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Understanding Interest in Personal Ownership and Use of Autonomous Vehicles for Running Errands: An Exploration Using a Joint Model Incorporating Attitudinal Constructs

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Abstract

Transportation has been experiencing disruptive forces in recent years. One key disruption is the development of autonomous vehicles (AVs) that will be capable of navigating roadways on their own without the need for human presence in the vehicle. In a utopian scenario, AVs may enter the transportation landscape and foster a more sustainable and livable ecosystem with shared autonomous electric vehicles (SAEV) serving mobility needs and eliminating the need for private ownership. In a more dystopian scenario, AVs would be personally owned by households—enabling people to live farther away from destinations, inducing additional travel, and roaming roadways with zero occupants. Concerned with the potential deleterious effects of having personal AVs running errands autonomously, this paper aims to shed light on the level of interest in sending AVs to run errands and how that variable affects the intent to own an AV. Using data from a survey conducted in 2019 in four automobile-oriented metropolitan regions in the United States, the relationship is explored through a joint model system estimated using the generalized heterogeneous data model (GHDM) methodology. Results show that even after accounting for socio-economic and demographic variables as well as latent attitudinal constructs, the level of interest in having AVs run errands has a positive and significant effect on AV ownership intent. The findings point to the need for policies that would steer the entry and use of AVs in the marketplace in ways that avoid a dystopian future.

Keywords

autonomous vehicles, planning and analysis, traveler behavior and values, attitudes/attitudinal data, behavior analysis

Rapid developments in the autonomous vehicle (AV) industry, coupled with technological advances in hardware, software, automation, and sensor systems, will enable vehicles of the future to navigate roadways without the need for human intervention (*1*). Although many of the early prognostications about the development, adoption, market penetration, and availability of AVs have not materialized because of the complexities involved in AV development (*2*), it is expected that transportation futures will increasingly be characterized by AVs (*3*).

There is considerable discussion on the manner in which AVs may enter the marketplace and be deployed in metropolitan areas and local communities (e.g., Litman [*2*], Fraedrich et al. [*4*]). On the one hand, a utopian future may be envisioned—one in which electric AVs are deployed by mobility service providers such that individuals can summon vehicles and share AV rides at an affordable cost. In such a scenario, the need for households to personally own vehicles would drop

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dramatically, the need for parking would reduce substantially thus enabling land to be put to enhanced uses that improve quality of life, and land use patterns would densify and diversify as individuals seek to position themselves such that trip lengths (and ride costs) are modest. On the other hand, a dystopian future may be envisioned—one in which households choose to purchase and own an AV for every household member, individuals send zero-occupant AVs to go park themselves in faraway places where parking is cheap or free, land use patterns become sprawled as households and businesses no longer feel the need to be near one another, and households deploy their personally owned AVs (with zero occupants) to run errands on their own. Several modeling exercises have suggested that the adoption of AVs will lead to increases in vehicle-miles traveled and associated adverse impacts on the transportation system (e.g., Auld et al. [*5*], Zhang et al. [*6*]). In addition, some studies have demonstrated through a variety of simulations that a future of shared autonomous electric vehicles (SAEV) would lead to considerable reductions in traffic volumes, congestion, air pollution, and parking needs (e.g., Zhang and Guhathakurta [*7*], Gurumurthy et al. [*8*], Jones and Leibowicz [*9*]).

In an effort to understand better how people may adopt and use AVs in the future, this study explores the relationship between the level of interest in using AVs to run personal errands (without vehicle occupants) and the level of interest in personally owning AVs. Although there is some survey-based research and evidence in the literature on the level of interest in purchasing AVs, there is little evidence on the level of interest in using AVs to run personal errands (autonomously). It may be hypothesized that households interested in sending AVs to run errands on their own are likely to be more inclined to own AVs personally. Thus, if technological capabilities allow AVs to be deployed autonomously to run errands, then that may spur greater levels of AV ownership—creating a dystopian future in which zero-occupant AVs roam the streets and households own AVs much like they own vehicles today.

The objective of this paper is to understand and assess the level of interest in sending AVs to run errands on their own and the extent to which this level of interest affects potential household ownership of personal AVs. The study utilizes data from an in-depth survey of a sample of households located in four metropolitan regions of the United States, namely, Phoenix, Austin, Atlanta, and Tampa. Households were asked detailed questions about their attitudes toward, and potential adoption and use of, AVs in the future. To account for the possibility that the two behavioral phenomena considered in this paper may constitute an activity-travel-lifestyle choice bundle, a simultaneous equations model system is estimated. The system jointly models the levels of interest in using AVs to run errands and personally owning AVs while accounting for common unobserved attributes that may affect both endogenous variables. In addition, the modeling framework incorporates latent attitudinal factors that may affect how individuals use and adopt AVs. The model system is estimated using the framework of the generalized heterogeneous data model (GHDM) developed by Bhat (*10*); the methodology enables the computation of all model parameters in a single step while accounting for error correlation structures that capture the jointness of the phenomena under investigation.

The literature has identified the importance of these choice dimensions (i.e., using AVs to run errands autonomously and personally owning AVs) as key determinants of the sustainability of future transportation systems in which AVs are widely prevalent (e.g., Lavieri et al. [*11*], Haboucha et al. [*12*], Nazari et al. [*13*], Harb et al. [*14*], Moore et al. [*15*]). If individuals wish to deploy AVs independently to run errands and consequently they own AVs personally, then it is more likely that a dystopian future will be realized. An understanding of the factors that contribute to levels of interest in deploying AVs to run errands and personally owning AVs, and of the extent to which the desire to have AVs run errands might influence the choice of personal AV ownership, is critical to designing an AV future that is sustainable and devoid of unintended consequences.

The remainder of this paper is organized as follows. The next section offers a description of the survey data and presents a descriptive analysis of the data with a focus on the dimensions of interest in this study. The third section presents the model framework and the modeling methodology. The fourth section presents model estimation results. The fifth section offers a discussion of the implications of the study and presents some concluding thoughts.

Data Description

This section provides a brief description of the survey and the data set used in this study. First, the survey and the sample characteristics are described. Second, a more in-depth descriptive analysis of endogenous variables and attitudinal indicators is provided.

Survey Overview and Sample Characteristics

The data used in this study were collected through a survey conducted in the fall of 2019 in four automobile-centric U.S. metropolitan areas. The areas were Phoenix (Arizona), Austin (Texas), Atlanta (Georgia), and Tampa (Florida). The survey gathered rich information about people's attitudes toward and perceptions of new and emerging transportation technologies including ride-hailing services, micromobility, and AVs. The survey also gathered data on socio-economic and demographic characteristics, current mobility choices, and general lifestyle attitudes and preferences. Across the four regions, data were collected from 3,465 respondents. The same survey instrument was administered in all regions; however, the sampling methodology differed to a modest degree between metropolitan areas as customized attempts were made to enhance response rates and obtain a robust respondent sample size. Respondents were largely recruited through invitations sent to a random set of e-mail and mail addresses purchased from a commercial vendor. All respondents who furnished complete responses to a core set of questions received a $10 gift card as a post-completion incentive. After some filtering and cleaning of the survey data for obviously erroneous and missing data, the final data set comprised 3,358 records. Complete details about the survey and respondent sample may be obtained from the comprehensive survey reports (*16*). Table 1 presents the socio-economic, demographic, and endogenous variable characteristics of the sample used in this study.

Overall, the sample characteristics are reasonable, consistent with expectations, and exhibit the desired level of variability to support an econometric simultaneous equations model estimation effort of the type undertaken in this study. The sample is slightly skewed in favor of females and the younger age group; 58.3% of respondents are female, and just over one-quarter of respondents are in the 18 to 30 year age group. There is however a good representation of all age groups in the sample. Just over 93% of respondents report having a driver's license. Over one-half of the sample reported being a worker (full or part-time), while over 26% reported being neither a worker nor a student. With respect to educational attainment, 36.7% report having a bachelor's degree and 24.5% report having a graduate degree, suggesting that the respondent sample is skewed toward a higher level of educational attainment relative to the general population. All races are represented, with over three-quarters White, just under 10% Asian or Pacific Islander, and nearly 8% of African American descent.

The income distribution of the sample represents a rich variation and representativeness of all income segments of the population. About 20% report incomes in the $100,000 to $149,999 range; about 27% report incomes less than $50,000; and nearly 19% report incomes greater than $150,000. It is found that 40% of respondents reside in households with three or more persons and 21% constitute single-person households. Just about 70% of individuals reside in stand-alone homes while another 20% reside in condo/apartment communities. Consistent with the residential dwelling unit type distribution, it is found that 68% own their home. On access to private vehicles, 40% of respondents reside in two-vehicle households, and 32.3% reside in households with three or more vehicles. The sample is evenly split between Phoenix, Atlanta, and Austin; Tampa accounts for a smaller fraction of the sample.

The level of interest in having AVs run errands is measured on a five-point Likert scale from strongly disagree to strongly agree with the following statement: "I would send an AV to pick up groceries/laundry/food orders by itself." Nearly one-half of the respondents strongly agree or somewhat agree that they would like to send AVs to run errands; 30% are not inclined to use AVs to run errands, and 20 % are neutral toward such usage. The level of interest in purchasing an AV for personal ownership is captured in three categories. Just 3.4% indicate that they will be the first to buy an AV, about 60% indicate that they will eventually purchase an AV, while another 36.4% of respondents indicate that they will never buy an AV (it is uncertain whether that is because they do not wish to adopt the technology at all or simply wish to adopt the technology in a pure sharing mode as opposed to an ownership mode). The first two response categories were combined, thus yielding a binary dependent variable with two levels: *will buy* or *will never buy*.

It is important to note that, when answering questions about AVs, respondents were asked to imagine a hypothetical future in which AVs are widely adopted (either personally owned or operated by ridehailing companies), but human-driven vehicles are still present. Also, respondents were provided with the following description of AVs as a preamble to the AV-related questions: "An Autonomous Vehicle 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, older adults), goes and parks itself, and picks up and delivers laundry, groceries, or food orders on its own." While one may argue that this description is not necessarily neutral (it conveys a positive image of AVs' capabilities), this description was necessary and appropriate to set the context for the AV-related questions presented to the survey respondents.

Endogenous Variables and Attitudinal Indicators

One of the key features of the survey dataset is that it includes a battery of attitudinal statements that can be used to develop latent attitudinal constructs which can, in turn, be incorporated into the modeling framework. By controlling for attitudes, it will be possible to obtain a deeper understanding of the extent to which interest in having AVs run errands would influence personal AV ownership. Three latent attitudinal constructs are

Table 1. Socio-Economic and Demographic Characteristics of the Sample

Individual characteristics (N = 3,358)		Household characteristics (N = 3,358)	
Variable	%	Variable	%
Gender		Household annual income	
Female	58.3	Less than $25,000	11.2
Male	41.7	$25,000 to $49,999	15.6
Age category		$50,000 to $74,999	18.9
18–30 years	26.3	$75,000 to $99,999	15.1
31–40 years	11.5	$100,000 to $149,999	20.4
41–50 years	14.8	$150,000 to $249,999	12.6
51–60 years	16.6	$250,000 or more	6.2
61–70 years	16.1	Household size	
71+ years	14.7	One	21.3
Driver's license possession		Two	38.5
Yes	93.4	Three or more	40.2
No	6.6	Housing unit type	
Employment status		Stand-alone home	70.2
Student (part-time or full-time)	10.2	Condo/apartment	20.6
Worker (part-time or full-time)	52.1	Other	9.1
Both worker and student	11.1	Homeownership	
Neither worker nor student	26.6	Own	68.3
Education attainment		Rent	26.0
High school or less	9.4	Other	5.7
Some college or technical school	29.4	Vehicle ownership	
Bachelor's degree(s)	36.7	Zero	3.9
Graduate degree(s)	24.5	One	23.8
Race		Two	40.0
Asian or Pacific Islander	9.6	Three or more	32.3
Black or African American	7.9	Location	
Multi race	3.9	Atlanta, GA	29.5
Native American	0.6	Austin, TX	32.3
Other	1.8	Phoenix, AZ	30.7
White or Caucasian	76.3	Tampa, FL	7.5
Endogenous variables			
Interest in having autonomous vehicles run errands		Interest in owning an autonomous vehicle	
Strongly agree	15.7	Will be one of the first to buy	3.4
Somewhat agree	33.8	Will eventually buy	60.2
Neutral	20.5	Will never buy	36.4
Somewhat disagree	15.8	na	na
Strongly disagree	14.2	na	na

Note: na = not applicable.

considered in this study. They are depicted in Figure 1, together with the set of indicators that define them.

The latent attitudinal construct representing "driving enjoyment" is encapsulated by three indicators, the construct representing "technology savviness" is captured using three indicators, and the latent construct of "environmental consciousness" is comprised of two indicators. The attitudinal indicators are measured on a five-point Likert scale ranging from strongly disagree to strongly agree. All of the indicators depict plausible distributions; in the interest of brevity, each and every statement is not described in detail, rather a few noteworthy patterns are highlighted here.

It is found that 50% of individuals prefer being a driver rather than a passenger when traveling in a vehicle. Nearly 37% somewhat or strongly disagree that AVs would make traveling by car less stressful for the individual, suggesting that many individuals do not necessarily see AVs as eliminating the stress of travel. Most of the respondents appear comfortable learning how to use new technologies; about 62% disagree that learning new technologies is frustrating. About 48% of the respondents are not in favor of the government raising the gas tax to combat pollution. Just about 39% are committed to using a less polluting means of transportation, while 30% indicate that they are neutral toward this statement.

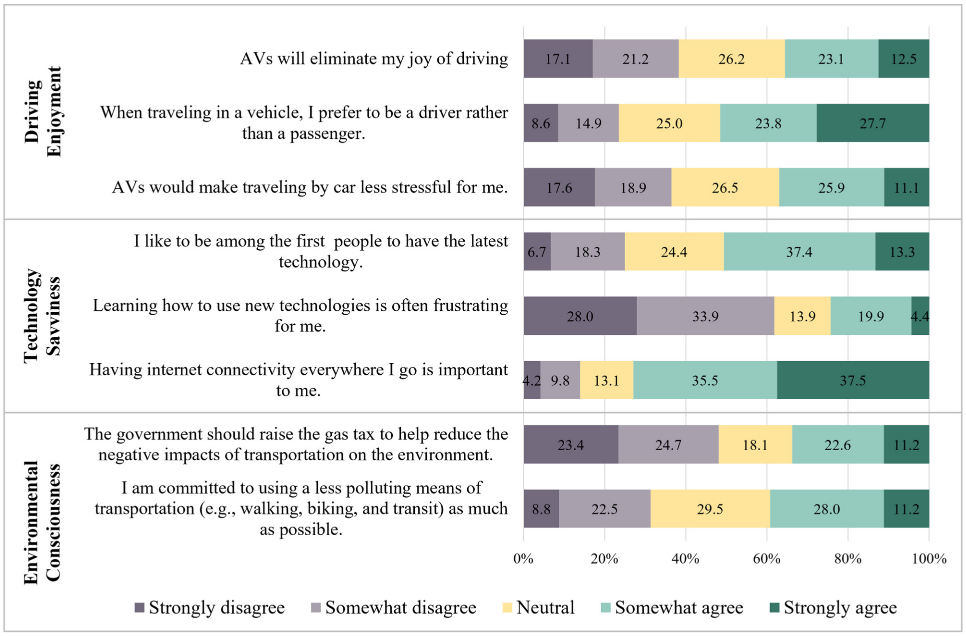

Figure 1. Distribution of attitudinal indicators defining latent constructs (N = 3,358).

Figure 2 shows the pattern of the relationship between the two endogenous variables. A reasonably clear inverse relationship is discernible. Among those who intend never to buy an AV, 30% strongly disagree that they will send an AV to run errands and just 6% strongly agree that they would. At the other end of the spectrum, among those who intend to be one of the first to buy an AV (arguably, these are few), just 4% strongly disagree that they would deploy AVs to run errands autonomously and a much larger 39% indicate strong interest in sending AVs to run errands on their own. The figure suggests that there is a relationship between the level of interest in having AVs run errands and the intended acquisition of AVs for personal ownership. A joint equations model system would help illuminate the nature of this relationship while controlling for other influential variables.

Modeling Framework

This section presents the modeling framework adopted in this paper. Recognizing the presence of multiple endogenous variables, and the desire to explicitly control for latent attitudinal constructs which are endogenous variables themselves, the study adopts a joint equations modeling framework capable of reflecting error correlations across latent constructs and endogenous variables.

Model Structure

The model framework is depicted in Figure 3. Exogenous variables include individual and household-level socioeconomic and demographic attributes and a host of other travel-related variables that characterize the established and routine mobility patterns of the individual (and therefore may be considered exogenous). The three latent attitudinal constructs constitute the intermediate layer of the model structure. They are influenced by exogenous variables and, in turn, influence the endogenous variables of interest. The exogenous variables can influence the endogenous variables directly or indirectly through the latent attitudinal constructs. The latent attitudinal constructs are not directly observable but concern unobserved stochastic variables revealed through individuals' responses to a set of attitudinal statements or indicators. Finally, the endogenous variables are related to one another, with the level of interest in sending AVs to run errands directly influencing the propensity to purchase an AV for personal ownership. Error correlations across the stochastic latent constructs are explicitly incorporated, and the latent construct errors engender an implied error correlation between the endogenous variables themselves. Thus, the framework accounts for the presence of correlated unobserved attributes simultaneously affecting latent constructs and the endogenous variables themselves. For purposes of parameter efficiency and to account fully for the endogeneity and error correlations

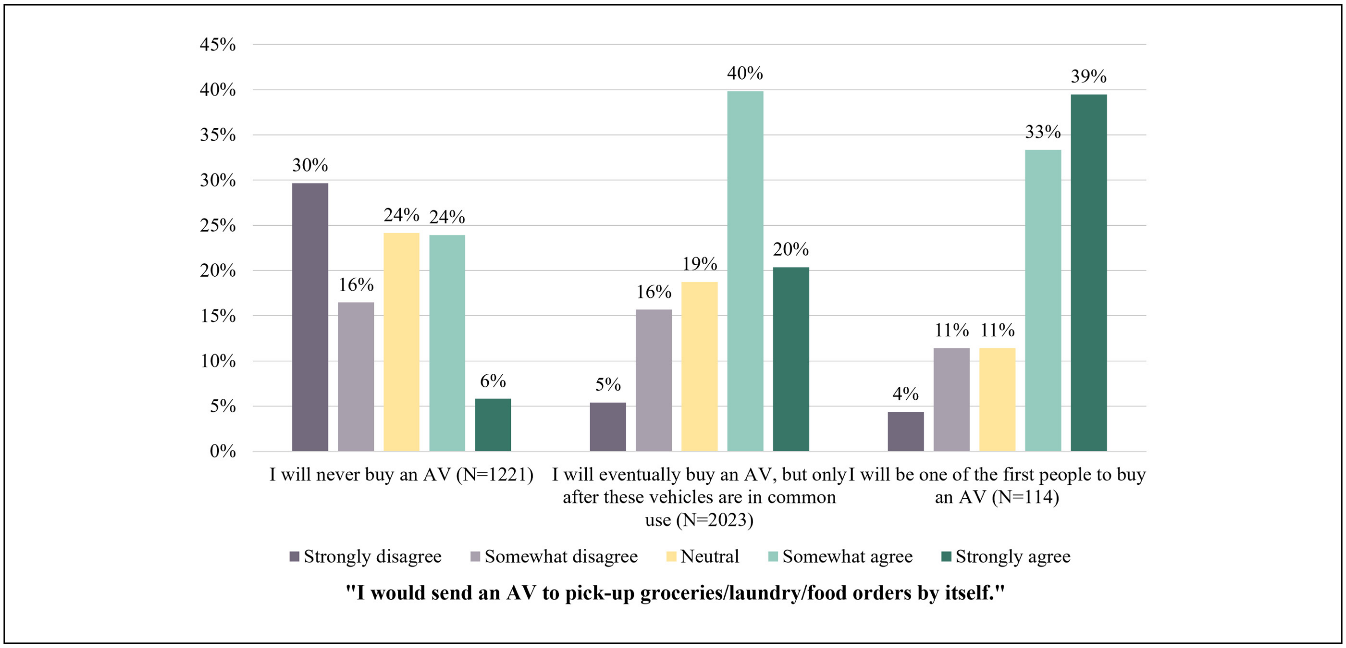

Figure 2. Intent toward ownership of autonomous vehicles (AVs) by interest in sending AVs to run errands (N = 3,358).

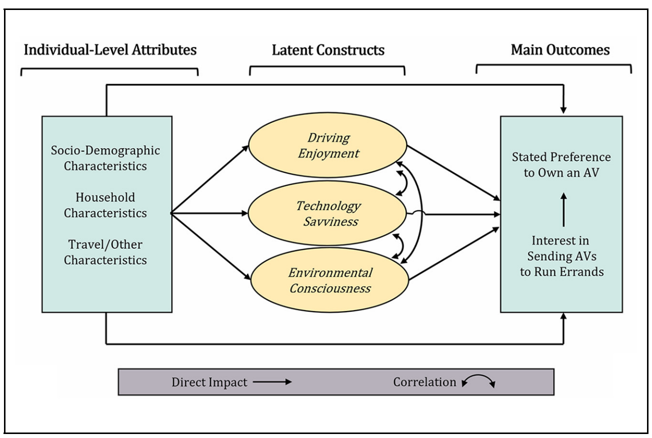

Figure 3. Framework of simultaneous equations model.

embedded in the model structure, it is desirable to estimate all parameters in the model system in a single step. The GHDM approach developed by Bhat (*10*) offers a rigorous methodology for estimating the model system. The methodology is presented in the next subsection.

Model Estimation Methodology

As all of the outcomes and indicators are ordinal in nature, the GHDM for this study is formulated for exclusively ordinal outcomes. Consider the case of an individual $q \in \{1, 2, \ldots, Q\}$. Let $l \in \{1, 2, \ldots, L\}$ be the index of the latent constructs and let z_{ql}^* be the value of the latent variable l for the individual q. z_{ql}^* is expressed as a function of its explanatory variables as,

$$z_{ql}^* = \boldsymbol{w}_{\boldsymbol{ql}}^{\mathrm{T}} \boldsymbol{\alpha} + \eta_{ql}, \tag{1}$$

where $\boldsymbol{w_{ql}}$ $(D \times 1)$ is a column vector of the explanatory variables of latent variable l and $\boldsymbol{\alpha}$ $(D \times 1)$ is a vector of its coefficients. η_{ql} is the unexplained error term and is assumed to follow a standard normal distribution. Equation 1 can be expressed in the matrix form as,

$$\boldsymbol{z_q^*} = \boldsymbol{w_q} \boldsymbol{\alpha} + \boldsymbol{\eta_q}, \tag{2}$$

where $\boldsymbol{z_q^*}$ $(L \times 1)$ is a column vector of all the latent variables, $\boldsymbol{w_q}$ $(L \times D)$ is a matrix formed by vertically stacking the vectors $(\boldsymbol{w}_{\boldsymbol{q1}}^{\mathrm{T}}, \boldsymbol{w}_{\boldsymbol{q2}}^{\mathrm{T}}, \ldots, \boldsymbol{w}_{\boldsymbol{qL}}^{\mathrm{T}})$, and $\boldsymbol{\eta_q}$ $(D \times 1)$ is formed by vertically stacking $(\eta_{q1}, \eta_{q2}, \ldots, \eta_{qL})$. $\boldsymbol{\eta_q}$ follows a multivariate normal distribution centered at the origin and having a correlation matrix of $\boldsymbol{\Gamma}$ $(L \times L)$, that is, $\boldsymbol{\eta_q} \sim MVN_L(\boldsymbol{0_L}, \boldsymbol{\Gamma})$, where $\boldsymbol{0_L}$ is a vector of zeros. The variance of all elements in $\boldsymbol{\eta_q}$ is fixed as unity because it is not possible to identify a unique scale for the latent variables. Equation 2 constitutes the structural component of the framework.

Let $j \in \{1, 2, \ldots, J\}$ denote the index of the outcome variables (including the indicator variables). Let y_{qj}^* be the underlying continuous measure associated with the outcome variable y_{qj}. Then,

$$y_{qj} = k \text{ if } t_{jk} < y_{qj}^* \leq t_{j(k+1)}, \tag{3}$$

where $k \in \{1, 2, \ldots, K_j\}$ denotes the ordinal category assumed by y_{qj} and t_{jk} denotes the lower boundary of the kth discrete interval of the continous measure associated with the jth outcome. $t_{jk} < t_{j(k+1)}$ for all j and all k. Since y_j^* may take any value in $(-\infty, \infty)$, the value of $t_{j1} = -\infty$ and $t_{j(K_j+1)} = \infty$ is fixed for all j. Since the location of the thresholds on the real line is not uniquely identifiable, $t_{j2} = 0$ is also set. y_j^* is expressed as a function of its explanatory variables and other observed dummy variable endogenous outcomes (only in a recursive fashion, if specified),

$$y_{qj}^* = \boldsymbol{x}_{qj}^{\mathrm{T}} \boldsymbol{\beta} + \boldsymbol{z}_q^{*\mathrm{T}} \boldsymbol{d}_j + \xi_{qj}, \tag{4}$$

where $\boldsymbol{x}_{qj}$ is an $(E \times 1)$ vector of the size of explanatory variables including a constant as well as including the possibility of other dummy variable endogenous outcome variables. $\boldsymbol{\beta}$ $(E \times 1)$ is a column vector of the coefficients associated with $\boldsymbol{x}_{qj}$ and $\boldsymbol{d}_j$ $(L \times 1)$ is the vector of coefficients of the latent variables for outcome j. ξ_{qj} is a stochastic error term that captures the effect of unobserved variables on y_{qj}^*. ξ_{qj} is assumed to follow a standard normal distribution. Jointly, the continuous measures of the J outcome variables may be expressed as,

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q \boldsymbol{\beta} + \boldsymbol{d} \boldsymbol{z}_q^* + \boldsymbol{\xi}_q, \tag{5}$$

where $\boldsymbol{y}_q^*$ $(J \times 1)$ and $\boldsymbol{\xi}_q$ $(J \times 1)$ are the vectors formed by vertically stacking y_{qj}^* and ξ_{qj}, respectively, of the J dependent variables. $\boldsymbol{x}_q$ $(J \times E)$ is a matrix formed by vertically stacking the vectors $\left(\boldsymbol{x}_{q1}^{\mathrm{T}}, \boldsymbol{x}_{q2}^{\mathrm{T}}, \ldots, \boldsymbol{x}_{qJ}^{\mathrm{T}}\right)$ and $\boldsymbol{d}$ $(J \times L)$ is a matrix formed by vertically stacking $\left(\boldsymbol{d}_1^{\mathrm{T}}, \boldsymbol{d}_2^{\mathrm{T}}, \ldots, \boldsymbol{d}_J^{\mathrm{T}}\right)$. $\boldsymbol{\xi}_q$ follows a multivariate normal distribution centered at the origin with an identity matrix as the covariance matrix (independent error terms). $\boldsymbol{\xi}_q \sim MVN_J(\boldsymbol{0}_J, \mathbf{I}_J)$. The terms in $\boldsymbol{\xi}_q$ are assumed to be independent because it is not possible to identify uniquely all correlations between the elements in $\boldsymbol{\eta}_q$ and all correlations between the elements in $\boldsymbol{\xi}_q$. Further, because of the ordinal nature of the outcome variables, the scale of $\boldsymbol{y}_q^*$ cannot be uniquely identified. Therefore, the variances of all elements in $\boldsymbol{\xi}_q$ are fixed to one. The reader is referred to Bhat (*10*) for further nuances on the identification of coefficients in the GHDM framework.

Substituting Equation 2 in Equation 5, $\boldsymbol{y}_q^*$ can be expressed in the reduced form as

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q \boldsymbol{\beta} + \boldsymbol{d}\left(\boldsymbol{w}_q \boldsymbol{\alpha} + \boldsymbol{\eta}_q\right) + \boldsymbol{\xi}_q, \tag{6}$$

$$\boldsymbol{y}_q^* = \boldsymbol{x}_q \boldsymbol{\beta} + \boldsymbol{d} \boldsymbol{w}_q \boldsymbol{\alpha} + \boldsymbol{d} \boldsymbol{\eta}_q + \boldsymbol{\xi}_q. \tag{7}$$

On the right side of Equation 7, $\boldsymbol{\eta}_q$ and $\boldsymbol{\xi}_q$ are random vectors that follow the multivariate normal distribution and the other variables are non-random. Therefore, $\boldsymbol{y}_q^*$ also follows the multivariate normal distribution with a mean of $\boldsymbol{b} = \boldsymbol{x}_q \boldsymbol{\beta} + \boldsymbol{d} \boldsymbol{w}_q \boldsymbol{\alpha}$ (all elements of $\boldsymbol{\eta}_q$ and $\boldsymbol{\xi}_q$ have a mean of zero) and a covariance matrix of $\boldsymbol{\Sigma} = \boldsymbol{d} \boldsymbol{\Gamma} \boldsymbol{d}^{\mathrm{T}} + \mathbf{I}_J$.

$$\boldsymbol{y}_q^* \sim MVN_J(\boldsymbol{b}, \boldsymbol{\Sigma}). \tag{8}$$

The parameters to be estimated are the elements of $\boldsymbol{\alpha}$, strictly upper triangular elements of $\boldsymbol{\Gamma}$, elements of $\boldsymbol{\beta}$, elements of $\boldsymbol{d}$, and t_{jk} for all j and $k \in \{3, 4, \ldots, K_j\}$. Let $\boldsymbol{\theta}$ be a vector of all parameters to be estimated. The maximum likelihood approach can be used for estimating these parameters. The likelihood of the qth observation is,

$$L_q(\boldsymbol{\theta}) = \int_{v_1 = t_{1y_{q1}} - b_1}^{v_1 = t_{1(y_{q1}+1)} - b_1} \int_{v_2 = t_{2y_{q2}} - b_2}^{v_2 = t_{2(y_{q2}+1)} - b_2} \cdots \int_{v_J = t_{Jy_{qJ}} - b_J}^{v_J = t_{J(y_{qJ}+1)} - b_J} , \\ \phi_J(v_1, v_2, \ldots, v_J | \boldsymbol{\Sigma}) dv_1 dv_2 \ldots dv_J \tag{9}$$

where $\phi_J(v_1, v_2, \ldots, v_J | \boldsymbol{\Sigma})$ denotes the probability density of a J dimensional multivariate normal distribution centered at the origin with a covariance matrix $\boldsymbol{\Sigma}$ at the point $(v_1, v_2, \ldots, v_J)$. Since a closed form expression does not exist for this integral and evaluation using simulation techniques can be time consuming, the one-variate vnivariate Screening technique proposed by Bhat (*17*) was used to approximate this integral.

Model Estimation Results

This section presents a summary of the model estimation results. The entire model framework presented in the previous section was estimated in a single step using the GHDM methodology.

Latent Construct Model Components

Table 2 presents results of the latent variable model components. The table shows the factor loadings for each of the attitudinal indicators used to construct the latent variables. Several different latent variable indicators were considered, and the set of indicators and latent constructs shown in Table 2 were adopted as the final set based on behavioral intuitiveness, past research, and statistical significance and goodness-of-fit metrics. The factor loadings are all intuitive and the latent constructs capture a range of proclivities that are likely to influence an individual's adoption and manner of usage of new transportation technologies such as AVs.

The latent factors are influenced by a host of socioeconomic variables as expected. There is a significant gender effect, with women less likely to be tech-savvy and less inclined to enjoy driving. These findings mirror those in the literature, with Asmussen et al. (*18*)

Table 2. Determinants of Latent Variables and Loadings on Indicators (N = 3,358)

	Structural equations model component					
	Driving enjoyment		Technology savviness		Environmental consciousness	
Explanatory variables (base category)	Coefficient	t-Statistic	Coefficient	t-Statistic	Coefficient	t-Statistic
Individual characteristics						
Gender (not female)						
Female	−0.13	−10.97	−0.32	−22.07	na	na
Age (*)						
18–30 years	na	na	0.85	41.17	na	na
31–40 years	na	na	0.73	29.05	na	na
31–65 years	na	na	na	na	−0.33	−19.24
61–70 years	0.43	26.97	na	na	na	na
71 years or older	0.53	31.09	na	na	na	na
Education (*)						
Some college or technical school	na	na	na	na	−0.22	−11.40
Bachelor's or graduate degree(s)	−0.23	−19.72	na	na	na	na
Graduate degree(s)	na	na	na	na	0.31	15.20
Household characteristics						
Household income (*)						
Up to $50,000	na	na	na	na	0.15	7.94
$150,000 or more	na	na	0.33	17.79	na	na
Correlations between latent constructs						
Driving enjoyment	1	na	−0.08	−1.25	−0.45	−6.53
Technology savviness	na	na	1	na	−0.17	−3.26
Environmental consciousness	na	na	na	na	1	na
Attitudinal indicators	Loadings of latent variables on indicators (measurement equations model component)					
Autonomous vehicles will eliminate my joy of driving.	1.07	38.97	na	na	na	na
When traveling in a vehicle, I prefer to be a driver rather than a passenger.	0.58	34.84	na	na	na	na
Autonomous vehicles would make traveling by car less stressful for me.	−0.73	−37.94	na	na	na	na
I like to be among the first people to have the latest technology.	na	na	0.54	30.46	na	na
Learning how to use new technologies is often frustrating for me.	na	na	−1.04	−25.98	na	na
Having internet connectivity everywhere I go is important to me.	na	na	0.28	20.56	na	na
The government should raise the gas tax to help reduce the negative impacts of transportation on the environment.	na	na	na	na	0.87	20.66
I am committed to using a less polluting means of transportation (e.g., walking, biking, and public transit) as much as possible.	na	na	na	na	0.48	22.71

Note: na = not applicable.

reporting similar gender effects for technology savviness and Rahimi et al. (*19*) reporting similar effects for driving enjoyment. On the other hand, gender is not significant for environmental consciousness, a finding also reported by Blazanin et al. (*20*) and Rahimi et al. (*19*). As expected, younger individuals appear to be more comfortable with technology, confirming earlier findings reported by Kang et al. (*21*). Older individuals exhibit a greater likelihood of enjoying driving, which is also consistent with recent literature which suggests that younger generations are eschewing driving in favor of alternative modes of transportation (*22*, *23*). The middle age group of 31 to 65 years is less likely to be environmentally conscious relative to other age groups. Although there are some mixed findings reported in the literature on the connection between age and environmental consciousness, this finding is supported by Lavieri et al. (*11*) and Otto and Kaiser (*24*). In general, it appears that environmental consciousness diminishes during the peak travel years in an individual's lifecycle. A negative correlation is found between technology savviness and environmental consciousness. This finding conflicts with results reported in the literature, with a few studies documenting a positive relationship (*25*, *26*). However, a statistically insignificant relationship between these specific latent constructs is also reported in the literature (*19*, *27*). This suggests that the nature of the relationship between technology savviness and environmental consciousness is yet to be fully resolved and may not be uniformly consistent across all locations.

Education is a significant determinant of the latent constructs. Higher education is associated with a greater level of environmental consciousness, a finding also reported by Lavieri et al. (*11*), and a lower level of desire for driving control, a finding similar to that reported by Asmussen et al. (*28*). On the other hand, education is not a significant determinant of technology savviness, suggesting that educational attainment is not necessarily a barrier to technology adoption. This is similar to findings reported in Lavieri and Bhat (*29*) and Moore et al. (*15*). There is, however, a significant income effect associated with technology savviness. Those in the highest annual income group of \$150,000+ appear to be more tech-savvy than lower income groups, suggesting that higher income households are more comfortable with being early adopters of new technology, a finding also reported by Dannemiller et al. (*30*). Individuals in lower income households reported a greater level of environmental consciousness, confirming findings reported in Lavieri et al. (*11*). As lower income communities have historically been disproportionately affected adversely when it comes to environmental impacts (e.g., Bullard and Wright [*31*]), this finding is not entirely unexpected.

Bivariate Model of Behavioral Outcomes

Table 3 shows the estimation results for the model components corresponding to the behavioral outcomes of interest, namely, level of interest in sending AVs to run errands and intention to own an AV. The key finding of this study is that there is a clear and significant positive impact of the level of interest in using AVs to run errands on the intention to own an AV, even after controlling for all other socio-economic, demographic, and latent attitudinal variables. This means that, if AVs are able to run errands on their own, then individuals who have an interest in engaging vehicles in such a manner will be significantly more inclined to own AVs personally. (Note that this effect of the desire to have AVs run errands on AV ownership may be considered a "true" causal effect, after accommodating the spurious unobserved correlation between the two variables engendered by the stochastic latent construct effects.)

All other findings reported in the table are consistent with expectations and behaviorally intuitive. Latent variables significantly influence behavioral dimensions in this study. The latent variable representing driving enjoyment reduces the propensity to send AVs to run errands and reduces the propensity to own an AV. This is consistent with the notion that those who enjoy driving would prefer to continue driving (manually) traditional vehicles rather than transition to AVs (*12*, *32*). Those who are tech-savvy, on the other hand, are more likely to send AVs to run errands and more likely to purchase and own AVs. Clearly, tech-savvy individuals are more likely to embrace new technology and use it to the fullest extent (*11*). Finally, environmental consciousness is associated with a reduced proclivity to own an AV, although the effect appears to be small as evidenced by the magnitude of the coefficient. Overall, latent attitudinal traits significantly influence an individual's proclivities toward embracing and using new and emerging transportation technologies.

Socio-economic and demographic characteristics affect the behavioral outcomes of interest along expected lines. Women are less inclined to own an AV, consistent with findings reported by Asmussen et al. (*18*) and Sener et al. (*32*). However, there is no gender effect on the level of interest in sending AVs to run errands. The youngest age group, aged 18 to 30 years, is most inclined to own AVs while those in the next age group of 31 to 40 years exhibit the greatest proclivity to send AVs to run errands. The youngest group is inclined to embrace the technology by virtue of their technology savviness and those in the 31 to 40 year age group are inclined to use AVs to run errands to take care of household obligations associated with this stage of the life cycle.

Contrary to previous studies that have largely reported no differences among racial groups with respect to AV adoption (e.g., Lavieri and Bhat [*29*], Wang and Zhao [*33*], Rahimi et al. [*19*]), the analysis in this paper reveals significant race effects, with Asians more inclined to own an AV and Whites exhibiting a greater proclivity toward sending AVs to run errands. Although the underlying reasons for these racial differences are not immediately apparent, recognizing their presence is critical to advancing equity in AV deployment. Not surprisingly, workers—who are likely to be more time-stressed—exhibit a greater proclivity to send AVs to run errands, but do not necessarily show a greater tendency to own AVs, a finding also reported by Asmussen et al. (*18*).

In general, higher income is associated with a higher probability of sending AVs to run errands and a greater proclivity toward purchasing AVs; these income effects are consistent with expectations and similar to those reported in prior studies (e.g., Moody et al. [*34*]). A

Table 3. Estimation Results of AV Errands and AV Ownership Model Components (N = 3,358)

	Main outcome variables			
	AV errands		AV ownership	
	Five levels: strongly disagree (1) to strongly agree (5)		Two levels: never buy (0) or buy (1)	
Explanatory variables (base category)	Coefficient	t-Statistic	Coefficient	t-Statistic
Endogenous variable				
Interest in sending AVs to run errands	na	na	0.39	48.99
Latent constructs				
Driving enjoyment	−0.37	−24.90	−0.54	−19.52
Technology savviness	0.20	13.20	0.24	8.95
Environmental consciousness	na	na	−0.06	−2.14
Individual characteristics				
Gender (not female)				
Female	na	na	−0.36	−15.68
Age (*)				
18–30 years	na	na	0.36	11.95
31–40 years	0.26	11.55	na	na
Race (*)				
Asian or Pacific Islander	na	na	0.41	11.23
White or Caucasian	0.08	5.21	na	na
Employment (not a worker)				
Worker	0.11	7.37	na	na
Household characteristics				
Household income (*)				
$150,000 to $250,000	0.19	8.96	na	na
$100,000 or more	na	na	0.33	16.60
Household structure (not a nuclear family)				
Nuclear family	na	na	0.15	6.24
Household vehicles (less than three)				
Three or more	−0.16	−10.93	na	na
Other characteristics				
Weekly vehicle miles traveled (less than 1 or over 25 mi)				
1 to 25 mi	na	na	−0.14	−6.02
Location (Austin, Phoenix, Tampa)				
Atlanta	0.05	3.62	na	na
Online shopping (zero delivery)				
At least one online delivery in last month	0.32	14.89	na	na
Thresholds				
1|2	−0.72	−28.22	0.90	30.30
2|3	−0.11	−4.40	na	na
3|4	0.49	19.29	na	na
4|5	1.61	58.95	na	na
Correlation				
AV errands	na	na	0.21	na

Data fit measures	GHDM	Independent model
Log-likelihood at convergence	−6966.52	−6990.25
Log-likelihood at constants	−7408.59	
Number of parameters	79	32
Likelihood ratio test	0.0597	0.0565
Average probability of correct prediction	0.153	0.152

Note: na = not applicable.
*Base category is not identical across the model equations and corresponds to all omitted categories.

nuclear family household (household with multiple adults and children) is more likely to purchase an AV, presumably because of the convenience that personal vehicle ownership affords in meeting the varied mobility needs of such a household. Households with three or more vehicles are less inclined to send AVs to run errands, presumably because there is a reduced need to share vehicles among household members in such households. Among the survey respondents, Atlanta residents indicated a higher propensity to send AVs to run errands; given that Atlanta suffers from some of the worst traffic congestion in the nation (*35*), this finding is not surprising. Other intuitive findings include the result that those who travel limited miles on a weekly basis (1–25 mi) are less inclined to own an AV and those who received at least one online delivery in the previous month are more likely to send AVs to run errands. Both results are consistent with expectations; those who do not travel much are naturally inclined to feel a lower need for personal ownership of an AV, while those who engage in online shopping are likely to use an AV to run errands (pick up goods and deliver to the home).

From a goodness-of-fit standpoint, the joint model is found to offer a modest but statistically significant better fit than a corresponding independent model system in which error correlations engendered through the endogenous treatment of latent attitudinal constructs are ignored (restricted to zero by virtue of treating attitudinal variables as exogenous variables, similar to socio-economic and demographic variables). This shows that modeling latent attitudinal constructs and behavioral outcomes of interest in an integrated framework that recognizes endogeneity is critical to capturing the jointness in attitudes and behaviors.

Discussion and Conclusions

Using data from a survey conducted in 2019 in four large automobile-oriented metropolitan regions (Phoenix, Austin, Atlanta, and Tampa) in the United States, this paper aims to shed light on the relationship between level of interest in sending AVs to run errands autonomously and the intent to purchase and own an AV personally. If households are interested in using AVs to run errands autonomously, then they may be more inclined to own AVs for themselves (rather than depend on a shared fleet for mobility services), thus contributing to a less sustainable transport future.

The relationship between interest in sending AVs to run errands and acquiring AVs for private ownership is explored through the specification and estimation of a joint simultaneous equations model system. The model structure adopted in this study explicitly accounts for the role of attitudinal factors in shaping the nature of the relationship between the two endogenous variables. The paper considers three latent attitudinal factors that are endogenous variables themselves. The model structure accounts for possible error correlations that may arise from the presence of correlated unobserved attributes that simultaneously affect multiple endogenous variables, thus capturing jointness in the behavioral dimensions of interest. The entire model system is estimated in a single step using the GHDM methodology.

The model estimation results show that, even after accounting for all socio-economic and demographic variables as well as latent attitudinal constructs, the level of interest in having AVs run errands has a positive and significant effect on AV ownership. In other words, those who have an interest in sending AVs to run errands are more likely to purchase and own AVs privately. The three latent constructs considered in this paper are measures of driving enjoyment, technology savviness, and environmental consciousness. These latent attitudinal factors influence both behavioral dimensions of interest and are themselves influenced by socio-economic and demographic characteristics. It is found that those who enjoy driving or are environmentally conscious are less likely to acquire AVs for personal ownership. Those who are tech-savvy are more likely to be interested in sending AVs to run errands and acquiring AVs for private ownership.

The findings point to the need to prepare for the advent of this technology in the transportation landscape. If and when AVs become a widespread reality, would it be desirable to have the technology capable of running errands autonomously? While such a feature may be of value to special market segments (such as those with mobility limitations), it is unclear if this capability is truly desirable on a widespread basis. Such technological capabilities may result in large numbers of AVs being used to run errands and roam the streets in zero-occupant mode. In addition, such capabilities could lead to private ownership of AVs on a larger scale, as evidenced by the findings in this study. For AVs to enter the transportation landscape in a more sustainable manner, it may be advisable to ensure that AVs cannot function in autonomous zero-occupant mode. This will limit the potential for induced travel and avoid a scenario where large numbers of zero-occupant vehicles are traveling on roadways.

If the technology is going to be capable of such zero-occupant travel (for running errands, parking itself, and picking up people at remote locations), then policies should be put in place to curtail the amount of such travel. Every zero-occupant vehicle trip could be assessed as liable to a fee to disincentivize the indiscriminate use of such technology. This would help ensure that only those zero-occupant trips that are truly necessary will be undertaken. In addition, the fee can vary by time of day, location, and size and fuel type of vehicle to advance a more sustainable approach to AV adoption and use. The other key finding is that environmental consciousness (latent factor) is associated with a lower proclivity toward AV ownership as well as a lower level of interest in sending AVs to run errands (relative to tech-savvy individuals). It may be helpful to organize information and awareness campaigns to raise environmental consciousness, especially concerning the adoption and use of AVs. Through such campaigns, it may be possible to prevent a dystopian scenario characterized by the unbridled use of AVs to run errands in autonomous mode.

Finally, these conclusions should be interpreted with caution as the study is limited in several ways. First, the data used in this study were collected through a survey conducted in the fall of 2019 in four automobile-centric U.S. metropolitan areas. Therefore, the findings reflect pre-pandemic conditions in auto-centric areas. It is entirely possible that the COVID-19 pandemic may have substantially changed the perceptions, attitudes, and lifestyle preferences of at least certain segments in the population—thus affecting the magnitude and significance of the effects of variables considered in the study. Second, respondents were asked to assume a future in which AVs are widely adopted (personally owned or operated by ridehailing companies), but human-driven vehicles are still present. For the question eliciting level of interest in using AVs to run errands, respondents were not explicitly told whether the AVs to run errands are personally owned or part of a shared service fleet operated by a ridehailing company. Future research efforts should strive to distinguish between running errands with personal AVs and running errands using a shared service. Another limitation is that the directionality between the main outcome variables assumed in this study may be reversed. It is hypothesized in this study that the level of interest in running errands with AVs affects the level of interest in personally owning AVs. However, the reverse relationship may also hold true. In other words, people who would like to own personal AVs may end up using them to run autonomous zero-occupant errands simply because the vehicle is available to them at all times in their own household. Unraveling the nature of the causal relationship would be a fruitful direction for future research.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: I. Batur, R. M. Pendyala, C. R. Bhat; data collection: I. Batur, T. B. Magassy, S. Khoeini, R. M. Pendyala, C. R. Bhat; analysis and interpretation of results: I. Batur, K. E. Asmussen, A. Mondal, R. M. Pendyala, C. R. Bhat; draft manuscript preparation: I. Batur, K. E. Asmussen, A. Mondal, T. B. Magassy, R. M. Pendyala, C. R. Bhat. All authors reviewed the results and approved the final version of the manuscript.

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