MODELING INDIVIDUAL PREFERENCES FOR OWNERSHIP AND SHARING OF AUTONOMOUS VEHICLE TECHNOLOGIES

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ABSTRACT

There is considerable interest in modeling and forecasting the impacts of autonomous vehicles on travel behavior and transportation network performance. In an autonomous vehicle future, individuals may privately own such vehicles, or use mobility-on-demand services provided by transportation network companies that operate shared autonomous vehicle fleets, or adopt a combination of these two. This paper presents a comprehensive model system of autonomous vehicle adoption and use. A Generalized Heterogeneous Data Model system is estimated on data collected as part of the Puget Sound Regional Travel Study. Results show that lifestyle factors play an important role in shaping autonomous vehicle usage. Younger urban residents who are more educated and tech-savvy are more likely to be early adopters of autonomous vehicle technologies, favoring a sharing-based service model over private ownership. Models such as that presented in this paper can be used to predict adoption of autonomous vehicle technologies, which will in turn help forecast autonomous vehicle impacts under alternative future scenarios.

1   INTRODUCTION

The autonomous vehicle (AV) era is rapidly approaching with a number of self-driving vehicle technologies in various stages of development and testing. General Motors, Nissan, Toyota, and Tesla – to name a few – expect to be shipping fully automated self-driving vehicles by 2020 (*1*). Selected Tesla automobiles are currently equipped with a number of sensors and software systems that provide automated driving capabilities beyond basic adaptive cruise control, such as automated lane changing, steering, and parallel parking (*2*).   Self-driving car prototypes developed by Google, Inc. have now logged more than 1.5 million miles as they undergo testing in a number of US cities (*3*).

Although the technology is rapidly evolving, there is considerable uncertainty related to consumer acceptance, adoption, and use of these technologies. Understanding and predicting the potential impacts of AV technologies on vehicle ownership and use, activity-travel behavior, and residential and employment location choices is critical to land use and transportation systems planning. The uncertainty related to traveler adoption and use of AVs stems from a number of sources. The exact specifications and attributes of the automated vehicles that will eventually find their way into the marketplace and be available for purchase by the public remain fuzzy. The few data sets that have been collected regarding people's attitudes towards these technologies are largely proprietary and based on surveys with a variety of differing assumptions and specifications to describe automated vehicle technologies and scenarios.

This study is motivated by the limited understanding of the adoption and impacts of AV technologies in the marketplace. On the one hand, households and individuals may replace their current vehicles with self-driving vehicles. These vehicles may have the ability to chauffeur household members between origins and destinations in a demand-responsive manner. On the other hand, these vehicles may be acquired by mobility providers including taxi companies, ride-sourcing services (such as Uber), and car-sharing services (such as ZipCar). Mobility service providers could operate AV fleets with travelers purchasing transportation by the trip, by the mile, by the minute, or any combination thereof.   In order to better understand consumer preferences for, attitudes toward, and adoption and potential use of AVs, this study uses a travel survey data set collected in the Puget Sound region of the State of Washington in the United States. The objective of the current research is to analyze travelers' interest in adopting AV technology and determine the extent to which they are inclined to acquire such vehicles for private ownership or use them in a shared mobility service configuration. To accomplish this objective, a generalized heterogeneous data model (GHDM) capable of accounting for latent lifestyle preference variables is developed and estimated (*4*). The model system accounts for existing household and individual choices such as current vehicle ownership, use of car-sharing and ride-sourcing services, and residential location. Through the computation of elasticity measures, the paper identifies potential early adopters of AVs, both in a private ownership mode as well as a shared mode.

The remainder of this paper is organized as follows. The next section provides a brief discussion on the role of AVs in personal travel. The third section presents the behavioral modeling approach, while the fourth section presents a description of the survey data set. Estimation results are presented in the fifth section. The sixth section offers an assessment of model performance and elasticity measures for AV usage. Conclusions and directions for future research are in the seventh section.

2 ROLE OF AUTONOMOUS VEHICLES IN PERSONAL TRAVEL

There is a growing body of literature devoted to the study of the potential adoption and impacts of transformative technologies in transportation. The two major transformative technologies of relevance in this paper are AV and mobility-on-demand services that are facilitated through car-sharing and ride-sourcing enterprises. With the advent of AV, the distinction between these two services is likely to fade as shared autonomous vehicle (SAV) fleets service transport demand in metropolitan areas.

Recognizing potential changes in transportation system performance in an AV future, researchers have examined the possible impacts of AV technology on highway capacity, vehicle ownership, vehicle miles traveled, and parking infrastructure needs. For instance, AV technology is conjectured to bring about substantial gains in highway capacity as vehicles are able to travel in platoons and communicate with one another and with infrastructure systems (*5*). While some studies do not differentiate between private AV ownership and mobility-on-demand SAV configurations (*6,7*), others do. For example, Spieser et al. (*8*) modeled the potential replacement of all modes of personal transportation by a fleet of SAVs in the city of Singapore, and found that mobility needs of the entire population may be met with one-third of the total number of passenger vehicles currently in operation. Other studies have focused on the current impacts of car-sharing services on vehicle ownership and travel demand (*9,10*). Firnkorn and Müller (*11*) conducted a survey of car2go car-sharing service users in the city of Ulm, Germany and concluded that membership in car2go services led to a significant increase in willingness to forego a private car purchase.

A critical shortcoming of many of the AV studies presented above is that they rely on a number of assumptions regarding market adoption and user acceptance of the emerging services and technologies to perform their assessment. Although there is some literature that addresses user preferences, concerns, and adoption of automated vehicle technologies, much remains to be learned in this particular domain. Kyriakidis et al. (*12*) reported that there is considerable heterogeneity in preferences and willingness to pay for automated vehicles, with those who drive more being more amenable to adopting and paying for automated vehicles. Bansal et al. (*13*) conducted a survey of 347 people in the city of Austin, Texas, and found that more than 80 percent of the respondents are interested in owning and using fully automated vehicles. Howard and Dai (*14*) collected data on opinions about self-driving cars in Berkeley, California, and reported that enhanced safety was the most attractive feature of self-driving cars to individuals, while lack of control was the most troubling feature.

While the literature cited above provides some insights on consumer preferences for advanced transportation technologies and services, there is limited understanding of how human attitudes and lifestyle factors affect potential adoption and use of these technologies. Schaefers (*15*) uses interviews and qualitative analysis methods to investigate the motivations behind car-sharing usage. She concludes that sense of community and identification with the lifestyle of other users are important motivating factors for car-sharing membership. More recently, de Almeida Correia and van Arem (*16*) noted that despite recent signs of shifts in car ownership and travel patterns brought on by the shared economy, "owning and using an automobile is still linked to both instrumental and symbolic-affective motives". Thus, lifestyle preferences, consumer attitudes, and perceptions need to be taken into account when modeling consumer adoption and use of transformative transportation technologies. This paper aims to shed light on the role played by lifestyle and attitudinal factors in shaping consumer interest in AV technology

as well as the preferred adoption configuration (private vehicle ownership versus using shared AV systems).

3 METHODOLOGY
This section presents the behavioral framework followed by a brief overview of the modeling methodology.

3.1 Behavioral Framework
In this paper, consumer interest in the adoption and use of AVs is modeled as a function of individual lifestyle preferences, attitudinal factors, and current use of disruptive transportation services. The current choices that are assumed to affect the interest in AV adoption include the use of car-sharing and/or ride-sourcing services, vehicle ownership, and density of the residential location. It may be expected that individuals who currently own vehicles are more likely to favor private ownership of AVs over shared use.

Among underlying lifestyle factors that may affect the propensity to adopt AVs, two key aspects are considered in this paper. These include "green lifestyle propensity" and "technology savviness". These factors have been identified in the literature as important determinants of transport choices (*15,17,18*). Consistent with the literature, we hypothesize that individuals who are green lifestyle oriented and technology-savvy are more likely to adopt AVs in private ownership mode or shared mobility-on-demand service mode, or both.

The use of latent lifestyle factors is critical to explaining traveler choices in different contexts. Lifestyle constructs are modeled in our framework as a function of demographic characteristics, as well as a function of characteristics unobserved to the analyst. Assuming lifestyle variables as independent variables in choice models, when in fact they are stochastic functions of socio-economic and demographic variables, will result in inconsistent model parameter estimates and erroneous inferences regarding the magnitude of the impacts of various factors on choice behaviors (*19*). At the same time, treating lifestyle factors as determinants of choice variables requires the specification and estimation of joint model systems (such as the one used in this study) capable of accounting for unobserved exogenous factors that jointly affect multiple endogenous outcomes. The joint model system also recognizes that individuals may be selecting a lifestyle package or bundle where a multitude of choices are made together. Figure 1 shows a simplified representation of the behavioral framework adopted in this study. The two lifestyle factors, green lifestyle and tech-savviness, are assumed to affect both current mobility choices as well as interest in AV adoption and use in the future.

The factor that represents the propensity for a green lifestyle corresponds to a number of variables present in the survey data set. These include the following:
- Frequency of transit usage, measured on a seven-point scale
  - Never
  - Have used transit, but not in the past month
  - 1-3 times per month
  - 1 day per week
  - 2-4 days per week
  - 5 days per week
  - 6-7 days per week
- Importance of a walkable neighborhood and being close to activities in choice of home location (five-point scale "very unimportant" to "very important")

- Importance of being close to public transit in choice of home location (same scale as above)
- Importance of being within a 30-minute commute to work in choice of home location (same scale as above)

The factor that captures tech-savviness corresponds to the following variables present in the survey data set:

- Smartphone ownership, measured on a three-point scale
  - Do not have and do not plan to buy a smartphone
  - Do not have but plan to buy a smartphone
  - Have a smartphone
- Frequency of use of smartphone apps for travel information, measured on a seven-point scale (same as scale used for "frequency of transit use" above)
- Frequency of use of in-vehicle GPS, measured on a seven-point scale (same as scale used for "frequency of transit use")

The choice variables are modeled as a bundle within a simultaneous equations modeling framework with latent constructs and socio-demographic variables serving as explanatory variables. There are five simultaneous choice models for the following endogenous outcomes:

- One multinomial choice variable representing interest in future adoption/use of AV
  - No interest
  - AV sharing only
  - AV ownership only
  - Both AV sharing and ownership
- Three binomial choice variables representing current choices including:
  - Has ever used car-sharing service (yes/no)
  - Has ever used ride-sourcing service (yes/no)
  - Household resides in high-density area (yes/no)
- One count variable representing household vehicle ownership

A number of model specifications were tested, and the final model specification was selected based on statistical significance and fit, behavioral intuitiveness of the model structure/relationships, and desired sensitivity in the model system.

3.2 Modeling Approach

The modeling methodology adopted in this study is based on the GHDM approach proposed by Bhat (*4*). This model enables the consideration of multiple ordinal, count, continuous, and nominal variables jointly using a latent variable structural equation model that ties latent constructs to exogenous variables, and a measurement model that links the latent variables and possibly other explanatory variables to a set of different types of outcomes. The approach uses a multinomial probit kernel for the discrete choices (nominal, binary, and ordinal outcomes) and captures the relationships among a large set of mixed data outcomes through a parsimonious set of unobservable latent factors. Details regarding the GHDM formulation, including sufficiency conditions for identification of model parameters, and the Maximum Approximate Composite Marginal Likelihood (MACML) estimation approach may be found in (*4*). The merits of the GHDM approach relative to other modeling methods in accounting for unobserved heterogeneity and self-selection effects (e.g., random parameters models and latent class analysis) are discussed in (*4,19*).

4   DATA

Data for this study is derived from the Puget Sound Regional Travel Study that involved survey data collection efforts in 2014 and 2015. The survey data includes detailed information about socio-economic, demographic, activity-travel characteristics, attitudes and preferences. For this research effort, the subset of households that provided complete data in both 2014 and 2015 surveys was used. Within this sample, individuals less than 18 years of age and individuals whose survey responses were collected through the use of a proxy were excluded. The final sample includes 1,832 individuals.

Autonomous vehicles were defined in the survey as follows: "Autonomous cars, also known as "self-driving" or "driverless" cars, are capable of responding to the environment and navigating without a driver controlling the vehicle". The survey included five questions about level of interest in AV adoption and usage. Two of the questions were used to construct a four-alternative multinomial choice variable that captures the level of interest in AV use. The two variables are:

- Level of interest in owning an autonomous car (five-point scale: "not at all interested", "somewhat uninterested", "neutral", "somewhat interested", and "very interested")
- Level of interest in participating in a SAV system for daily travel (same scale as above).

A descriptive analysis showed a substantial percent of respondents in the "not at all interested" category, with an additional small percentage in the "somewhat uninterested" category. Further, because of the ambiguity of the "neutral" category, the ordinal expression of interest was collapsed into a binary variable. Individuals who were somewhat interested and very interested were considered as being interested in the technology, while all others were treated as being uninterested. It should be noted that including the individuals that have a neutral interest in using AV technology in the category of "not interested" would provide a conservative estimate of adoption rates if the model is used for prediction purposes. Since the survey did not offer detailed explanations about the AV technology and service characteristics to respondents, being conservative and leaning towards a lower adoption rate estimate was considered prudent in this context. The binary indicators of the levels of interest in AV ownership and AV sharing were combined into a single multinomial variable with four alternatives as follows: (1) Not interested in AV sharing or AV ownership (68.5%); (2) Interested in AV sharing only (7.6%); (3) Interested in AV ownership only (8.5%); and (4) Interested in AV sharing and AV ownership (15.4%).

In addition, the survey collected information about the general level of concern that individuals had with respect to AV technology. Five questions captured the level of concern related to AV equipment and system safety, system and vehicle security, ability to react to the environment, performance in poor weather or other unexpected conditions, and legal liability for drivers or owners. The highest level of concern expressed on any of the questions except for the last one (related to liability) was considered the level of concern with AV technology, while the level of concern on the liability question was considered separately. AV technology concern was tested as an endogenous variable, but the influence of tech-savviness was found to be insignificant; hence it was treated as an exogenous variable in the final model specification.

The current usage of car-sharing or ride-sourcing services is represented by two binary dependent variables. Individuals who used either service at least once in their lifetime were considered "users" as opposed to those who had never used either service ("non-users").

Residential density was calculated for each census block, with blocks that had a density of 3,000 households per square mile or more treated as high-density locations. For the sake of brevity, a detailed table of descriptive statistics of the sample is not furnished. Overall, the sample exhibits characteristics that render it suitable for a modeling exercise such as that undertaken in this paper. It was found that 51% of the respondents resided in low-density neighborhoods, 12% resided in zero-vehicle households, and 39% resided in one-vehicle households. Those between 18 and 44 years of age constitute 37.5% of the sample. Among other characteristics of interest, 60% of respondents are workers, 44% are males, 93% have a driver's license, 38% have an undergraduate degree, and 29% have a graduate degree. Within the sample, 14% used a ride-sourcing service at least once, while 9.2% used a car-sharing service at least once in their lifetime. With respect to smartphone ownership, 67.7% of the respondents own a smartphone, and 28.5% of the respondents stated that they do not currently have a smartphone and have no plans to buy one.

5 MODEL RESULTS
This section provides a brief discussion of the model estimation results, which are furnished in Tables 1 and 2.

5.1 Structural Equation Model Results
The results of the structural equation model component are presented in the top half of Table 1. Both green lifestyle propensity and tech-savviness are associated with a higher level of education attainment. This finding is consistent with the prior literature; for example, Bhat (*20*) found education to be associated with green lifestyle, while Seebauer et al. (*18*) found a strong association between education level and technology adoption/use. Younger individuals show a greater propensity towards a green lifestyle, consistent with the findings of Garikapati et al. (*21*) who find that millennials use alternative modes of transportation more than other generations. Gender was not found to be significant in explaining lifestyle preferences.

Lower income households are more likely to be associated with a green lifestyle. Indeed, Bhat et al. (*22*) noted that a lower overall consumption level and higher alternative mode use in these households places them into the green lifestyle category relative to higher income households that tend to have a larger carbon footprint. On the other hand, lower income respondents tended to be less technology-oriented, which is consistent with expectations as there may be cost barriers involved. Workers are more prone to be tech-savvy, consistent with the notion that such individuals are likely to be exposed to technology in the workplace (*23*). Respondents in households with children are less likely to be associated with a green lifestyle; this finding is consistent with Bhat (*20*) who notes that households with children tend to favor suburban residential locations with larger homes and open spaces, leading to a less green lifestyle.

The correlation between tech-savviness and green lifestyle propensity was found to be statistically insignificant. It appears that the model specification captured the key variables associated with green lifestyle propensity and tech-savviness, resulting in an insignificant error correlation for the structural equation model component. Alternatively, the specification may have been such that positive and negative correlations caused by unobserved factors may have cancelled out, leading to the result found here.

5.2 Measurement Equation Results

The second half of Table 1 provides estimation results for the non-binary and non-multinomial endogenous variables of the measurement equation component. There are seven ordinal indicators (four indicators corresponding to green lifestyle propensity and three indicators corresponding to tech-savviness) and one count variable corresponding to number of vehicles in the household. The constant indicates the overall proclivity of the survey respondents, but does not have a behavioral interpretation per se. Focusing on the factor loadings, it can be seen that a green lifestyle is associated with a higher frequency of transit use, and a higher level of importance for living in a walkable neighborhood, close to transit, and within a 30-minute commute of work. Tech-savvy individuals exhibit a greater frequency of the use of apps for travel information, tend to own smartphones, and are more prone to using GPS for travel information. These findings are consistent with those reported in prior literature (*18*).

Table 2 presents estimation results for the measurement equation component associated with the binary/multinomial variables. With respect to AV use, it appears that the respondent sample is generally *not* inclined to use AV as evidenced by the negative alternative specific constants. Males are more inclined (than females) to be interested in both AV-ownership and sharing, while education does not have a statistically significant impact (though education does play a role through the latent constructs). Younger adults aged 18-24 years old appear to be less inclined towards AV ownership than adults 25 years or older. However, both age groups show a positive propensity to both own and share AVs. Note that these age effects go beyond those permeating to AV choice through the latent lifestyle constructs. As expected, lower levels of vehicle ownership are associated with a greater proclivity towards AV-sharing.

Fewer current vehicle holdings and residing in higher density neighborhoods lead to a higher propensity for AV sharing relative to no interest at all in AV, interest in AV ownership only, or interest in both AV ownership and AV sharing. Those residing in higher density neighborhoods are likely to favor AV sharing as they do not need to travel long distances to access destinations and may experience parking constraints. Individuals who have experienced car-sharing are less likely to favor ownership in an AV era, a finding that is consistent with that reported by Clewlow (*24*). Similarly, those who have used ride-sourcing services are more likely to favor AV-sharing, or AV-ownership coupled with sharing services. As expected, those who have a higher level of concern about AV technology are less likely to adopt it.

The latent variables have the expected impacts on future AV use, with a green lifestyle favoring AV sharing, and tech-savviness leading to a higher likelihood of embracing AV technology in general, and especially a combination of both AV ownership and AV sharing. The effects of these latent variables create heteroscedasticity and covariances across the utilities of the AV adoption alternatives in ways that are not likely to be as readily obvious as a covariance specification if a direct multinomial probit type model were to be estimated for the future AV use outcome. At the same time, the latent variables also impact current car-sharing and ride-sourcing experience, and current residential density living choice. This indicates that the effects of these latter variables on future AV use would be over-estimated if the stochastic latent variables were not included in the model system (and instead, car-sharing and ride-sourcing experience, and residential location density, were introduced directly as exogenous variables in the future AV choice component).

Results consistent with expectations are found in the other endogenous variables models. In the model of car-sharing experience, it is found that males are more likely than females to have tried car-sharing. Those with a driver's license, those residing in households with fewer

vehicles, and those in high density neighborhoods are more likely to have utilized car-sharing services. Similar indications are found in the model of ride-sourcing experience, except that gender and driver's license holding do not appear to be significant in the ride-sourcing model. As a driver's license is not needed to use ride-sourcing services, it is not surprising that this variable is insignificant in this specific model component. Green lifestyle propensity and tech-savviness are positively associated with the current use of car-sharing and ride-sourcing services.

6   MODEL ASSESSMENT AND ELASTICITY COMPUTATIONS

This section presents an assessment of model performance and offers pseudo-elasticity measures that may be used to determine the sensitivity of the adoption and use of AV technology to various factors. Table 3 presents results of the model assessment and elasticity computations.

The performance of the GHDM structure used here may be compared to one that assumes independence across the many endogenous outcomes (that is, across the current choices and future intentions shown in Figure 1). To arrive at a good initial specification for the second structure, an independent heterogeneous data model (IHDM) is estimated in which the determinants of the latent constructs are included directly as exogenous variables. This is an independent model because error term correlations across the choice dimensions are ignored. The GHDM and the IHDM models are not nested, but may be compared using the composite likelihood information criterion (CLIC) (20). The model that provides a higher value of CLIC is preferred. The two models can also be compared through a non-nested adjusted likelihood ratio test as described in Bhat (20). The results of these disaggregate data fit evaluations are provided in the first part of Table 3. The CLIC values clearly favor the GHDM over the IHDM. The same result is obtained when comparing the predictive likelihood values and adjusted likelihood ratio indices, and computing the non-nested likelihood ratio statistic.

Next, to examine the performance of the GHDM more intuitively, an "average probability of correct prediction" measure is computed for the future AV multinomial choice dimension of the model system. This is calculated to be 0.53. At the aggregate level, the actual sample shares and GHDM predicted shares are computed for the different alternatives related to future AV use and adoption. The predicted shares are computed by drawing 1,000 samples of 1,832 observations from a multivariate normal distribution and taking an average over the predictions. The absolute percent bias values in the predicted shares are quite small, suggesting that the model is able to recover overall shares quite well.

Elasticity measures were computed to identify early adopters of AV technology in general, and to identify market segments that may favor one form of AV adoption over another (i.e., sharing versus ownership or both). The elasticity results in Table 3 represent the percentage change in the probability of being in one of the four user categories. For example, being a worker increases the probability of an individual being interested in AV sharing by 20% (from 0.072 to 0.086). Overall, early adopters of AV technology are likely to be those with a higher level of education, individuals between 18 and 44 years of age, and workers. In particular, individuals in the youngest age group of 18-24 years show the greatest propensity for AV sharing and an aversion towards the AV ownership-only alternative. Individuals with a higher level of education are also more likely to adopt AV sharing as opposed to ownership or both, as evidenced by the higher elasticity measures within the AV sharing column. Lower income individuals appear to be largely averse to the adoption of AV technology in any form with those in the lowest income category showing the greatest level of resistance to adoption. While experience with the use of ride-sourcing services is associated with a propensity to adopt AV sharing and both sharing and

ownership, experience with car-sharing services does not contribute to adoption of AV. High density neighborhood residents are also more inclined to adopt AV sharing services as opposed to any model that involves ownership.

7   CONCLUSIONS

It is difficult to account for the potential impacts of AV technologies on transportation without an adequate understanding of how these vehicles might be adopted and used in the marketplace. There have undoubtedly been a few attempts to model the impacts of AVs on travel demand and transportation network performance, but these scenario tests often make exogenous assumptions about the level of penetration of AVs in the market, thus rendering the forecasts largely driven by speculative assumptions about how these vehicles will be adopted. There is very little research on consumer preferences for and potential adoption and use of AV technologies. This paper aims to contribute to this critical gap through a systematic modeling effort aimed at unraveling relationships underlying this behavioral phenomenon.

To better understand the level of interest of consumers in AV ownership and/or AV sharing, this paper utilizes travel survey data from the Puget Sound Region Travel Study to estimate a model that is capable of reflecting the bundle of mobility choices that people make simultaneously. Variables representing attitudes towards the built environment and technology use are used to construct two lifestyle factors, namely, green lifestyle propensity and technology-savviness. These latent lifestyle constructs are explicitly incorporated in models of current mobility choices and future intended use of AVs.

The model system presented in this paper identifies the market segments that are likely to be early (or late) adopters and the users inclined to sharing rather than ownership of AVs. Through this understanding, public and private entities can target specific information campaigns or policy interventions to bring about more socially and environmentally desirable outcomes. It is important for public agencies to identify users inclined to adopt different AV ownership and sharing paradigms because the impacts of AV technology on the transportation system are likely to be very different depending on the AV usage paradigm that prevails in the market. For instance, AV private ownership may lead to a larger increase in empty-vehicle-miles traveled because the vehicles may drop users and seek inexpensive parking in peripheral areas or go serve other household members in different parts of the city. In addition, being able to spend time in the comfort of one's own AV while making a trip may drastically reduce AV users value of travel time. Significant reductions in value of travel time could negate network efficiency gains brought about by AV platooning and even lead to an increase in congestion. On the other hand, a greater adoption of the AV-sharing model may help reduce empty-vehicle-miles and parking space requirements, while providing the ability to vary fares and avoid drastic reductions in value of travel time that could contribute to an increase in vehicle miles of travel.

This paper provides important insights for planners and modelers regarding the current use of shared mobility services and future AV adoption preferences. First, the results indicate that individuals with green lifestyle preferences and who are tech-savvy are more likely to adopt car-sharing services, use ride-sourcing services, and embrace SAV in the future. Further, the importance of considering these latent lifestyle constructs is clear from the rejection of the IHDM model relative to the GHDM model. Second, notwithstanding the need for more research on psychological motivations and factors to target those who may be positively disposed toward specific new mobility technologies and services, the results from this research effort show that younger, urban residents with a high level of education are more likely to be early adopters of

AV technologies, with a greater proclivity towards the use of vehicle-sharing services, *after controlling for lifestyle preferences*. Third, individuals who currently eschew vehicle ownership, and have already experienced car-sharing or ride-sourcing services, are especially likely to be early adopters of AV sharing services. On the other hand, individuals who currently own vehicles, and have not yet experienced car-sharing services, are more inclined to adopt AV technologies in an ownership or combined ownership and sharing mode. While ignoring lifestyle preferences would exaggerate the impacts of current vehicle ownership and current mobility choices on future AV adoption, the results clearly show impacts of current mobility choices even after controlling for self-selection. Fourth, the elasticity effects in Table 3 indicate that perhaps the most effective way to move AV adoption toward a sharing model (rather than an ownership model) is to enhance neighborhood densification. The fact that this effect prevails even after any residential self-selection effect brought on by the green lifestyle propensity (that increases the likelihood of locating in dense neighborhoods and adopting AV-sharing in the future) is very significant. It motivates the consideration of neo-urbanist land-use policies in an entirely new light relative to the traditional focus of such policies as a potential way to solely reduce motorized private car travel. This is especially so because, separate from a direct neighborhood effect, densification increases AV sharing adoption propensity through a reduction in vehicle ownership. Fifth, and related to the first point, green lifestyle is an important determinant of high density living and is associated with walking and public transit use, while also directly and indirectly (through high density living) influencing adoption of AV sharing. This suggests that a goal of increased AV sharing may be advanced through campaigns that increase awareness of the benefits of green living (especially targeted towards demographic groups who are traditionally not "green").

A larger issue to examine in the context of AV adoption in general, and AV sharing in particular, is whether these new mobility options will reduce bicycling and walking, and the use of public transportation (PT) services. Those who are "green" and those who reside in high density residential neighborhoods today are the very individuals most likely to currently use non-motorized and PT services. These individuals are also most likely to embrace AV sharing. It may be conjectured then that AV sharing will take modal share away from walking, bicycling, and PT. As a result, VMT or GHG reductions may not be realized (through shared AV services) as expected. Reduced walking and bicycling due to increased adoption of AV sharing services may also have adverse public health implications. This research effort not only provides important insights into future AV adoption, but also presents a model component that can be implemented within an agent-based microsimulation model system to predict adoption of AV technologies in the future. By considering latent (and stochastic) psychological constructs, it provides "true" estimates of the effects of current residential and mobility choices on future AV-related choices. Combined with the structural equation system that "connects" the latent constructs to observed demographic variables, the future AV adoption component of the joint model system provides a platform to forecast AV impacts under alternative future scenarios.

Future research efforts should strive to address the data limitations of this study. In this research effort, the intended AV use is derived from survey questions in which respondents express their level of interest in owning/using such technology in the future. The survey does not constitute a full-fledged stated choice experiment in which respondents are provided detailed descriptions of various AV options and attributes, pricing levels, and any incentives for owning or sharing AVs. A fruitful direction for future research involves an application of the modeling

framework of this study to stated choice data to gain further insights into user preferences for adoption/use of AV technologies.

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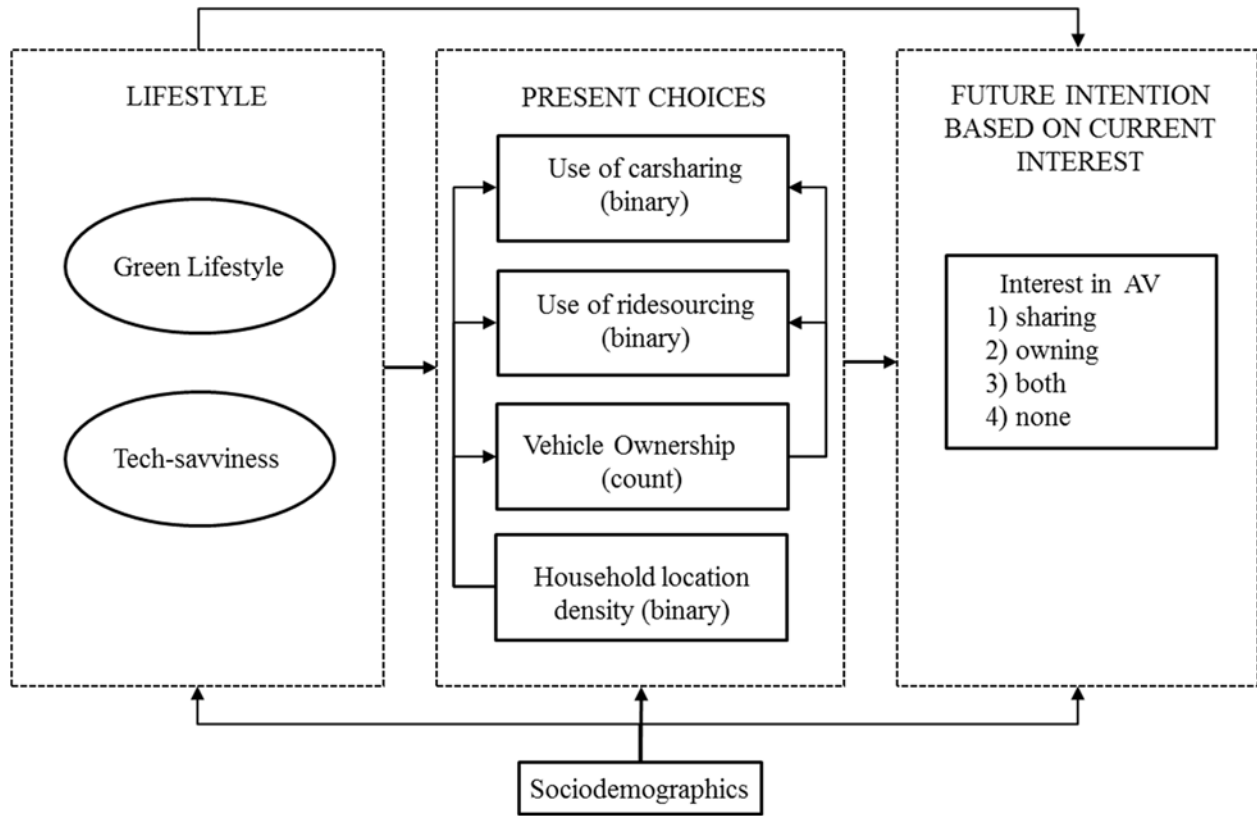
FIGURE 1 Simplified representation of behavioral modeling framework.

TABLE 1 Estimation Results for Structural and Non-Nominal Measurement Equations

Structural Equation Component	Green Lifestyle		Tech-savviness	
Variable	**Coefficient**	**(t-stat)**	**Coefficient**	**(t-stat)**
Education (base: less than Bachelor's degree)				
Bachelor's degree	0.363	(3.76)	0.180	(1.37)
Graduate degree	0.607	(4.41)	0.180	(1.37)
Age (base: 65+ years old)				
18 to 24 years old	0.986	(7.49)	1.196	(3.07)
25 to 44 years old	0.986	(7.49)	0.837	(6.07)
45 to 64 years old	0.482	(4.11)	--	--
Income (base: $75,000 or more per year)				
Under $24,999 per year	0.464	(4.70)	-0.769	(-1.23)
$25,000-$34,999 per year	0.464	(4.70)	-0.358	(-2.06)
$35,000-$74,999 per year	--	--	-0.358	(-2.06)
Employment status(base: non-worker)				
Worker	--	--	0.595	(1.73)
Household Composition (Base: no kids)				
Kids under 5 years old	-0.503	(-3.34)	--	--
Kids 5-17 years old	-0.743	(-5.01)	--	--
Correlation between latent variables	--			

Latent variables	Indicators/outcomes	Constant (t-stat)		Factor loading (t-stat)	
	Ordinal				
Green Lifestyle	Frequency that uses transit	0.002	(0.02)	0.889	(8.60)
	Importance of having a walkable neighborhood	1.439	(11.97)	0.586	(16.57)
	Importance of being close to public transit	0.692	(4.37)	1.085	(16.19)
	Importance of being within a 30-min commute to work	1.048	(12.51)	0.360	(9.33)
Tech-savviness	Frequency of smartphone app use for travel info	-3.450	(-1.76)	3.374	(5.89)
	Smartphone ownership	0.386	(0.10)	2.523	(6.72)
	Frequency of GPS use for travel info	-0.701	(-3.24)	0.248	(2.32)
	Count				
Green Lifestyle	Number of vehicles in the household	0.540	(1.24)	-0.322	(-3.22)

Exogenous variables impacting the number of vehicles in the household (count outcome)	
Number of adults in the household	0.806 (2.79)
High residential density of household census bock (more than 3000hh/mi²)	-0.653 (-1.69)

(--) coefficient was not statistically significant and was removed from the model.

TABLE 2 Model Estimation Results for Binary/Multinomial Endogenous Variables

Variable	Coef	t-stat	Coef	t-stat	Coef	t-stat
Type of AV Use (Base: not interested in AV)	**AV sharing**		**AV Ownership**		**Both**	
Constant	-1.578	(-8.70)	-0.707	(-6.19)	-2.876	(-9.61)
Gender (base: female)						
Male	--	--	--	--	0.337	(5.60)
Education (base: less than Bachelor's degree)						
Bachelor's degree	0.091	(1.40)	0.091	(1.40)	0.091	(1.40)
Graduate degree	0.091	(1.40)	0.091	(1.40)	0.091	(1.40)
Age (base: 45+ years old)						
18 to 24 years old	--	--	-0.168	(-1.89)	0.827	(3.75)
25 to 44 years old	--	--	--	--	0.827	(3.75)
Vehicles in the household (base: 2 or more)						
No vehicle	0.409	(6.08)	--	--	--	--
One vehicle	0.121	(2.01)	--	--	--	--
Residential density of household census bock (base: less than 3000hh/mi^2)						
High density	0.223	(5.05)	--	--	--	--
Has Experienced Carsharing (base: never)						
Used	--	--	-0.167	(-3.08)	--	--
Has Experienced Ridesourcing (base: never)						
Used	0.424	(4.42)	--	--	0.424	(4.42)
Concern about AV technol. problems (base: low)						
High level of concern	-0.088	(-2.17)	-0.088	(-2.17)	-0.088	(-2.17)
Latent Variable: Green Lifestyle Propensity	0.114	(1.33)	--	--	--	--
Latent Variable: Tech-savviness	0.207	(1.61)	0.132	(1.92)	0.300	(1.61)
Carsharing Experience (Base: never used)	**Used at least once**					
Constant	-5.632	(-10.15)				
Gender (base: female)						
Male	0.187	(3.22)				
Driver's license (base: doesn't have a license)	1.887	(9.74)				
Vehicles in the household (base: 2 or more)						
No vehicle	1.811	(9.86)				
One vehicle	0.486	(6.67)				
Residential density of household census bock (base: less than 3000hh/mi^2)						
High density	0.650	(8.29)				
Latent Variable: Green Lifestyle Propensity	0.454	(4.43)				
Latent Variable: Tech-savviness	0.706	(4.73)				
Ridesourcing Experience (Base: never used)	**Used at least once**					
Constant	-3.470	(-6.75)				
Vehicles in the household (base: 2 or more)						
No vehicle or one vehicle	0.213	(2.92)				
High residential density of household census bock (base: less than 3000hh/mi^2)						
High density	0.931	(11.63)				
Latent Variable: Green Lifestyle Propensity	0.451	(4.40)				
Latent Variable: Tech-savviness	0.941	(5.32)				
Residential Density (Base: < 3000hh/mi^2)	**High density**					
Constant	-0.869	(-11.95)				
Latent Variable: Green Lifestyle Propensity	0.990	(13.03)				
Latent Variable: Tech-savviness	--	--				

(--) coefficient was not statistically significant and was removed from the model.

TABLE 3 Model Assessment and Elasticity Computations

Summary Statistics	GHDM	IHDM
Composite Marginal log-likelihood value at convergence	-241,784.0	-277,212.7
Composite Likelihood Information Criterion (CLIC)	-242,606.7	-278,257.6
Log-likelihood at constants	-10,097.2	
Predictive log-likelihood at convergence	-9,466.4	-9,555.2
Number of parameters	97	112
Number of observations	1,832	1,832
Predictive adjusted likelihood ratio index	0.046	0.032
Non-nested adjusted likelihood ratio test between the GHDM and IHDM	Φ[-63.11]<<0.0001	

Disaggregate Goodness -of-fit				
Overall probability of correct prediction	0.53			

Shares of Level of Interest				
	Not interested	AV sharing	AV ownership	Both
Real sample shares	68.50%	7.64%	8.46%	15.39%
Predicted shares	68.98%	7.20%	7.96%	15.86%
Absolute percentage bias	0.70%	5.79%	5.92%	3.03%
Predicted shares for the population (after applying weights)	70.30%	4.88%	7.76%	17.06%

Elasticities				
Variable	Not interested	AV sharing	AV ownership	Both
Bachelor's degree (base: less than Bachelor's degree)	-2.33%	15.68%	4.94%	1.20%
Graduate degree (base: less than Bachelor's degree)	-2.91%	21.77%	4.94%	1.20%
Age 18 to 24 (base: ≥ 65 years)	-14.86%	24.24%	-42.86%	118.18%
Age 25 to 44 (base: ≥ 65 years)	-16.08%	12.12%	-10.71%	109.09%
Age 45 to 64 (base: ≥ 65 years)	-1.22%	12.12%	--	0.91%
Annual income < $25,000 (base: > $75,000)	6.62%	-10.67%	-20.00%	-11.45%
Annual income $25-35,000 (base: > $75,000)	3.09%	1.33%	-14.12%	-6.25%
Annual income $35-75,000 (base: > $75,000)	2.94%	-12.00%	-12.94%	--
Worker (base: non-worker)	-4.23%	20.31%	18.06%	6.67%
Kids under 5 years old (base: no kids)	2.17%	-6.62%	1.41%	2.31%
Kids 5-17 years old (base: no kids)	3.04%	-7.94%	2.09%	3.30%
Experienced carsharing (base: never)	4.29%	--	-40.96%	--
Experienced ridesourcing (base: never)	-9.86%	92.31%	-17.07%	18.75%
High density household census block (base: <3,000 hh/mi^2)	-5.59%	44.86%	--	-5.96%

(--) coefficient was not statistically significant and was removed from the model.