	0.18	5.86
Mobility service perception		na	na	0.19	5.57	0.29	6.86	0.14	5.14
Pro-environment attitude		0.24	5.57	na	na	na	na	na	na
Individual characteristics									
Gender (not female)	Female	0.20	3.02	na	na	na	na	na	na
Age (*)	31-40 years	na	na	na	na	na	na	0.13	1.95
	41-50 years	-0.40	-4.04	na	na	na	na	na	na
	65 years or older	na	na	na	na	-0.34	-4.39	na	na
	71 years or older	na	na	-0.14	-1.82	na	na	na	na
Race (*)	Black or African American	na	na	na	na	na	na	0.19	2.32
	White or Caucasian	na	na	na	na	0.05	—	na	na
Ethnicity (Not Hispanic)	Hispanic	na	na	na	na	na	na	0.28	4.56
Education (*)	High school or less	0.49	4.47	na	na	-0.24	-2.39	na	na
	Graduate degree(s)	na	na	na	na	na	na	-0.10	-2.15
Driving limitations (*)	General	na	na	0.33	3.31	na	na	0.23	2.42
	During night	na	na	na	na	na	na	0.24	3.21
Household characteristics									
Household income (*)	$100,000 to $150,000	0.17	2.08	na	na	na	na	na	na
	$100,000 or more	na	na	0.26	3.97	0.31	4.16	-0.10	-2.19
Household size (*)	One	0.40	5.74	na	na	na	na	na	na
	Two	na	na	na	na	na	na	-0.11	-2.61
	Three or more	na	na	0.27	4.85	na	na	na	na
Household structure (other)	Nuclear family	na	na	na	na	0.18	2.61	na	na
Household vehicle (one or more)	Zero	na	na	na	na	na	na	0.27	2.56

TABLE 3 (Continued)

Explanatory Variables (base category)		**Main Outcome Variables**							
		AVAM *(base: Averse)*						LMAT *5-level: strongly disagree (1) to strongly agree (5)*	
		Service only		Ownership only		Ownership and service			
		Coef	t-stat	Coef	t-stat	Coef	t-stat	Coef	t-stat
Other attributes									
Location (Austin, Atlanta, Tampa)	Phoenix	0.32	5.01	na	na	na	na	na	na
Online shopping (zero delivery)	1 or more monthly delivery	na	na	na	na	0.57	6.39	na	na
Work modality (other)	Telecommuter	na	na	na	na	0.25	3.93	na	na
Weekly VMT (0 or over 25 mi)	1 to 25 miles	na	na	-0.18	-2.58	-0.16	-2.15	na	na
Constant		-1.24	-16.22	-0.30	-5.04	-0.31	-2.63	na	na
Thresholds									
1|2		na	na	na	na	na	na	0.08	—
2|3		na	na	na	na	na	na	0.91	15.02
3|4		na	na	na	na	na	na	1.50	23.53
4|5		na	na	na	na	na	na	2.68	36.79
Correlation									
AVAM *(differenced w.r.t the base alt.)*	Service only	1	na	0.59	na	0.61	na	0.08	na
	Ownership only			1	na	0.67	na	0.11	na
	Ownership and service					1	na	0.15	na
LMAT								1	Na

Data Fit Measures	**GHDM**	**Independent (IOP) Model**
Predictive log-likelihood at convergence	-7553.04	-7770.84
Number of non-constant parameters	102	63
Constants-only predictive log-likelihood	-8317.15	
Predictive adjusted likelihood ratio index	0.0796	0.0582
Informal non-nested adjusted likelihood ratio test	$\Phi[-19.03] \approx 0.000$	
Average probability of correct prediction	0.113	0.111

Note: Coef = coefficient; "na" = not applicable; "—" = not statistically significant at the 90% confidence level.
*Base category is not identical across the model equations and corresponds to all omitted categories.

There are some interesting findings related to race. Blacks and Hispanics exhibit a stronger LMAT in an AV future, suggesting that they may have unmet travel needs at the present time (Klein and Smart, 2017). The race variables do not have any other significant coefficients, suggesting that – after controlling for other variables and latent attitudinal traits – race may not be all that much of a factor in determining adoption modality. Those with a lower level of education (high school or less) are more likely to adopt AVs in service-only mode and unlikely to adopt a full ownership-and-service modality, suggesting that they are likely to tread more carefully in the adoption of new technologies. Those with driving limitations likely experience diminished mobility at the current time and are therefore more likely to make additional trips in an AV future as AVs are likely to enhance their ability to travel. In addition, those with driving limitations exhibit a greater propensity to own AVs, presumably because that modality offers the greatest degree of control and flexibility.

Among household characteristics, income, household size and structure, and household vehicle ownership are influential variables. Higher income individuals are more likely to embrace ownership-based modalities, consistent with their propensity to own more vehicles at the present time. Those in the middle-high income bracket of $100,000 - $150,000 are more likely to adopt AVs in service-only mode, a finding that is worthy of further investigation. In general, higher income individuals use mobility services more than other income groups at the present time and this finding may be reflective of that experience (e.g., Magassy et al., 2023). Higher income individuals also depict a lower likelihood of making additional trips in an AV future, presumably because they are time constrained (higher income individuals tend to work longer hours) and are not mobility limited or constrained in any way at the present time. So, they do not have unmet travel needs that would motivate them to undertake net additional trips in an AV future.

Single individuals are more likely to embrace AVs in a service-only modality, consistent with what is found today with on-demand ridehailing service use (Lavieri and Bhat 2019; Magassy et al., 2023). Conversely, larger households are more likely to embrace an ownership modality while a nuclear family is likely to embrace AV technology in all its forms (ownership and service). These findings are consistent with expectations as larger households may desire to have the flexibility that comes with auto ownership. Household size and structure do not influence LMAT, except for individuals in two-person households who seem to more strongly disagree that they are likely to make additional trips in an AV future. Individuals in such households may not feel a need to make additional trips as their travel needs are largely met in the current transportation ecosystem.

Those residing in zero-vehicle households are likely mobility constrained at the current time, and hence exhibit a higher propensity to travel more in an AV future. This suggests that people who are currently mobility constrained hold out hope that they will be able to access opportunities and destinations to a greater degree when AVs become widely available. In terms of other attributes, those who currently travel only a modest amount on a weekly basis (1-25 vehicle miles of travel per week) are less likely to adopt AVs in ownership-based modalities, a finding consistent with expectations. Those in Phoenix exhibit a higher propensity to adopt AVs in service-only modality, possibly because residents of Phoenix have been exposed to AV testing and AV-based ridehailing services (Stopher et al., 2021). Those who embrace technology-enabled modalities for shopping and work are more likely to adopt AVs in both ownership and service modality, presumably because they are technophiles (Batur et al., 2023; Magassy et al., 2023). None of these attributes are found to significantly affect the likelihood of making additional trips directly (although they have an indirect effect through the AV adoption modality). Finally, goodness-of-fit measures are presented in the final section of Table 3. It is found that the joint model system offers a moderate, but statistically significant, improvement in fit over the independent model that ignores error correlations. The log-likelihood at convergence and the predictive adjusted likelihood ratio index are superior for the GHDM specification.

5. DISCUSSION AND CONCLUSIONS

The results of this study suggest that AV adoption modality (AVAM) significantly influences the likelihood of making additional trips (LMAT) in an AV future. Due to the discrete nature of the choice variables (one being multinomial and the other being ordinal), the coefficients shown in Table 3 do not represent the actual effects of AVAM on LMAT. To shed light on the magnitude of these effects, this section offers estimates of the Average Treatment Effects (ATEs) together with a discussion of the implications of the findings for planning and policy making.

When converting estimated coefficients into estimates of effects, it should be noted that the effects will vary across individuals due to the nonlinear nature of the model specification. To adjust for this, average effects are calculated by determining the mean effect of a variable across all individuals in the sample. The ATEs can then be calculated by computing the difference in mean outcomes between those assigned to the treatment group and those assigned to the control (base) group (in the case of the AVAM variable). Within the context of this study, ATEs demonstrate the influence of a downstream posterior variable resulting from a treatment that impacts an antecedent variable from state A to state B. For example, in this study, state A could represent individuals who are AV-averse while state B could represent individuals who fall solely into the service-only category. The impact of this transition is quantified as the change in the likelihood of making additional trips (LMAT). Further details regarding the calculation of ATEs, including mathematical formulations, may be found in Bhat and Eluru (2009).

Before calculating the ATEs of AVAM on LMAT, the LMAT variable is transformed into a binary variable from its original five-level ordered state for the sake of simplicity in interpretation of ATEs. The binary categories are "likely", which comprises the original categories of "very likely" and "somewhat likely", and "unlikely", which is a combination of the original response categories of "neutral", "somewhat unlikely", and "very unlikely". Following this transformation, the ATEs are calculated and tabulated as shown in Table 4. In addition to ATEs, the table also presents Percent Average Treatment Effects (PATEs), which indicate the magnitude of change in the outcome variable due to the treatment, relative to the base group.

TABLE 4 Average Treatment Effects for Making Additional Local Trips (N = 3,032)

Variable	Base level	Treatment	ATE	PATE (%)
AV Adoption Modality	Averse	Service only	0.14	239.5
		Ownership only	0.21	360.0
		Ownership and service	0.38	647.9
	Service only	Averse	-0.14	-70.5
		Ownership only	0.07	35.5
		Ownership and service	0.24	120.3
	Ownership only	Averse	-0.21	-78.3
		Service only	-0.07	-26.2
		Ownership and service	0.17	62.6
	Ownership and service	Averse	-0.38	-86.6
		Service only	-0.24	-54.6
		Ownership only	-0.17	-38.5

The values in Table 4 may be interpreted through an illustrative example. The impact of the service-only category of AVAM, relative to the AV-averse category, is 0.14 as measured by the ATE. This means that, if 100 individuals who initially expressed aversion towards AVs switched their adoption modality to service-only mode, the sample would see 14 additional instances of individuals likely to make additional trips. Although this number may seem small, the corresponding PATE for this effect is 239.5 percent. This means that the number of those in the "likely" category of LMAT (for these 100 individuals) increased by 239.5 percent as a result of this switch in adoption modality. The other values in the table can be interpreted similarly. The table does exhibit symmetry in the ATE and it is seen that the ownership-and-service modality consistently depicts the largest switch to the "likely" category of LMAT.

The findings of this study clearly demonstrate the potential induced demand effects of alternative AV adoption modalities. The likelihood of individuals making additional trips increases as the adoption modality becomes stronger – transitioning from a service-only adoption modality to one that involves *both* private AV ownership and use of AVs in a ridehailing service mode. The descriptive sample characteristics showed that only 7.4 percent expressed an intention to adopt AVs in service-only mode, while 44 percent expressed an intent to adopt AVs in *both* an ownership and service modality. Based on the findings reported in Tables 3 and 4, it would appear that this adoption modality exhibits the largest influence on the likelihood of making additional trips – thus pointing to a possible future in which AVs induce substantial additional vehicular travel.

While it may certainly be argued that these additional trips enhance mobility and access to opportunities (especially for historically mobility disadvantaged groups), cities should carefully consider the implications of alternative AV deployment modalities on their communities. In the midst of the excitement and hype surrounding AV developments and deployments, there is a growing concern that the convenience of AVs may lead to an increase in trip-making, including zero-occupant vehicle trips as AVs run errands, park themselves, and roam the streets. The convenience of AVs may also entice individuals to switch away from using alternative modes of transportation, thus leading to a more dystopian future of sprawl, more vehicular trips and congestion, and reduced use of alternative modes of transportation. The findings of this study, based on a survey conducted in 2019 in the car-centric metropolitan areas of Phoenix, Austin, Atlanta, and Tampa in the United States, suggest that this may indeed happen if jurisdictions do not adequately plan for the advent of AVs and AV-based mobility services.

This is not to say that AVs do not hold considerable promise to enhance mobility. Model results in this paper show that AVs may offer considerable mobility benefits for those who have driving limitations, the elderly, and the low income population. What is clear, however, is that ownership-based modalities tend to increase the likelihood of making additional trips in an AV future when compared with the service-only modality. In other words, the deployment of AVs in a (largely) service-only modality would enable the realization of the benefits of AV technology without an amplification of the potential negative consequences of such technological advances. AV ownership (and associated use) needs to be priced, taxed, and disincentivized so that the market embraces a service-only modality to a greater degree. AV-based mobility services should be subsidized, at least for the mobility disadvantaged groups, so that such services are embraced, experienced, and adopted to a greater degree than ownership-based modalities. Other policies restricting the use of AVs in zero-occupant vehicle mode may also help disincentivize AV ownership and prevent the unbridled growth in vehicle miles of travel.

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